INEX

Initiative for the Evaluation of XML retrieval

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Preface

The aim of the workshop is to bring together researchers in the field of XML retrieval who participated in the Initiative for the Evaluation of XML retrieval (INEX) during 2003. The aim of the INEX initiative is to provide means, in the form of a large XML test collection and appropriate scoring methods, for the evaluation of XML retrieval systems. During the past year participating organisations contributed to the building of a large-scale XML test collection by creating topics, performing retrieval runs and providing relevance assessments along two relevance dimensions for XML components of varying granularity. The workshop concludes the results of this large-scale effort, summarises and addresses encountered issues and devises a work plan for the evaluation of XML retrieval systems.

The workshop was organised into presentation and workshop sessions. During the presentation sessions participants had the opportunity to present their approaches to XML indexing and retrieval. The workshop sessions (organised as working groups) served as discussion forums to review issues related to the creation of the INEX topics, the definition of the two relevance dimensions, the use of the on-line assessment system, and the development of evaluation metrics.

These proceedings start with an overview paper describing INEX 2003, and then continue with research papers that were submitted to INEX 2003. These papers are revised versions of those appearing in the pre-proceedings, and have been through peer reviewing. Theses papers have been classified according to the following approaches:

Model-Oriented Approaches: these are approaches based on established information retrieval models like e.g. vector space model, language model, logistic regression model or Bayesian inference model. This type of approaches was further classified according to sub-categories such as language models, (other) probabilistic models, result fusion, enriched representations and other models.

System-Oriented Approaches: these are approaches that focused more on system aspects, like e.g. adding an XML-specific post processing step to “normal” text retrieval engine, using a relational database for query processing, or performing retrieval in a distributed environment. Further classification was made according to sub-categories such as database systems and information retrieval systems.

In addition to the overview paper and research papers, these proceedings include papers on a query language and a metric for INEX, and papers summarising the discussion and outcome of the working groups. The guideline documents distributed to the participants are also included.

Schloss Dagstuhl

Schloss Dagstuhl or Dagstuhl manor house was built in 1760 by the then reigning prince Count Anton von Öttingen-Soetern-Hohenbaldern. After the French Revolution and occupation by the French in 1794, Dagstuhl was temporarily in the possession of a Lorraine ironworks. In 1806 the manor house along with the accompanying lands was purchased by the French Baron Wilhelm de Lasalle von Louisenthal. In 1959 the House of Lasalle von Louisenthal died out, at which time the manor house was then taken over by an order of Franciscan nuns, who set up an old-age home there. In 1989 the Saarland government purchased the manor house for the purpose of setting up the International Conference and Research Center for Computer Science. The first seminar in Dagstuhl took place in August of 1990. Every year approximately 2,000 research scientists from all over the world attend the 30-35 Dagstuhl Seminars and an equal number of other events hosted at the center.

http://www.dagstuhl.de/

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Overview of the INitiative for the Evaluation of XML Retrieval (INEX) 2003

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1. INTRODUCTION

The widespread use of the extensible Markup Language (XML) in scientific data repositories, digital libraries and on the web, brought about an explosion in the development of XML retrieval systems. These systems exploit the logical structure of documents, which is explicitly represented by the XML markup, to retrieve document components, the so-called XML elements, instead of whole documents, in response to a user query. This means that an XML retrieval system needs not only to find relevant information in the XML documents, but also determine the appropriate level of granularity to return to the user, and this with respect to both content and structural conditions.

Evaluating the effectiveness of XML retrieval systems requires a test collection (XML documents, tasks/queries, and relevance judgements) where the relevance assessments are provided according to a relevance criterion that takes into account the imposed structural aspects. A test collection as such has been built as a result of two rounds of the Initiative for the Evaluation of XML Retrieval (INEX 2002 and INEX 2003). The aim of this initiative is to provide means, in the form of a large testbed and appropriate scoring methods, for the evaluation of content-oriented retrieval of XML documents.

This paper presents an overview of INEX 2003. In section 2, we give a brief summary of the INEX participants and their systems. Section 3 outlines the retrieval tasks. Section 4 provides an overview of the INEX test collection along with the description of how the collection was constructed. Section 5 briefly reports on the submission runs for the retrieval tasks. Section 6 describes the relevance assessment phase. Section 7 discusses the different metrics used. Section 8 summarises the evaluation results. The paper finishes with some conclusions and outlook for INEX 2004.

2. PARTICIPATING ORGANISATIONS

In response to the call for participation issued in March 2003, around 40 organisations registered from 18 different countries within six weeks. Throughout the year, the number of participants decreased due to insufficient contribution while a number of new groups joined later at the assessment phase. The active participants are listed in Table 1.

The participating groups used a broad variety of approaches for performing XML retrieval. We tried to categorise them into two approaches [Fuhr & Lalmas 04]:

Model-oriented approaches (MO) were based on established information retrieval (IR) models; e.g. vector space model, language model, logistic regression or Bayesian inference model.

System-oriented approaches (SO) focused more on systems aspects; e.g. adding an XML-specific post-processing step to a normal text retrieval engine, using a relational database system for query processing, performing retrieval in distributed environment.

Participants and their corresponding approaches (i.e. MO vs. SO) are shown in Table 1.

3. THE RETRIEVAL TASKS

In INEX 2003, we focused on ad hoc retrieval. This task has been described as a simulation of how a library might be used, where the collection of documents is known while the queries to be asked are unknown [Voorhees & Harman 02]. Three ad hoc retrieval sub-tasks were defined in INEX 2003: the CO (content-only), SCAS (strict content-and-structure) and VCAS (vague content-and-structure) ad-hoc retrieval of XML documents. Within the CO task, the aim of an XML retrieval system is to point users to the specific relevant portions of documents, where the user's query contains no structural hints regarding what the most appropriate granularity of relevant XML elements should be. Within the SCAS task, the aim of a retrieval system is to retrieve relevant nodes that strictly match the structural conditions specified within the query. In the VCAS task, the goal of a system is to retrieve relevant nodes that may not exactly conform to the structural conditions expressed within the user's query, but are structurally similar. CO and (S/V)CAS are discussed in Section 4.2.

4. THE TEST COLLECTION

Like most IR collections, the INEX test collection is composed of three parts: the set of documents, the set of topics and the relevance assessments.

4.1 Documents

The document collection was donated to INEX by the IEEE Computer Society. It consists of the full-text of 12,107 articles, marked up in XML, from 12 magazines and 6 transactions of the IEEE Computer Society's publications, covering the period of 1995-2002, and totalling 494 MB in size, and 8 millions in number of elements. The collection contains scientific articles of varying length. On average, an article contains 1,532 XML nodes, where the average depth of the node is 6.9. More details can be found in [Gövert & Kazai 03]

Organisations	Retrieval approach	no of runs submitted	Assessed topics
University Of Otago	SO	2	68 100 101
LIP 6	MO	3	82 116
Carnegie Mellon University	MO	3	75 113
University of California, Berkeley	MO	6	70 102
Tarragon Consulting Corporation	MO		88 105
Queensland University of Technology	SO	11	89 124
RMIT University	SO	6	86 117
Nara Institute of Science and Technology	MO	5	65 125
doctronic GmbH & Co. KG	SO	4	107 108
University of the Saarland	MO	4	69 79
University of Amsterdam	MO	9	71 103 104
University of Helsinki	MO	3	111 112
University of Bayreuth	SO	9	95 96
University of California, Los Angeles	MO	3	92 98
IBM, Haifa Research Lab	MO	9	85 90
University of Minnesota Duluth	MO	2	87 121
University of Tampere	MO	6	64 93
Royal School of LIS	MO	3	62 97
Institut de Recherche en Informatique de Toulouse	SO	9	73 91 94
Cornell University	MO	1	80 81 123
University of Rostock	MO	0	61 115 122
University of Michigan	MO	2	77
University of Twente and CWI	SO	5	74 109 110
Hebrew University	MO	6	72 119
Universität Duisburg-Essen	MO	9	66 99
Organisations joining at the relevance assessments phase:			
Waterloo University			76
Oslo University College			63 67
Seoul National University			78 126
Czech Technical University			83 84
Illinois Institute of Technology			118

Table 1: List of INEX 2003 participants

4.2 Topics

The topic format and guidelines were based on TREC guidelines, but were modified to accommodate the two types of topics used in INEX: CO and CAS topics:

Content-and-Structure (CAS) queries are topic statements that allow the query conditions to explicitly refer to XML document structure by restricting either the context of interest or context of certain search concepts.

Content-Only (CO) queries are requests that ignore document structure and contain only content-related conditions.

4.2.1 Topic format

The topic is made up of four parts: topic title, topic description, narrative and keywords. The DTD of the topic is shown in Figure 1.

As in TREC, the topic title is a short version of the topic description and usually consists of a number of keywords identifying the user need. CO topics are the same as the standard TREC topics for ad hoc retrieval tasks. CAS topic title may contain structure and content related conditions. In INEX 2003, the format of the title part of CAS topic was based on an enhanced subset of XPath. A concept of “aboutness” in the form of *about(path,string)* was added. The about function usually applies to a context element (CE) that can be described by the syntax "CE[about(path,string)]". For example //article[about(//sec,’"XML retrieval"’)] represents the request to retrieve articles, article being the context element, that contain within them a section about "XML retrieval". The string parameter in the about condition may contain a number of terms separated by a space, where a term can be a single word, or a phrase encapsulated in double quotes. Furthermore symbols +,- maybe used to express additional preference regarding the importance of some terms, where + can be used to prioritise terms while - can be used to mention unwanted terms.

The topic description consists of one or two sentences in natural language describing the information need. The narrative is the detailed explanation of the topic statement and description of what makes a document or component relevant. The keyword component contains the set of terms separated by comma that were collected during the topic development process (see Section 4.2.2).

The attributes of the topic are: topic_id (which ranges from 61 to 126), query_type (with value CAS or CO) and ct_no, which refers to the candidate topic number (which ranges from 1 to 120). Examples of both types of topic can be seen in Figure 2 and Figure 3.

4.2.2 The topic development process

The topics were created by participating groups. Each participant was asked to submit up to 6 candidate topics (3 CO and 3 CAS). A detailed guideline was provided to the participants for the topic creation [Kazai et al. 04b]. Four steps were identified for this process: 1) Initial Topic Statement creation 2) Collection Exploration 3) Topic Refinement and 4) Topic Selection. The first three steps were performed by the participants themselves while the selection of topics was decided by the organisers.

During the first step, participants created their initial topic statement. These were treated as a user’s description of his/her information need and were formed without regard to system capabilities or collection peculiarities to avoid artificial or collection biased queries. During the collection exploration phase, participants estimated the number of relevant documents/components to their candidate topics. The HyREX retrieval system [Fuhr et al. 02] was provided to participants to perform this task. Participants had to judge the top 100 retrieved results and were asked to record the relevant document/component XPath paths in the top 25 retrieved components/documents and the number of relevant documents/components in the top 100. We were interested in topics that would have at least 2 relevant documents/components and less than 20 documents/components in the top 25 retrieved elements. In the topic refinement stage, the topics were finalised ensuring coherency and that each part of the topic can be used in stand-alone fashion.

After the completion of the first three stages, topics were submitted to INEX. A total of 120 candidate topics were received, of which 66 topics (36 CO and 30 CAS) were selected. The topic selection was made on the basis of a combination of criteria such as 1) balancing the number of topics across all participants, 2) eliminating topics that were considered too ambiguous or too difficult to judge and 3) uniqueness of topics. Table 2 shows some statistics on the INEX 2003 topics.

5. SUBMISSIONS

Participants processed the final set of topics with their retrieval systems and produced ranked lists of 1500 result elements in a specific format. Details of the submission format and procedure were given in [Kazai et al. 04a]. For the CO task, they were asked to submit up to 3 runs per topic and for the two CAS sub-tasks, SCAS and VCAS, up to 3 runs for each could be submitted per topic. In total 120 runs were submitted by 24 participating organisations. Out of the 120 submissions, 56 contained results for the CO topics, 38 contained results for the SCAS topics and 26 contained results for the VCAS topics. For each topic, the top 100 results (of 1,500) from all the submissions for that topic were merged to create the pool for assessment. Table 3 shows the pooling effect on the CAS and CO topics.

6. ASSESSMENTS

The assessments pools were assigned then to participants; either to the original authors of the topic when this was possible, or on a voluntary basis, to groups with expertise in the topic’s subject area. Each group was responsible for about two topics. The topic assignments are shown in Table 1. Note that this list excludes topics 105,106,114 and 120 as their relevance assessment process is still in progress.

Two dimensions were employed to define relevance:

Exhaustivity (e-value) measures the extent to which the given element covers or discusses the topic of request.

Specificity (s-value) measures the extent to which the given element is focused on the topic of request.

For both dimensions, a multi-grade scale was adopted. With respect to exhaustivity:

Not exhaustive (0): the document component does not discuss the topic of request at all.

Marginally exhaustive (1): the document component discusses only few aspects of the topic of request.

Fairly exhaustive (2): the document component discusses many aspects of the topic of request.

Highly exhaustive (3): the document component discusses most or all aspects of the topic of request.

With respect to specificity:

Not specific (0): the topic of request is not a theme of the document component.

```
<!ELEMENT inex_topic  (title,description,narrative,keywords)>
<!ATTLIST inex_topic
  topic_id   CDATA  #REQUIRED
query_type CDATA  #REQUIRED
ct_no      CDATA  #REQUIRED
>
<!ELEMENT title (#PCDATA)>
<!ELEMENT description   (#PCDATA)>
<!ELEMENT narrative     (#PCDATA)>
<!ELEMENT keywords      (#PCDATA)>
```

Figure 1: Topic DTD

```
<inex_topic topic_id="76" query_type="CAS" ct_no="81">
<title>
  //article[(./fm//yr = ’2000’ OR ./fm//yr = ’1999’) AND about(.,
  ’"intelligent transportation system"’)]//sec[about(.,’automation
  +vehicle’)]
</title>
<description>
  Automated vehicle applications in articles from 1999 or
  2000 about intelligent transportation systems.
</description>
<narrative>
  To be relevant, the target component must be from an
  article on intelligent transportation systems published in 1999 or
  2000 and must include a section which discusses automated vehicle
  applications, proposed or implemented, in an intelligent
  transportation system.
</narrative>
<keywords>
   intelligent transportation system, automated vehicle,
   automobile, application, driving assistance, speed, autonomous
   driving
</keywords>
</inex_topic>
```

Figure 2: A CAS topic from the INEX 2003 test collection

```
<inex_topic topic_id="98" query_type="CO" ct_no="26">
<title>
   "Information Exchange", +"XML", "Information Integration"
</title>
<description>
   How to use XML to solve the information exchange
   (information integration) problem, especially in heterogeneous data
   sources?
</description>
<narrative>
   Relevant documents/components must talk about techniques of
   using XML to solve information exchange (information integration)
   among heterogeneous data sources where the structures of participating
   data sources are different although they might use the same ontologies
   about the same content.
</narrative>
<keywords>
   information exchange, XML, information integration,
   heterogeneous data sources
</keywords>
</inex_topic>
```

Figure 3: A CO topic from the INEX 2003 test collection

	CAS	CO
no of topics	30	36
avg no of words in title	7	4
no of target elements representing article	13	-
no of target elements representing non-article element	17	-
avg no of words in topic description	16	11
avg no of words in keywords component	5	7

Table 2: Statistics on CAS and CO topics on the INEX test collection

	CAS topics	CO topics
no of documents submitted	30 071	36 113
no of documents in pools	15 077	18 163
reduction	50 %	50 %
no of components submitted	58 828	80 537
no of components in pools	27 633	38 264
reduction	53 %	52 %

Table 3: Pooling effect for CAS and CO topics

Marginally specific (1): the topic of request is a minor theme of the document component.

Fairly specific (2): the topic of request is a major theme of the document component.

Highly specific (3): the topic of request is the only theme of the document component.

The relevance assessment document guideline [Kazai et al. 04c] explaining the above relevance dimensions and how and what to assess were distributed to the participants. This guide also contained the manual to the online assessment tool developed by LIP6 to perform the assessments of the XML documents/components. Features of the tool include user friendliness, implicit assessment rules whenever possible, keyword highlighting, consistency checking and completeness enforcement.

Initially, the collected assessments were with respect to CAS and CO topics. Later, a distinction was made between VCAS and SCAS assessment by filtering elements targeted by the topics from the CAS assessments. Table 4 shows a statistics of the relevance assessments. Figures 4 and 5 show the distribution of relevance for (some of) the elements.

7. EVALUATION METRICS

A number of evaluation metrics were used in INEX 2003.

7.1 inex_eval: INEX 2003 metric for CO and SCAS topics

This metric was developed during INEX 2002, and was adapted to deal with the INEX 2003 new dimensions of relevance (i.e. exhaustivity and specificity). inex_eval is based on the traditional recall and precision measures. To obtain recall/precision figures, the two dimensions need to be quantised onto a single relevance value. Quantisation functions for two different user standpoints were used:

- A "strict" quantisation to evaluate whether a given retrieval approach is capable of retrieving highly exhaustive and highly specific document components (e3s3).
- In order to credit document components according to their degree of relevance, a "generalised" quantisation has been used.

Based on the quantised relevance values, procedures that calculate recall / precision curves for standard document retrieval can be directly applied to the results of the quantisation functions. The method of *precall* described by [Raghavan et al. 89] was used to obtain the precision values at standard recall values. Further details are available in [Gövert et al. 03].

7.2 inex_eval_ng: INEX 2003 metric for CO topics

This metric developed for INEX 2003 is for CO topics and is based on the notion of an ideal concept space [Wong & Yao 95]. This metrics considers the size of retrieved elements. Two variants were used, one that does not consider overlaps in the ranking of document components and a second one that considers overlaps within the components of a ranking. Details can be found in [Gövert et al. 03].

7.3 ERR: Expected Ration of Relevant Units

This measure provides an estimate of the expectation of the number of relevant document elements a user sees when he/she consults the list of the first N returned relevant elements divided by the expectation of the number of relevant elements a user would see when he/she explores all the relevant elements in the collection. This measure is based on an hypothetical user behaviour:

1. The user consults the structural context (parent, children, siblings) of a returned document element.
2. The specificity of a relevant element influences the behaviour of the user.
3. The user will not use any hyper-link. More precisely, he/she will not jump to another document. This hypothesis is valid in the INEX corpus but can easily be removed in order to cope with hyper-linked corpora.

Details can be found in [Piwowarski & Gallinari 04].

8. SUMMARY OF EVALUATION RESULTS

As mentioned in Section 5, out of the 120 submissions, 56 contained results for the CO task, 38 contained results for the SCAS task and 26 contained results for the VCAS task. A summary of the

e+s	VCAS		CO		SCAS	
	article level	non-article	article	non-article	article	non-article
e3s3	188	1 389	180	1 316	122	577
e3s2	111	1 269	112	616	28	151
e3s1	186	663	150	635	25	90
e2s3	148	2 417	124	2 105	46	644
e2s2	147	3 110	103	1 779	35	650
e2s1	360	2 159	222	1 358	64	437
e1s3	223	11 135	148	5 029	100	2 701
e1s2	81	5 726	50	3 872	33	493
e1s1	769	17 617	673	8 074	361	1 185
e0s0	8 897	88 816	10 021	70 530	5 652	19 922
All	11 110	134 301	11 783	95 314	6 466	26 850

Table 4: Assessments at article and component levels

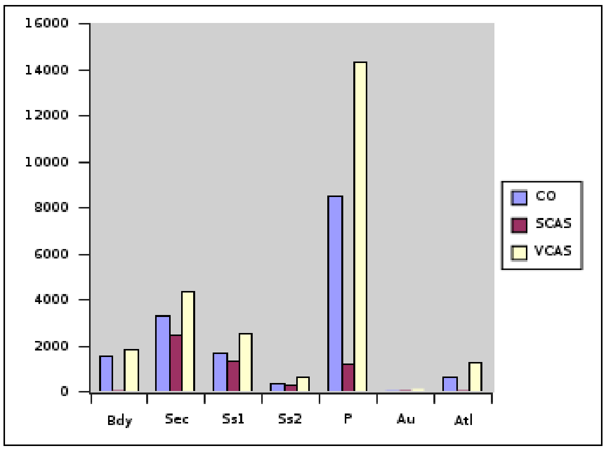

Figure 4: Distribution of relevant elements

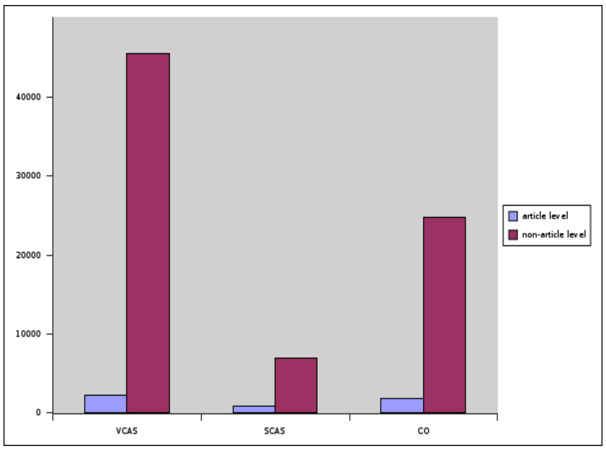

Figure 5: Distribution of relevant article and non-article elements (e > 0 and s > 0)

results obtained with the different metrics is given in the next two sub-sections[1].

8.1 inex_eval and inex_eval_ng mertics

The submissions have been ranked according to the average precision. The top ten submissions, according to average precision, for each task and each quantisation function are listed in Table 5 (inex_eval) and in Table 6 (inex_eval_ng).

When comparing the rankings for the two different quantisation functions and two different user standpoints (considering overlap and ignoring overlap) it becomes evident that they are quite similar. A regression analysis based on average precision values for the submissions shows a strong linear correlation between results obtained using the strict quantisation and results obtained using the generalised quantisation, and result obtained by ignoring and by considering overlap between the retrieved components. Figure 6 shows the scatter plots for the SCAS and CO tasks and the respective regression lines. For the SCAS task the correlation coefficient is 0.9515, and for the CO task, it is 0.7347. Figure 7 shows the scatter plot for the CO task by considering component overlap and by ignoring component overlap for the two quantisations. For strict quantisation, the correlation coefficient is 0.8775, and for generalised quantisation it is 0.9174.

8.2 ERR metric

Table 7 shows a summary of the evaluation results obtained using the ERR metric. The rankings of the submissions were done according to a specific rank (10,100,1500) and averaged over all values. The top ten submissions are shown in Table 7.

9. CONCLUSION AND OUTLOOK ON INEX 2004

INEX 2003 was a success and showed that XML retrieval is a challenging new field within IR research. In addition to learning more about XML retrieval approaches, INEX 2003 has made further steps in the evaluation methodology for XML retrieval. In addition to the presentation of retrieval approaches, four working groups were formed to discuss issues regarding the evaluation of content-oriented XML retrieval approaches: topic format, relevance definition and assessment, online assessment tool, and metrics.

INEX 2004 will start in March of this year, and in addition to the standard ad-hoc retrieval tasks, has 4 new tracks:

Interactive track focusing on interactive XML retrieval, considering also navigation through the hierarchical structure,

Heterogeneous collection track comprising various XML collections from different digital libraries, as well as material from other computer science-related resources,

Relevance feedback track dealing with relevance feedback methods for XML,

Natural language track where natural language formulations of CAS queries have to be answered.

10. ACKNOWLEDGEMENTS

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[1]All evaluation results have been compiled using the assessment package version 2.5 and evaluation package version 2003.007.

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Wong, S. K. M.; Yao, Y. Y. (1995). On modeling information retrieval with probabilistic inference. *ACM Trans. Inf. Syst. 13(1)*, pages 38–68.

rank	avg precision	organisation	run ID
1.	0.3182	U. of Amsterdam	UAmsI03-SCAS-MixedScore
2.	0.2987	U. of Amsterdam	(UAmsI03-SCAS-ElementScore
3.	0.2601	Queensland University of Technology	CASQuery_1
4.	0.2476	University of Twente and CWI	LMM-ComponentRetrieval-SCAS
5.	0.2458	IBM, Haifa Research Lab	SCAS-TK-With-Clustering
6.	0.2448	Universität Duisburg-Essen	scas03-way1-alias
7.	0.2437	RMIT University	RMIT_SCAS_1
8.	0.2419	RMIT University	RMIT_SCAS_2
9.	0.2405	IBM, Haifa Research Lab	SCAS-TDK-With-No-Clustering
10.	0.2352	RMIT University	RMIT_SCAS_3

a) SCAS task; strict quantisation

rank	avg precision	organisation	run ID
1.	0.2989	U. of Amsterdam	UAmsI03-SCAS-MixedScore
2.	0.2456	U. of Amsterdam	UAmsI03-SCAS-ElementScore
3.	0.2451	U. of Amsterdam	UAmsI03-SCAS-DocumentScore
4.	0.2399	IBM, Haifa Research Lab	SCAS-TDK-With-No-Clustering
5.	0.2378	IBM, Haifa Research Lab	SCAS-TK-With-Clustering
6.	0.2222	IBM, Haifa Research Lab	SCAS-TDK-With-Clustering
7.	0.2212	University of Twente and CWI	LMM-ComponentRetrieval-SCAS
8.	0.2050	Queensland University of Technology	CASQuery_1
9.	0.1934	Universität Duisburg-Essen	scas03-way1-alias
10.	0.1893	Queensland University of Technology (QUT)	scas_ps

b) SCAS task; generalised quantisation

rank	avg precision	organisation	run ID
1.	0.1214	U. of Amsterdam	UAmsI03-CO-lamda=0.20
2.	0.1144	U. of Amsterdam	UAmsI03-CO-lambda=0.5
3.	0.1102	U. of Amsterdam	UAmsI03-CO-lambda=0.9
4.	0.1001	Universität Duisburg-Essen	factor 0.2
5.	0.0952	IBM, Haifa Research Lab	CO-TDK-With-No-Clustering
6.	0.0929	LIP 6	local-okapi-element,list,ef
7.	0.0915	Universität Duisburg-Essen	difra_sequential
8.	0.0780	Carnegie Mellon University	LM_context_TDK
9.	0.0708	Universität Duisburg-Essen	factor 0.5
10.	0.0688	University of Bayreuth	_co_second

c) CO task; strict quantisation

rank	avg precision	organisation	run ID
1.	0.1032	U. of Amsterdam	UAmsI03-CO-lamda=0.20
2.	0.1009	U. of Amsterdam	(UAmsI03-CO-lambda=0.5
3.	0.0962	IBM, Haifa Research Lab	CO-TDK-With-No-Clustering
4.	0.0960	U. of Amsterdam	UAmsI03-CO-lambda=0.9
5.	0.0881	LIP 6	local-okapi-element,list,ef
6.	0.0839	Carnegie Mellon University	LM_context_TDK
7.	0.0740	University of Bayreuth	_co_second
8.	0.0691	University of Bayreuth	CO-third
9.	0.0687	Universität Duisburg-Essen	factor 0.2
10.	0.0676	Universität Duisburg-Essen	difra_sequential

d) CO task; generalised quantisation

Table 5: Ranking of submissions w. r. t. average precision
using inex_eval metric

rank	avg precision	organisation	run ID
1.	0.1626	IBM, Haifa Research Lab	CO-TDK-With-No-Clustering
2.	0.1575	University of Minnesota Duluth	01
3.	0.1483	Universität Duisburg-Essen	factor 0.2
4.	0.1464	U. of Amsterdam	UAmsI03-CO-lamda=0.20
5.	0.1429	IBM, Haifa Research Lab	CO-TDK-With-Clustering
6.	0.1409	Universität Duisburg-Essen	difra_sequential
7.	0.1403	University Of Otago	CO4
8.	0.1380	University of Twente and CWI	LMM-CLengthModifie
9.	0.1374	U. of Amsterdam	UAmsI03-CO-lambda=0.5
10.	0.1328	doctronic GmbH & Co. KG	1

a) CO task; strict quantisation; overlapping considered

rank	avg precision	organisation	run ID
1.	0.1500	University Of Otago	CO4
2.	0.1489	University of Twente and CWI	LMM-CLengthModified
3.	0.1447	University of Twente and CWI	LMM-Component
4.	0.1365	University of Minnesota Duluth	01
5.	0.1113	IBM, Haifa Research Lab	CO-TDK-With-Clustering
6.	0.1110	IBM, Haifa Research Lab	CO-TDK-With-No-Clustering
7.	0.1091	IBM, Haifa Research Lab	CO-T-With-Clustering
8.	0.1063	U. of Amsterdam	UAmsI03-CO-lamda=0.20
9.	0.1051	doctronic GmbH & Co. KG	1
10.	0.1011	Carnegie Mellon University	LM_context_TDK

b) CO task; generalised quantisation; overlapping considered

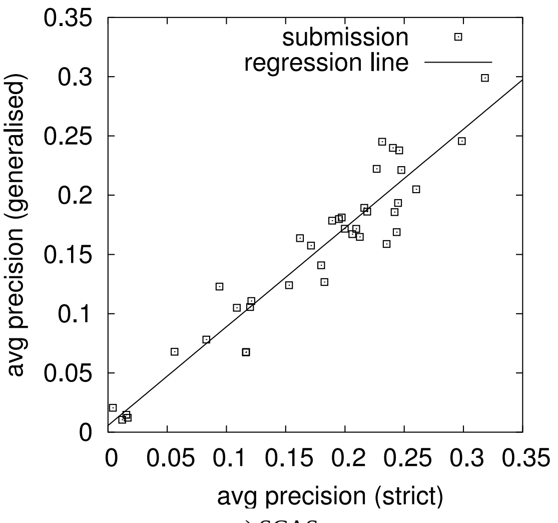
rank	avg precision	organisation	run ID
1.	0.1915	U. of Amsterdam	UAmsI03-CO-lamda=0.20
2.	0.1780	University of Twente and CWI	LMM-CLengthModified
3.	0.1755	U. of Amsterdam	UAmsI03-CO-lambda=0.5
4.	0.1707	University of Twente and CWI	LMM-Component
5.	0.1674	Carnegie Mellon University	LM_context_TDK
6.	0.1631	U. of Amsterdam	UAmsI03-CO-lambda=0.9
7.	0.1627	IBM, Haifa Research Lab	CO-TDK-With-No-Clustering
8.	0.1332	LIP 6	local-okapi-element,list,ef
9.	0.1312	University of Minnesota Duluth	01
10.	0.1281	IBM, Haifa Research Lab	CO-TDK-With-Clustering

c) CO task; strict quantisation; overlapping ignored

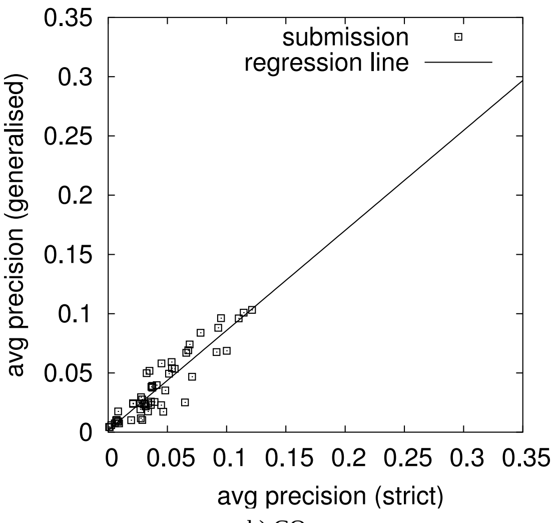
rank	avg precision	organisation	run ID
1.	0.1809	University of Twente and CWI	LMM-CLengthModified
2.	0.1749	University of Twente and CWI	LMM-Component
3.	0.1570	U. of Amsterdam	UAmsI03-CO-lamda=0.20
4.	0.1462	IBM, Haifa Research Lab	CO-TDK-With-No-Clustering
5.	0.1403	Carnegie Mellon University	LM_context_TDK
6.	0.1376	U. of Amsterdam	UAmsI03-CO-lambda=0.5
7.	0.1363	University Of Otago	CO4
8.	0.1269	U. of Amsterdam	UAmsI03-CO-lambda=0.9
9.	0.1268	University of Minnesota Duluth	01
10.	0.1231	Queensland University of Technology	co_ns

d) CO task; generalised quantisation; overlapping ignored

Table 6: Ranking of submissions w. r. t. average precision
using inex_eval_ng metric

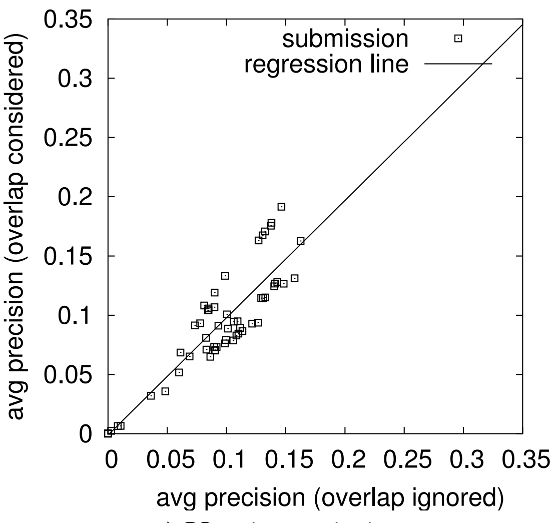


a) SCAS

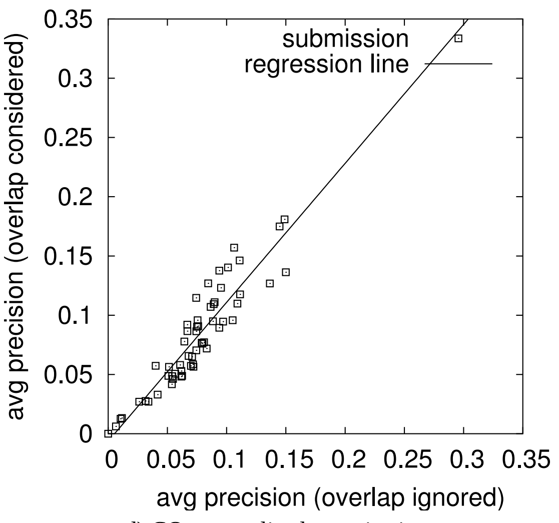


b) CO

Figure 6: Scatter plots and regression lines for average precision of submissions, using strict and generalised quantisation



c) CO: strict quantisation



d) CO: generalised quantisation

Figure 7: Scatter plots and regression lines for average precision of submissions, considering component overlap and ignoring component overlap

rank	avg	organisation	run ID
1.	49.9	IBM, Haifa Research Lab	CO-TDK-With-No-Clustering
2.	46.8	IBM, Haifa Research Lab	CO-TDK-With-Clustering
3.	45.2	Universität Duisburg-Essen	factor 0.2
4.	43.6	Universität Duisburg-Essen	difra_sequential
5.	42.0	U. of Amsterdam	UAmsI03-CO-lambda=0.5
6.	41.9	LIP 6	local-okapi-element,list,ef
7.	41.0	Carnegie Mellon University	LM_context_TDK
8.	40.2	U. of Amsterdam	UAmsI03-CO-lambda=0.9
9.	39.8	U. of Amsterdam	UAmsI03-CO-lamda=0.20
10.	39.5	IBM, Haifa Research Lab	CO-T-With-Clustering

a) CO task

rank	avg	organisation	run ID
1.	48.1	U. of Amsterdam	UAmsI03-SCAS-MixedScore
2.	47.4	U. of Amsterdam	UAmsI03-SCAS-ElementScore
3.	42.3	U. of Amsterdam	UAmsI03-SCAS-DocumentScore
4.	35.7	University of Bayreuth	first_scas
5.	35.7	Universität Duisburg-Essen	scas03-way3-noalias
6.	35.7	University of Bayreuth	cas_third
7.	34.5	Queensland University of Technology	CASQuery_1
8.	33.5	IBM, Haifa Research Lab	SCAS-TDK-With-Clustering
9.	33.5	University of Bayreuth	second_scas
10.	32.9	Queensland University of Technology	QUTscas_st

b) SCAS task

rank	avg	organisation	run ID
1.	40.9	U. of Amsterdam	UAmsI03-VCAS-NoStructure
2.	37.6	U. of Amsterdam	UAmsI03-VCAS-TargetFilter
3.	33.0	IBM, Haifa Research Lab	VCAS-TDK-With-No-Clustering
4.	32.4	IBM, Haifa Research Lab	VCAS-TK-With-Clustering
5.	32.2	IBM, Haifa Research Lab	VCAS-TDK-With-Clustering
6.	29.2	University of Twente and CWI	LMM-ComponentRetrieval-VCAS
7.	28.2	University of Bayreuth	second_vcas
8.	28.0	Universität Duisburg-Essen	vcas03-way2-alias
9.	28.0	University of Bayreuth	first_vcas
10.	27.9	University of Bayreuth	vcas_third

c) VCAS task

Table 7: Ranking of submissions w. r. t. average using ERR metric

Using Language Models for Flat Text Queries in XML Retrieval

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ABSTRACT

This paper presents a language modeling system for ranking flat text queries against a collection of structured documents. The retrieval system, built using the Lemur toolkit, produces probability estimates that arbitrary document components generated the query. This paper describes storage mechanisms and retrieval algorithms for the evaluation of unstructured queries over XML documents. The paper includes retrieval experiments using a generative language model on the content only topics of the INEX testbed, demonstrating the strengths and flexibility of language modeling to a variety of problems. We also describe index characteristics, running times, and the effectiveness of the retrieval algorithm.

1. INTRODUCTION

Language modeling has been studied extensively in standard Information Retrieval in the last few years. Researches have demonstrated that the framework provided by language models has been powerful and flexible enough to provide strong solutions to numerous problems, including ad-hoc information retrieval, known-item finding on the Internet, filtering, distributed information retrieval, and clustering.

With the success of language modeling for this wide variety of tasks and the increasing interest in studying structured document retrieval, it is natural to apply the language modeling framework to XML retrieval. This paper describes experiments using one way the generative language model could be extended to model and support queries on structured documents. We model documents using a tree-based language model. This is similar to many previous models for structured document retrieval [1][2][3][6][7][10], but differs in that language modeling provides some guidance in combining information from nodes in the tree and estimating term weights. This work is also similar to other works using language models for XML retrieval [5][9], but differs in that we also present context-sensitive language model smoothing and an implementation using information retrieval style inverted lists rather than a database.

The next section provides background in language modeling in information retrieval. In Section 3 we present our approach to modeling structured documents. Section 4 describes querying the tree-based language models presented in the previous section. In Section 5, we describe the indexes required to support retrieval and the retrieval algorithms. We describe the experiment setup and indexes used for INEX 2003 in Section 6. Section 7 describes experimental results. We discuss relationships to other approaches to structured document retrieval in Section 8, and Section 9 concludes the paper.

2. LANGUAGE MODELS FOR DOCUMENT RETRIEVAL

Language modeling applied to information retrieval problems typically models text using unigram language models. Unigram language models are similar to bags-of-words representations, as word order is ignored. The unigram language model specifically estimates the probability of a word given some text. Document ranking typically is done one of two ways: by measuring how much a query language model diverges from document language models [8], or by estimating the probability that each document generated the query string. Since we use the generative language model for our experiments, we will not describe the divergence based approaches here.

2.1 The Generative Language Model

The generative method ranks documents by directly estimating the probability of the query using the texts' language models [13][4][15][16]:

$$P(Q|\theta_T) = \prod_{w \in Q} P(w|\theta_T)^{qtf(w)}$$

where Q is the query string, and θ_T is the language model estimated for the text, and *qtf*(*w*) is the query term frequency of the term *w* (count of *w* in the query). Texts more likely to have produced the query are ranked higher. It is common to rank by the log of the generative probability as it there is less danger of underflow and it produces the same orderings:

$$\log(P(Q|\theta_T)) = \sum_{w \in Q} qtf(w) \log P(w|\theta_T)$$

Under the assumptions that query terms are generated independently and that the query language model used in KL-divergence is the maximum-likelihood estimate, the generative model and KL divergence produce the same rankings [11].

2.2 The Maximum-Likelihood Estimate of a Language Model

The most direct way to estimate a language model given some observed text is to use the maximum-likelihood estimate, assuming an underlying multinomial model. In this case, the maximum-likelihood estimate is also the empirical distribution. An advantage of this estimate is that it is easy to compute. It is very good at estimating the probability distribution for the language model when the size of the observed text is very large. It is given by:

$$P_{MLE}(w|\theta_T) = \frac{freq(w,T)}{|T|}$$

where T is the observed text, *freq*(*w*, T) is the number of times the word *w* occurs in T, and |T| is the length in words of T. The maximum likelihood estimate is not good at estimating low frequency terms for short texts, as it will assign zero probability to those words. This creates a problem for estimating document language models in both KL divergence and generative language model approaches to ranking documents, as the log of zero is negative infinity. The solution to this problem is smoothing.

2.3 Smoothing

Smoothing is the re-estimation of the probabilities in a language model. Smoothing is motivated by the fact that many of the language models we estimate are based on a small sample of the "true" probability distribution. Smoothing improves the estimates by leveraging known patterns of word usage in language and other language models based on larger samples. In information retrieval smoothing is very important [16], because the language models tend to be constructed from very small amounts of text. How we estimate low probability words can have large effects on the document scores. In addition to the problem of zero probabilities mentioned for maximum-likelihood estimates, much care is required if this probability is close to zero. Small changes in the probability will have large effects on the logarithm of the probability, in turn having large effects on the document scores. Smoothing also has an effect similar to inverse document frequency [4], which is used by many retrieval algorithms.

The smoothing technique most commonly used is linear interpolation. Linear interpolation is a simple approach to combining estimates from different language models:

$$\mathrm{P}(w|\theta) = \sum_{i=1}^{k} \lambda_i \mathrm{P}(w|\theta_i)$$

where k is the number of language models we are combining, and λ_i is the weight on the model θ_i. To ensure that this is a valid probability distribution, we must place these constraints on the lambdas:

$$\sum_{i=1}^{k} \lambda_i = 1 \quad \text{and for } 1 \le i \le k,\ \lambda_i \ge 0$$

One use of linear interpolation is to smooth a document's language model with a collection language model. This new model would then be used as the smoothed document language model in either the generative or KL-divergence ranking approach.

2.4 Another Characterization

When we take a simple linear interpolation of the maximum likelihood model estimated from text and a collection model, we can also characterize the probability estimates as:

$$\mathrm{P}(w|\theta_\mathrm{T}) = \begin{cases} \mathrm{P}_{\mathrm{seen}}(w|\theta_\mathrm{T}) & \text{\textit{if} } w \in \mathrm{T} \\ \mathrm{P}_{\mathrm{unseen}}(w|\theta_\mathrm{T}) & \textit{otherwise} \end{cases}$$

where

$$\mathrm{P}_{\mathrm{seen}}(w|\theta_\mathrm{T}) = (1-\omega)\mathrm{P}_{\mathrm{MLE}}(w|\theta_\mathrm{T}) + \omega \mathrm{P}(w|\theta_{collection})$$

and

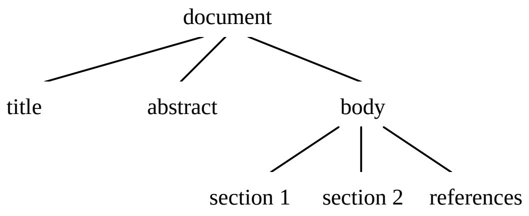
$$\mathrm{P}_{\mathrm{unseen}}(w|\theta_\mathrm{T}) = \omega \mathrm{P}(w|\theta_{collection})$$

This notation distinguishes the probability estimates for cases where the word has been seen in the text and where the word has not been seen will be in the sample text. We will use this notation later when describing the retrieval algorithm, as it simplifies the description and is similar to the notation used in previous literature [16]. The simple form of linear interpolation where ω is a fixed constant is often referred to as Jelinek-Mercer smoothing.

3. STRUCTURED DOCUMENTS AND LANGUAGE MODELS

The previous section described how language modeling is used in unstructured document retrieval. With structured documents such as XML or HTML, we believe that the information contained in the structure of the document can be used to improve document retrieval. In order to leverage this information, we need to model document structure in the language models.

We model structured documents as trees. The nodes in the tree correspond directly with tags present in the document. A partial tree for a document might look like:



Nodes in the document tree correspond directly to XML tags in the document. For each document node in the tree, we estimate a language model. The language models for leaf nodes with no children can be estimated from the text of the node. The language models for other nodes are estimated by taking a linear interpolation of a language model formed from the text in the node (but not in any of its children) and the language models formed from the children.

We have not specified how the linear interpolation parameters for combining language models in the document tree should be chosen. This could be task specific, and training may be required. The approach we will adopt in this paper is to set the weight on a child node as the accumulated length of the text in the child divided by the accumulated length of the node. By accumulated length we mean the number of words directly in the node plus the accumulated length of the node's children. Setting the parameters in this manner assumes that a word in a one node type is no more important than a word in any other node type; it is the accumulated length of the text in the node that determines how much information is contained in the node.

We also wish to smooth the maximum likelihood models that are estimated directly from the text with a collection language model. In this work, we will combine the maximum likelihood models with the collection model using a linear interpolation with fixed weights. The collection model may be specific to the node type, giving context sensitive smoothing, or the collection model may be one large model estimated from everything in the corpus, giving a larger sample size.

When the λ parameters are set proportional to the text length and a single collection model is used, this results a special case that is very similar to the models used in [5][9]. The tree-based language model estimated using these parameter settings will be identical to a language model estimated by taking a simple linear interpolation of a maximum likelihood estimate from the text in the node and its ancestors and the collection model.

4. RANKING THE TREE MODELS

In a retrieval environment for structured documents, it is desirable to provide support for both structured queries and unstructured, free-text queries. It is easier to adapt the generative language model to structured documents, so we only consider that model in this paper. It is simpler to support unstructured queries, so we will describe retrieval for them first.

4.1 Unstructured Queries

To rank document components for unstructured queries, we use the generative language modeling approach for IR described in Section 2. For full document retrieval, we need only compute the probability that the document language model generated the query. If we wish to return arbitrary document components, we need to compute the probability that each component generated the query.

Allowing the system to return arbitrary document components may result in the system stuffing the results list with many components from a single document. This behavior is undesirable, so a filter on the results is necessary.

One filter we employ takes a greedy approach to preventing overlap among components in the results list. For each result, it will be thrown out of the results if there is any component higher in the ranking that is an ancestor or descendent of the document component under consideration.

4.2 Structured Queries

Our previous paper on this subject [11] discusses how some structural query operators could be included in the model. We do not currently support any of these operators in our system, so we will not discuss in depth here. However, we will mention that the retrieval framework can support most desired structural query operators using relatively easy to implement query nodes.

4.3 Prior Probabilities

Given relevance assessments from past topics, we can estimate prior probabilities of the document component being relevant given its type. Another example prior may depend on the length of the text in the node. A way to incorporate this information is to rank by the probability of the document node given the query. Using Bayes rule, this would allow us incorporate the priors on the nodes. The prior for only the node being ranked would be used, and the system would multiply the probability that the node generated the query by the prior:

$$P(N|Q) = P(Q|\theta_N)\,P(N)/P(Q)$$

$$\text{which is proportional to}$$

$$P(Q|\theta_N)\,P(N)$$

This would result in ranking by the probability of the document component node given the query, rather than the other way around.

5. STORAGE AND ALGORITHMS

This section describes how we support structured retrieval in the Lemur toolkit. We first describe the indexes built to support retrieval. Then we describe how the indices are used by the retrieval algorithm. We also present formulas for the computation of the generative probabilities we estimate for retrieval.

5.1 Index Support

There are two main storage structures in Lemur that provide the support necessary for the retrieval algorithm. Lemur stores inverted indexes containing document and node occurrences and document structures information.

5.1.1 Inverted Indexes

The basic idea to storing structured documents in Lemur for retrieval is to use a modified inverted list. Similar to storing term locations for a document entry in an inverted list, we store the nodes and the term frequencies of the term in the nodes in the document entries of the inverted list. The current implementation of the structured document index does not store term locations, but could be adapted to store term locations in the future.

The inverted lists are keyed by term, and each list contains the following:

- document frequency of the term
- a list of document entries, each entry containing
  - document id
  - term frequency (count of term in document)
  - number of nodes the term occurs in
  - a list of node entries, each entry containing
    - node id
    - term frequency (count of term in node)

When read into memory, the inverted lists are stored in an array of integers. The lists are stored on disk using restricted-variable length compression and delta-encoding is applied to document ids and node ids. In the document entry lists, the documents entries are stored in order by ascending document id. The node entry lists are similarly stored in order by increasing node id. Document entries and node entries are only stored in the list when the term frequency is greater than zero. Access to the lists on disks is facilitated with an in-memory lookup table for vocabulary terms.

There is also an analogous set of inverted lists for attribute name/value pairs associated with tags. For example, if the document contained the text

<date calendar="Gregorian">,

the index would have an inverted list keyed by the triple date/calendar/Gregorian. The structure and information stored in the inverted lists for the attribute name/value pairs is identical to those in the inverted lists for terms.

5.1.2 Document Structure

The document structure is stored compressed in memory using restricted variable length compression. A lookup table keyed by document id provides quick access to the block of compressed memory for a document. We choose to store the document structure in memory because it will be requested often during retrieval. For each document, a list of information about the document nodes is stored. For each node, we store:

- parent of the node
- type of node
- length of the node (number of words)

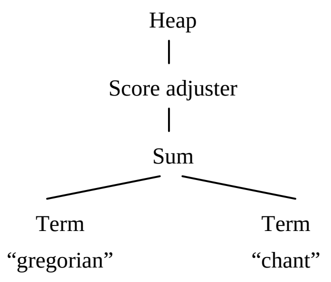
Since this list of information about the document structure is compressed using a variable length encoding, we must decompress the memory to provide efficient access to information about nodes. When the document structure for a document is being decompressed, we also compute:

- accumulated length of the node (length of text directly in the node + accumulated length of children)
- number of children of the node
- a list of the node's children

This decompression and computation of other useful information about the document structure is computed in time linear to the number of nodes in the document being decompressed.

5.2 Retrieval

We construct a query tree to process and rank document components. A typical query tree is illustrated below. The leaf nodes of the query tree are term nodes which read the inverted lists for a term off of disk and create result objects for document components containing the term. The term nodes are also responsible for propagating the term scores up the document tree. The sum node merges the result lists returned by each of the term nodes, combining the score estimates. The score adjuster node adjusts the score estimates to get the generation probabilities and also applies any priors. The heap node maintains a list of the top *n* ranked objects and returns a sorted result list. Efficient retrieval is achieved using a document at a time approach. This requires that the query tree be walked many times during the evaluation of a query, but results a large saving of memory, as only the result objects for a document and the top *n* results objects in the heap must be stored at any point in time.



A more detailed description of each of the query nodes follows. When each query node is called, they are passed a document id to evaluate. In order to know which document should be processed next, the term nodes pass up the next document id in the inverted list. For other query nodes, the minimum next document id among a node's children gets passed up the query tree with the results list. We will describe the query nodes bottom up, as that is how the scores are computed.

We first note that we can rewrite the log of the probability that the document node generated the query as

$$\log\left(\mathrm{P}\left(\mathrm{Q}\middle|\theta_{node}\right)\right)=\sum_{w\in Q,node} qtf\left(w\right)\log\left(\frac{\mathrm{P}_{\text{seen}}\left(w\middle|\theta_{node}\right)}{\mathrm{P}_{\text{unseen}}\left(w\middle|\theta_{node}\right)}\right)+\sum_{w\in Q} qtf\left(w\right)\log \mathrm{P}_{\text{unseen}}\left(w\middle|\theta_{node}\right)$$

as shown in [16]. This will allow us to easily compute the item in the first sum easily using term nodes, combine these components of the score using a sum node, and then add on the rest using a score adjustment node.

5.2.1 Term Node

The term nodes read in the inverted lists for a term *w* off of disk and create a list of results where the score for a result is initialized to

$$qtf\left(w\right)\cdot\log\left(\frac{\mathrm{P}_{\text{seen}}\left(w\middle|\theta_{node}\right)}{\mathrm{P}_{\text{unseen}}\left(w\middle|\theta_{node}\right)}\right)$$

The term node assumes that the parent id of a node is smaller than the node's id. It also assumes that the document entries in inverted lists are organized in increasing document id order and the node entries are organized in increasing term id order. The structured document index we built is organized this way. In the following algorithm description, indentation is used to denote the body of a loop.

```
1  Seek to the next entry in the inverted list where the
   document id is at least as large as the requested document
2  If the document id of the next entry is the requested
   document
3     Decompress the document structure information for the
      document
4     Read in the node entries from the inverted list
5     Create the result objects for the leaf nodes. For each
      node that contains the term:
6        Initialize the score for the result to the seen
         probability part for the node
         $seen(node)=(1-\omega)\,freq(w,node)\,\lambda(node,node)$
         where
         $\lambda(node,node)=\frac{length(node)}{accumulated\ length(node)}$
         and $\omega$ will be used to set the influence of the
         collection models.
7        Push the node id onto the candidate node heap
8        Store the result object in an array indexed by node id
         for fast access
9     While the candidate node heap isn't empty:
10       Pop the top node id off of the heap (the largest node
         id), set it to the current node id
11       Lookup the result from the result array
12       Lookup the node id for the parent of the current node
13       Lookup the parent node's result
14       If the parent node's result object is NULL:
15          Create a new result object for the parent node and
            put it in the result array, initializing the score to 0
16          Push the parent node's id onto the candidate node
            heap
17       Propagate the seen part of the score from the
         current node to the parent node, setting the parent
         node's seen part to
         $seen(parent)+seen(node)\lambda(node, parent)$
         where
         $\lambda(node, parent)=\frac{accumulated\ length(node)}{accumulated\ length(parent)}$
18       Push the result onto the front of the results list
```

19 Set the result in the result array for the node to NULL (initializing the result array for the next document)

[*Now each document node that contains the query term (or has a child containing the term) has a result in the results list where the score is the seen probability part for the query term*]

20 For each node in the result list

21 Compute the unseen part of the generative probability for each node. For linear interpolation with a constant ω and one single node type independent collection model, this is

$$unseen(w,node) = \omega \mathrm{P}(w|\theta_{collection})$$

For linear interpolation with a constant ω and node type specific collection models, this can be computed recursively

$$unseen(w,node) = \omega \mathrm{P}(w|\theta_{collection,type(node)})\lambda(node,node) + \sum_{child \in children(node)} unseen(w,child)\lambda(child,node)$$

22 Set the score for the result to

$$qtf(w) \cdot \log\left(\frac{seen(node) + unseen(w,node)}{unseen(w,node)}\right)$$

23 Return the result list and the next document id in the inverted list

The result list now contains results for a single document where the score is

$$qtf(w) \cdot \log\left(\frac{\mathrm{P}_{\mathrm{seen}}(w|\theta_{node})}{\mathrm{P}_{\mathrm{unseen}}(w|\theta_{node})}\right)$$

and the list is ordered by increasing node id.

5.2.2 Sum Node

The sum node maintains an array of result lists, with one result list for each of the children. It seeks to the next entry in each of the child result lists where the document id is at least as large as the requested document. If necessary, it calls the children nodes to get their next result lists. For the requested document, the sum node merges results from the result lists of the children, setting the score of the new result equal to the sum of the children's results with the same document and node id. This node assumes that results in a result list are ordered by increasing document id, then increasing node id. The results returned by this component have the score

$$\sum_{w \in Q, node} qtf(w) \log\left(\frac{\mathrm{P}_{\mathrm{seen}}(w|\theta_{node})}{\mathrm{P}_{\mathrm{unseen}}(w|\theta_{node})}\right)$$

and the minimum document id returned by the children is returned.

5.2.3 Score Adjustment Node

The score adjustment node adds

$$\sum_{w \in Q} qtf(w) \log \mathrm{P}_{\mathrm{unseen}}(w|\theta_{node})$$

to each of the results, where

$$\mathrm{P}_{\mathrm{unseen}}(w|\theta_{node}) = unseen(w,node)$$

as defined for the term node. If there is a prior probability for the node, the score adjustment node also adds on the log of the prior. The results in the list now have the score

$$\sum_{w \in Q, node} qtf(w) \log\left(\frac{\mathrm{P}_{\mathrm{seen}}(w|\theta_{node})}{\mathrm{P}_{\mathrm{unseen}}(w|\theta_{node})}\right) + \sum_{w \in Q} qtf(w) \log \mathrm{P}_{\mathrm{unseen}}(w|\theta_{node}) + \log(\mathrm{P}(node))$$

$$= \log(\mathrm{P}(\mathrm{Q}|\theta_{node})\mathrm{P}(node))$$

which is the log of the score by which we wish to rank document components.

5.2.4 Heap Node

The heap node repeatedly calls its child node for result lists until the document collection has been ranked. The next document id it calls for its child to process is the document id returned by the child node in the previous evaluation call. It maintains a heap of the top *n* results. After the document collection has been ranked, it sorts the results by decreasing score and stores them in a result list that is returned.

5.2.5 Other Nodes

There are many other useful nodes that could be useful for retrieval. One example is a node that filters the result lists so that the XML path of the node in the document tree satisfies some requirements. Another example is a node that throws out all but the top *n* components of a document.

6. EXPERIMENT SETUP

The index we created used the Krovetz stemmer and InQuery stopword list. Topics are similarly processed, and all of our queries are constructed from the title, description, and keywords fields. All words in the title, description, and keywords fields of the topic are given equal weight in the query. Table 3 shows the size of components created to support retrieval on the INEX document collection. The total index size including information needed to do context sensitive smoothing is about 70% the size of the original document collection. A better compression ratio could be achieved by compression of the context sensitive smoothing support files. Note that the document term file which is 100 MB is not necessary for the retrieval algorithms described above.

Component	**Size (MB)**
Inverted file	100
Document term file (allows iteration over terms in a document)	100
Document structure	30
Attributes inverted file	23
Smoothing – single collection model	4
Smoothing – context sensitive models (not compressed)	81
Other files (lookup tables, vocabulary, table of contents, etc.)	12
Total	**350**

Table 3: Lemur structured index component sizes

Topic Fields	Context	Prior	Path	inex_eval	
				Strict	Gen
TDK	YES	NO	NO	.0464	.0646
TDK	YES	YES	NO	.0488	.0653
TDK	NO	NO	NO	.0463	.0641
TDK	NO	YES	NO	.0485	.0654

Table 1: Performance of the retrieval system on INEX 2002 CO topics. Context refers to context sensitive smoothing, prior refers to the document component type priors, and path refers to the overlapping path filter.

Run Name (Official runs are bold)	Topic Fields	Context	Prior	Path	inex_eval		inex_eval_ng		w/o overlap	
					Strict	Gen	Strict	Gen	Strict	Gen
LM_context_TDK	TDK	YES	NO	NO	.0717	.0804	.2585	.3199	.2305	.2773
LM_context_typr_TDK	TDK	YES	YES	NO	.0769	.0855				
LM_context_typr_path_TDK	TDK	YES	YES	YES	.0203	.0240				
LM_base_TDK	TDK	NO	NO	NO	.0783	.0861				
LM_base_typr_TDK	TDK	NO	YES	NO	.0764	.0847				
LM_base_typr_path_TDK	TDK	NO	YES	YES	.0204	.0234				

Table 2: Summary of runs and results for INEX 2003 CO topics.

Table 4 shows approximate running times for index construction and retrieval. The retrieval time for context insensitive smoothing is reasonable at less than 20 seconds per query, but we would like to lower the average query time even more. We feel we can do this with some simple data structure optimizations that will increase memory reuse.

Action	Time (mins)
Indexing	25
Retrieval of 36 INEX 2003 CO topics – context insensitive smoothing	10
Retrieval of 36 INEX 2003 CO topics – context sensitive smoothing	45

Table 4: Indexing and retrieval times using Lemur

The higher retrieval time for the context sensitive retrieval algorithm is due to the recursive computation of the *unseen* component of the score as described Step 21 of Section 5.2.1. Clever redesign of the algorithm may reduce the time some. However, all of the descendent nodes in the document's tree must be visited regardless of whether the descendent nodes contain any of the query terms. This means that the computation of the *unseen* component of the scores is linear in the number of nodes in the document tree, rather than the typically sub-linear case for computation of the *seen* score components. If the λ and ω functions and their parameters are known, it is possible to precompute and store necessary information to reduce the running time to something only slightly larger than the context insensitive version. However, our implementation is meant for research, so we prefer that these parameters remain easily changeable.

7. EXPERIMENT RESULTS

We submitted three official runs as described in Table 2. All of our runs used the title, description, and keyword fields of the topics. Unfortunately, two of our runs performed rather poorly. This is either an error in our path filter or a problem with the component type priors. We would also like to evaluate the additional runs corresponding to the dashes in the table, but we have not been able to do these experiments yet.

The LM_context_TDK run has good performance across all measures. This is our basic language modeling system using context sensitive smoothing. The strong performance of the context sensitive language modeling approach speaks well for the flexibility of language modeling.

For the content only topics, context sensitive smoothing does not help. The node type priors also do not consistently help. There was a significant problem with the path filters we used.

With regards to context sensitive smoothing, it may not make much difference for content only tasks as they are typically searching for textual components such as paragraphs, sections, and articles. The characteristics of the text in these components tend to be very similar, so the context sensitive smoothing may not be helpful.

With regards to component type priors, we have observed similar puzzling behavior in [12]. We discovered that the distributions observed in the rankings after applying the prior probabilities are not the desired distributions. We are actively working on new techniques to incorporate information in a way that will provide the desired distributions of results in the rankings.

8. RELATED WORK

There exists a large and growing body of work in retrieving information from XML documents. Some work is described in our previous paper [11] and much of the more recent work is also described in the INEX 2002 proceedings [14]. With that in mind, we will focus our discussion of related work on language modeling approaches for structured document retrieval.

In [5] a generative language modeling approach for content only queries is described where a document component's language model is estimated by taking a linear interpolation of the maximum likelihood model from the text of the node and its ancestors and a collection model. This corresponds to a special case of our approach. Our model is more flexible in that it allows context sensitive smoothing and different weighting of text in children nodes.

The authors of [9] also present a generative language model for content only queries in structured document retrieval. They estimate the collection model in a different way, using document frequencies instead of collection term frequencies. As with [5], this model can be viewed as a special case of the language modeling approach presented here.

9. CLOSING REMARKS

We presented experiments using a hierarchical language model. The strong performance of language modeling algorithms demonstrates the flexibility and ease of adapting language models to the problem. In our preliminary experiments with standard text queries, context sensitive smoothing did not give much different performance than using a single collection model.

We described data structures and retrieval algorithms to support retrieval of arbitrary XML document components within the Lemur toolkit. We are reasonably pleased with the efficiency of the algorithms for a research system, but we will strive to improve the algorithms and data structures to reduce retrieval times even further.

In our future work, we would like to compare the component retrieval to standard document retrieval. We would also like to investigate query expansion using XML document components. Additionally, we would like to explore different ways of setting the λ weights on the nodes' language models, as we believe that words in some components may convey more useful information than words in other components.

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An Element-based Approach to XML Retrieval

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ABSTRACT

This paper describes the INEX 2003 participation of the Language & Inference Technology group of the University of Amsterdam. We participated in all three of the tasks, content-only, strict content-and-structure and vague content-and-structure. Our main strategic lines were to find the appropriate units of retrieval and to mix evidence from several layers in the XML hierarchy.

1. INTRODUCTION

One of the recurring issues in XML retrieval is finding the appropriate unit of retrieval. For the content-only (CO) task at INEX 2002, we followed an *article-based* approach, i.e. submitted runs in which whole articles were the unit of retrieval [5]. Much to our surprise, this turned out to be a competitive strategy. In [6] we experimented with going below the article level and returning elements. Our experiments showed that a successful element retrieval approach should be biased toward retrieving large elements. For the content-only task this year we followed an *element-based* approach, and our main aim was to experiment further with this size bias, in order to try to determine what is the appropriate unit of retrieval. Additionally, we experimented scoring elements by mixing evidence from article and element levels.

For the Strict Content-and-Structure (SCAS) task the unit of retrieval is usually explicitly mentioned in the query. Our research question for the content-only task does therefore not carry over to the strict content-and-structure task. The CAS queries are a mixture of content and structural constraints. We followed an *element-based* approach, and our main aim was to investigate how we could score elements by mixing scores, gained from evaluating the different constraints separately.

The Vague Content-and-Structure (VCAS) task is a new task and we could not base our experiments on previous experience. Since the definition of the task was underspecified, our aim for this task was to try to find out what sort of task this was. We experimented with a content-only approach, strict content-and-structure approach and article retrieval approach.

All of our runs were created using the `FlexIR` retrieval system developed by the Language & Inference Technology group. We use a multinomial language model for the scoring of retrieval results.

The structure of the remainder of this paper is as follows. In Section 2 we describe the setup of our experiments. In Section 3 we explain our runs for each of the three tasks, CO in 3.1, SCAS in 3.2, and VCAS in 3.3. Results are presented and discussed in Section 4, and in Section 5 we draw conclusions from our experiments.

2. EXPERIMENTAL SETUP

2.1 Index

We adopt an IR based approach to XML retrieval. We created our runs using two types of inverted indexes, one for XML articles only and another for all XML elements.

Article index

For the article index, the indexing unit is a whole XML document containing all the terms appearing at any nesting level within the ⟨`article`⟩ tag. This is thus a traditional inverted index as used for standard document retrieval.

Element index

For the element index, the indexing unit can be any XML element (including ⟨`article`⟩). For each element, all text nested inside it is indexed. Hence the indexing units overlap (see Figure 1). Text appearing in a particular nested XML element is not only indexed as part of that element, but also as part of all its ancestor elements.

The article index can be viewed as a restricted version of the element index, where only elements with tag-name ⟨`article`⟩ are indexed.

Both indexes were word-based, no stemming was applied to the documents, but the text was lower-cased and stop-words were removed using the stop-word list that comes with the English version on the Snowball stemmer [10]. Despite the positive effect of morphological normalization reported in [5], we decided to go for a word-based approach. Some of our experiments have indicated that high precision settings are desirable for XML element retrieval [4]. Word-based approaches have proved very suitable for achieving high precision.

2.2 Query processing

Two different topic formats are used, see Figure 2 for one of the CO topics, and Figure 3 for one of the CAS topics. Our queries were created using only the terms in the ⟨`title`⟩ and ⟨`description`⟩ parts of the topics. Terms in the ⟨`keywords`⟩ part of the topics may significantly improve retrieval effectiveness [4]. The keywords, which are used to assist during the assessment stage, are often based on human inspection of relevant documents during the topic creation. We think that using only the title and description fields is a more realistic use-case scenario for ad-hoc retrieval. Our system does not support +, - or phrases in queries. Words and phrases bound by a minus were removed, together with the minus-sign. Plus-signs and quotes were simply removed.

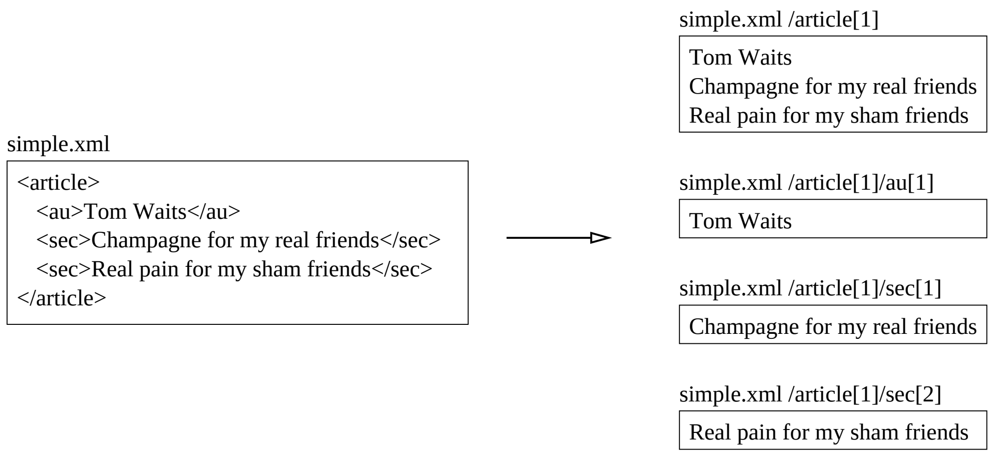
simple.xml
<article>
<au>Tom Waits</au>
<sec>Champagne for my real friends</sec>
<sec>Real pain for my sham friends</sec>
</article>
simple.xml /article[1]
Tom Waits
Champagne for my real friends
Real pain for my sham friends
simple.xml /article[1]/au[1]
Tom Waits
simple.xml /article[1]/sec[1]
Champagne for my real friends
simple.xml /article[1]/sec[2]
Real pain for my sham friends

Figure 1: Simplified figure of how XML documents are split up into overlapping indexing units

Like the index, the queries were word-based, no stemming was applied but the text was lower-cased and stop-words were removed.

Blind feedback

For some of our runs we used queries expanded by blind feedback. We considered it safer to perform the blind feedback against the article index since we do not know how the overlapping nature of the element index affects the statistics used in the feedback procedure. We used a variant of Rocchio feedback [7], where the top 10 documents were considered relevant; the top 501–1000 were considered non-relevant; and up to 20 terms were added to the initial topic. Terms appearing in more that 450 articles were not considered as feedback terms. The parameters for the feedback were based on experiments with the INEX 2002 collection. An example of an expanded query can be seen in Figure 2*c*.

Task specific query handling will be further described as part of the run descriptions in the following section.

2.3 Retrieval model

All our runs use a multinomial language model with Jelinek-Mercer smoothing [2]. We estimate a language model for each of the elements. The elements are then ranked according to the likelihood of the query, given the estimated language model for the element. That is, we want to estimate the probability

$$P(E,Q) = P(E) \cdot P(Q|E). \tag{1}$$

The two main tasks are thus to estimate the probability of the query, given the element, $P(Q|E)$; and the prior probability of the element, $P(E)$.

Probability of the query

Elements contain a relatively small amount of text, too small to be the sole basis of our element language model estimation. To account for this data sparseness we estimate the element language model by a linear interpolation of two language models, one based on the element data and another based on collection data. Furthermore, we assume that query terms are independent. That is we estimate the probability of the query, given the element language model, using the equation

$$P(Q|E) = \prod_{i=1}^{k} \left(\lambda \cdot P_{mle}(t_i|E) + (1-\lambda) \cdot P_{mle}(t_i|C)\right), \tag{2}$$

where Q is a query made out of the terms $t_1, \ldots, t_k$; E is an element; and C represents the collection. The parameter λ is the interpolation factor (often called the *smoothing parameter*). We estimate the language models, $P_{mle}(\cdot|\cdot)$ using maximum likelihood estimation. For the collection model we use element frequencies. The estimation of this probability can be reduced to the scoring function, $s(Q,E)$, for an element E and a query $Q = (t_1, \ldots, t_k)$,

$$s(E,Q) = \sum_{i=1}^{k} \log\left(1 + \frac{\lambda \cdot \mathrm{tf}(t_i,E) \cdot (\sum_t \mathrm{df}(t))}{(1-\lambda) \cdot \mathrm{df}(t_i) \cdot (\sum_t \mathrm{tf}(t,E))}\right), \tag{3}$$

where $\mathrm{tf}(t,E)$ is the frequency of term t in element E, $\mathrm{df}(t)$ is the element frequency of term t, and λ is the smoothing parameter.

The smoothing parameter λ played an important role in our submissions. Zhai and Lafferty [13] argue that bigger documents require less smoothing than smaller ones. In [4] we reported on the effect of smoothing on the unit of retrieval. The experiments suggested that there was a correlation between the value of the smoothing parameter and the size of the retrieved elements. The average size of retrieved elements increases dramatically as less smoothing (a higher value for the smoothing parameter λ) is applied. Increasing the value of λ in the language model causes an occurrence of a term to have an increasingly bigger impact. As a result, the elements with more matching terms are favored over elements with fewer matching terms. In the case of our overlapping element index, a high value for λ gives us an article biased run, whereas a low value for λ introduces a bias toward smaller elements (such as sections and paragraphs).

Prior probabilities

The second major task is to estimate the prior probability of an element. Basing the prior probability of a retrieval component on its length, has proved useful for several retrieval tasks [3, 9]. Length priors are particularly useful for XML retrieval. It is most common to have the prior probability of a component proportional to its length. That is, we calculate a so-called length prior:

$$\mathrm{lp}(E) = \log\left(\sum_t \mathrm{tf}(t,E)\right). \qquad (4)$$

With this length prior, the actual scoring formula becomes the sum of the length prior (Equation 4) and the score for the query probability (Equation 3),

$$s_{\mathrm{lp}}(E,Q) = \mathrm{lp}(E) + s(E,Q). \qquad (5)$$

Although not used here, previous results have indicated that it might be useful to have the prior proportional to the square or even the cube of the element length [6]. For an exact description of how we apply this length prior, see the individual run descriptions in Section 3.

Mixing evidence

Although we retrieve individual elements from the collection, the elements are not independent from the surrounding elements. It is therefore intuitive to judge elements, not only based on their own merit, but also based on the context in which they appear. In many of our runs we scored elements by mixing evidence from the element itself, $s(E,Q)$, and evidence from the surrounding article $s(A,Q)$, using the scoring formula

$$s_{comb}(E,Q) = \mathrm{lp}(E) + \alpha \cdot s(A,Q) + (1-\alpha) \cdot s(E,Q), \qquad (6)$$

where $s(\cdot,\cdot)$ is the score function from Equation 3 and $\mathrm{lp}(\cdot)$ is the length prior from Equation 4. This mixing could in principle be more cleanly implemented inside the language model framework, using a mixture model.

Index cut-off

Using a length prior and tweaking of the smoothing parameter are not the only methods applicable to eliminate the small elements from the retrieval set. One can also simply discard the small elements when building the index. Elements containing text that is shorter than a certain cut-off value can be ignored when the index is built. In some of our runs we imitated such index building by restricting our view of the element index to a such a cut-off version. We also recalculate collection statistics accordingly, making the run equivalent to Further details will be provided in the description of individual runs in the next section.

3. RUNS

3.1 Content-Only task

In [6] we tried to answer the question of what is the appropriate unit of retrieval for XML information retrieval. A general conclusion was that users have a bias toward large elements. With our runs for the content-only task we pursued this issue further.

We wanted to experiment with element length bias. Three length related parameters were introduced in the previous section: value of the smoothing parameter, length prior and index cut-off. All our runs used the normal length prior, formula (4). Cut-off value was set to 20, which is equivalent to having only indexed elements containing at least 20 terms. Our runs differed only in the value given to the smoothing parameter.

UAmsI03-CO-lambda=0.9

In this run we set the smoothing parameter λ to 0.9. This value of λ means that little smoothing was performed, which resulted in a run with a bias toward retrieving large elements such as whole articles.

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<!DOCTYPE inex_topic SYSTEM "topic.dtd">
<inex_topic topic_id="103" query_type="CO" ct_no="50">
 <title>UML formal logic</title>
 <description>Find information on the use of formal logics
  to model or reason about UML diagrams.</description>
 <narrative>...</narrative>
 <keywords>...</keywords>
</inex_topic>
```

(a) Original topic

```
uml formal logic find information use formal logics model
reason uml diagrams
```

(b) Cleaned query (TD)

```
uml formal logic find information use formal logics model
reason uml diagrams booch longman rumbaugh itu jacobson
wiley guards ocl notations omg statecharts formalism
mappings verlag sdl documenting stereotyped semantically
sons saddle
```

(c) Expanded query (TD+blind feedback)

Figure 2: Example of a Content-Only topic (Topic 103)

UAmsI03-CO-lambda=0.2

In this run we set the smoothing parameter λ to 0.2 which means that a considerable amount of smoothing is performed. This resulted in a run with a bias toward retrieving elements such as sections and paragraphs.

UAmsI03-CO-lambda=0.5

Here we went somewhere in between the two extremes above by setting $\lambda = 0.5$. Furthermore, we required elements to be either articles, bodies or nested within the body.

All runs used mixed evidence from the article and the element level. The same combination value, $\alpha = 0.4$, was used in the scoring equation (Equation 6). The value was chosen after experimenting with the INEX 2002 collection.

As described previously, queries were created using the terms from the title and description; they were not stemmed but stop-words were removed (See Figure 2*b*). The queries were expanded using blind feedback (See Figure 2*c*). Feedback is a risky business, some terms might help while other might lead the retrieval astray. For this particular query one can imagine that it is useful to include the founding fathers of UML: *Booch*, *Jacobson* and *Rumbaugh*; but it might be misleading to include the publishers: *Longman*, *(John) Wiley (&) sons* and *(Springer) Verlag*.

3.2 Strict Content-And-Structure task

The CAS topics have a considerably more complex format than the CO topics (see Figure 3*a* for an example). The description part is the same, but the title has a different format. The CAS title is written in a language which is an extension of a subset of XPath [12]. We can view the title part of the CAS topic as a mixture of path expressions and filters. Our aim with our SCAS runs was to try to cast light on how these expressions and filters could be used to assign scores to elements.

More precisely, we consider the topic title of CAS topics to be split

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<!DOCTYPE inex_topic SYSTEM "topic.dtd">
<inex_topic topic_id="76" query_type="CAS" ct_no="81">
 <title>//article[(./fm//yr='2000' OR
  ./fm//yr='1999') AND about(.,'"intelligent
  transportation system"')]//sec[about(.,
  'automation +vehicle')]</title>
 <description>Automated vehicle applications
  in articles from 1999 or 2000 about intelligent
  transportation systems.</description>
 <narrative>...</narrative>
 <keywords>...</keywords>
</inex_topic>
```

(a) Original topic

```
intelligent transportation system automation
vehicle automated vehicle applications in
articles from 1999 or 2000 about intelligent
transportation systems
```

(b) Full content query (TD)

76a `intelligent transportation system`

76b `automation vehicle`

(c) Partial content queries(T)

```
//article[about(., "76a")]//sec[about(.,"76b")]
```

(d) Fuzzy structure (T)

```
//article[./fm//yr='2000' or ./fm//yr='1999']//sec
```

(e) Strict structure (T)

Figure 3: Example of a Content-and-Structure topic (Topic 76)

into path expressions and filters as follows.

$$\texttt{rootPath}[F_r \cup C_r \cup S_r]\texttt{targetPath}[F_e \cup C_e \cup S_e], \qquad (7)$$

where `rootPath` and `targetPath` are XPath path-expressions and F_r, C_r, S_r, F_e, C_e, S_e are sets of filters (explained below). We distinguish between three types of filters.

Element filters (F) F is a set of filters that put content constraints on the current element, as identified by preceding path expression (`rootPath` or `targetPath`). Element filters have the format `about(.,'whatever')`

Nested filters (C) C is a set of filters that put content constraints on elements that are nested within the current element. Nested filters have the format `about(./path, 'whatever')`

Strict filters (S) S is a set of filters of the format `path op value`, where `op` is a comparison operator such as = or >=; and value is a number or a string.

The filters in the actual topics were connected with a boolean formula. We ignore this formula and only look at sets of filters. However we treat the filters in quite a strict fashion; the larger the number of filters that are satisfied, the higher the ranking of an element. The difference between our three runs lies in the way we decide the ranking of results that satisfy the same number of filters.

As an example, the title part of Topic 76 in Figure 3*a* can be broken up into path expressions and filters such as:

$\texttt{rootPath} = \texttt{//article}$

$F_r = \{\texttt{about(.,`"intelligent transportation system"')}\}$

$C_r = \emptyset$

$S_r = \{\texttt{./fm//yr=`2000',./fm//yr=`1999'}\}$

$\texttt{targetPath} = \texttt{//sec}$

$F_e = \{\texttt{about(.,`automation +vehicle')}$

$C_e = \emptyset$

$S_e = \emptyset$

We calculate the retrieval scores by combining 3 base runs. The base runs consist of an *article run*, a ranked list of articles answering the full content query (Figure 3*b*); an *element run*, a ranked list of target elements answering the full content query (Figure 3*b*); and a *filter run*, a ranked list of elements answering each of the partial content queries (Figure 3*c*). More precisely the base runs were created as follows.

Article run

We created an article run from the element index by filtering away, from an element retrieval run, all elements not having the tag-name $\langle$`article`$\rangle$. We used a value $\lambda = 0.15$ for the smoothing parameter. This is the traditional parameter settings for document retrieval. We used the full content query (Figure 3*b*), expanded using blind feedback. For each query we retrieved a ranked list of 2000 most relevant articles.

Element run

We created an element run in a similar fashion as for the CO task. Additionally, we filtered away all elements that did not have the same tag-name as the target tag-name (the rightmost part of the `targetPath`). For topics where the target was unspecified, a '*', we considered only elements containing at least 20 terms. We did a moderate smoothing by choosing a value of 0.5 for λ. We used the full content queries (Figure 3*b*), expanded using blind feedback. For each query we retrieved an exhaustive ranked list of relevant elements.

Filter run

We created an element run in a similar fashion as for the CO task, but using the partial content queries (Figure 3*c*). No blind feedback was applied to the queries. We filtered away all elements that did not have the same tag-name as the target tag-name of each filter. For filters where the target was a '*' we considered only elements containing at least 20 terms. We did minor smoothing by choosing the value 0.7 for λ. For each query we retrieved an exhaustive ranked list of relevant elements.

For all the base runs we used the scoring formula with a length prior (Equation 5). From the base runs we created three runs which we submitted: one where scores are based on the element run; another where scores are based on the article run; and a third which uses a mixture of the element run, article run and filter run. For all the runs, the elements are filtered using an XPath-parser and the strict filters (Figure 3*e*). Any filtering using tag-names used the tag equivalence relations defined in the topic development guidelines. Our three different runs we created as follows.

UAmsI03-SCAS-ElementScore

The articles appearing in the article run were parsed and their elements that matched any of the element- or nested-filters were kept aside as candidates for the final retrieval set. In other words, we kept aside all elements that matched the title fuzzy XPath expression (Figure 3*d*), where the about predicate returns the value `true` for precisely the elements that appear in the filter run. The candidate elements were then assigned a score according to the element run. Additionally, results that match all filters got 100 extra points. Elements that match only the target filters got 50 extra points. The values 100 and 50 were just arbitrary numbers used to guarantee that the elements matching all the filters were ranked before the elements only matching a strict subset of the filters. This can be viewed as a coordination level matching for the filter matching.

UAmsI03-SCAS-DocumentScore

This run is almost identical to the previous run. The only difference was that the candidate elements were assigned scores according to the article run instead of according to the element run.

UAmsI03-SCAS-MixedScore

The articles appearing in the article run are parsed in the same way as for the two previous cases. The candidate elements are assigned a score which is calculated by combining the RSV scores of the three base runs. Hence, the score of an element is a mixture of its own score, the score of the article containing it, and the scores of all elements that contribute to the XPath expression being matched. More precisely, the element score was calculated using the formula

$$RSV(e) = \alpha \cdot \left(s(r) + \sum_{f \in F_r} s(f) + \sum_{c \in C_r} \max s(c) \right) + (1-\alpha) \cdot \left(s(e) + \sum_{f \in F_e} s(f) + \sum_{c \in C_e} \max s(c) \right), \quad (8)$$

where F_r, C_r, F_e and C_e represent sets of elements passing the respective filter mentioned in Equation 7; $s(r)$ is the score of the article from the article run; $s(f)$ and $s(c)$ are scores from the filter run; and $s(e)$ is the score from the element run. In all cases we set $\alpha = 0.5$. We did not have any training data to estimate an optimal value for this parameter. We did not apply any normalization to the RSVs before combining them.

3.3 Vague Content-And-Structure task

Since the definition of the task was a bit underspecified, we did not have a clear idea about what this task was about. With our runs we tried to cast light on whether this task is actually a content-only task, a content-and-structure task, or a traditional article retrieval task.

UAmsI03-VCAS-NoStructure

This is a run that is similar to our CO runs. We chose a value $\lambda = 0.5$ for the smoothing parameter. We used the full content queries, expanded by blind feedback. We only considered elements containing at least 20 terms.

UAmsI03-VCAS-TargetFilter

This run is more similar to our SCAS runs. We chose a value $\lambda = 0.5$ for the smoothing parameter. We used the full content queries, expanded by blind feedback. Furthermore, we only returned elements having the same tag-name as the rightmost part of `targetPath`. Where the target element was not explicitly stated (*-targets), we only considered elements containing at least 20 terms.

UAmsI03-VCAS-Article

This run is a combination of two article runs using unweighted combSUM [8]. The two runs differ in the way that one is aimed at recall but the other at high precision. The one that aims at recall used $\lambda = 0.15$ and the full content queries, expanded by blind feedback. The high precision run used $\lambda = 0.70$ and as queries only the text appearing in the filters of the topic title. The RSV values of the runs were normalized before they were combined.

For all the VCAS runs, scores were calculated using the length prior (Equation 5).

4. RESULTS AND DISCUSSION

We evaluate our runs using version 2003.004 of the evaluation software provided by the INEX 2003 organizers. We used version 2.4 of the assessments. Below, all runs are evaluated using the strict quantization; i.e., an element is considered relevant if, and only if, it is highly exhaustive and highly specific.

4.1 Content-Only task

Table 1 shows the results of the CO runs. Figure 4 shows the precision-recall plots. The CO runs at INEX 2003 are evaluated using *inex_eval*, the standard precision-recall measure for INEX. At present, two other measures are being developed, *inex_eval_ng(s)*, a precision recall measure that takes size of retrieved components into account; and *inex_eval_ng(o)*, which considers both size and overlap of retrieved components [1]. At the time of writing, a working version of the latter two measures had not been released. We will therefore only report on our results using the inex_eval measure.

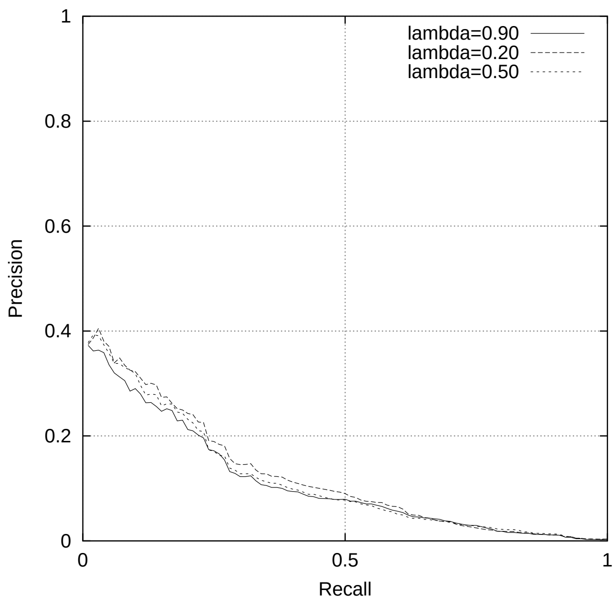

Figure 4: Precision-recall curves for our CO submissions, using the strict evaluation measure

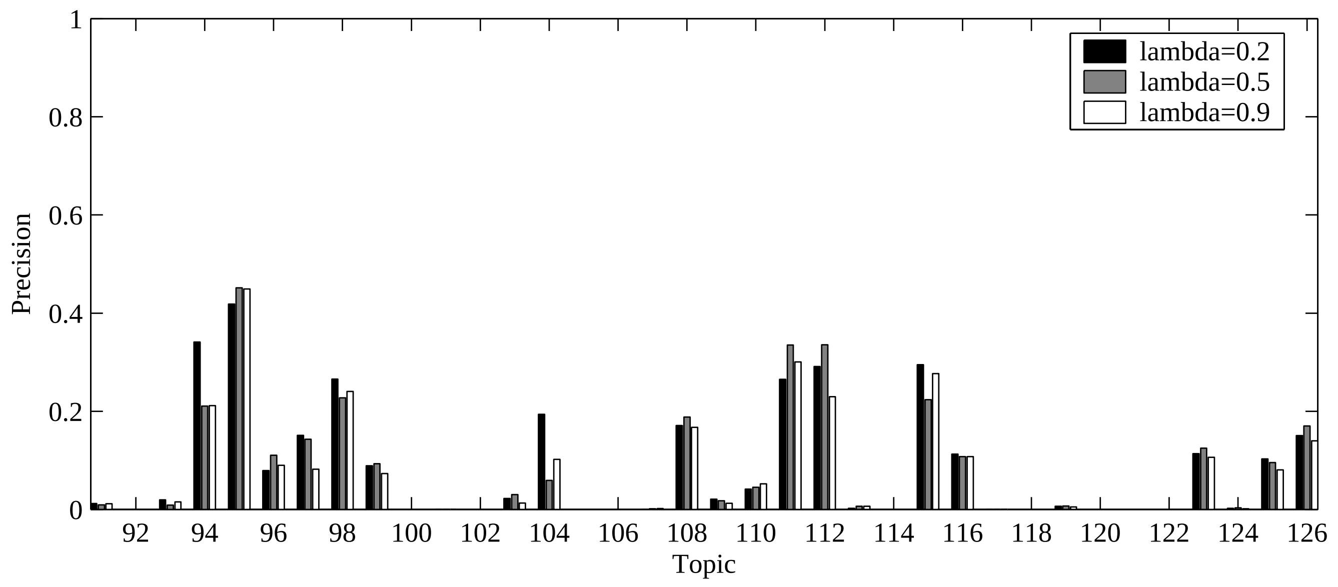

Figure 5: Precision for each of the CO topics. Note that assessments for topics 105, 106, 114, 118, 120, and 122 have not been completed. Furthermore, topics 92, 100, 102, and 121 have no strict judgments.

	MAP	p@5	p@10	p@20
$\lambda = 0.2$	**0.1214**	0.3231	**0.2923**	**0.2423**
$\lambda = 0.5$	0.1143	**0.3462**	**0.2923**	0.2346
$\lambda = 0.9$	0.1091	0.3308	0.2769	0.2250

Table 1: Results of the CO task

According to the inex_eval measure, the run using $\lambda = 0.2$ has over all highest MAP score. The run that uses $\lambda = 0.5$ and filters out elements outside the $\langle$`bdy`$\rangle$ tag, gives slightly higher precision when 5 elements were retrieved. The run using $\lambda = 0.2$ does however catch up quite quickly. The runs seem to be so similar that any differences are unlikely to be statistically significant.

Despite the similarity between the runs, let's take a closer look and see if there is any difference. Table 2 shows, for each run, the average length of retrieved elements and average length of the relevant elements retrieved. The table shows that the runs are indeed different. We are using the smoothing parameter to introduce a different length bias, the higher the value we give to the length prior, the larger elements we get on average. The difference between average length of retrieved elements and the average length of relevant elements retrieved, might indicate that a more length biased length prior is needed. Figure 5 shows the average precision of our runs for each topic separately. We see that for a vast majority of the topics the different runs give more or less the same score.

	Average element length	
	retrieved	relevant
$\lambda = 0.2$	1,335	2,499
$\lambda = 0.5$	1,839	2,965
$\lambda = 0.9$	2,166	3,330

Table 2: Some statistics of our submitted runs

From Figure 5 we see that our runs are far from being stable between topics. For 15 out of 30 assessed topics we score practically nothing at all. For 9 topics our score lies between 0.05 and 0.2. For 5 topics we score between 0.2 and 0.4. Finally only one topic reaches over 0.4. Let's take a closer look at the 15 topics where we score practically nothing. For 4 of them there were no strict judgments, i.e. no element was assessed as highly exhaustive and highly specific. A further 7 topics had 10 or less strict judgments. The remaining 4 had 21–90 strict judgments each. For all the 11 topics where were 10 or fewer strict judgments, we score poorly. For those topics the task turned out to be a real needle-in-the-haystack problem.

4.2 Strict Content-And-Structure task

In this section we will refer to our thee different runs as element-based, document-based and mixed. Table 3 shows the results of the SCAS runs. Figure 6 shows the precision-recall plots. The mixed run has higher MAP than the other two runs. The element-based run has slightly lower MAP than the mixed run. The document-based run has the lowest MAP.

	MAP	p@5	p@10	p@20
ElementScore	0.2987	**0.4160**	**0.3520**	0.2540
DocumentScore	0.2314	0.2960	0.2680	0.2160
MixedScore	**0.3182**	0.4000	0.3440	**0.2860**

Table 3: Results of the SCAS task

The element-based run outperforms the other two at low recall levels. We can see from the table that the element-based run has the highest precision after only 5 or 10 documents have been retrieved. The mixed run catches up with the element-based run once 20 documents have been retrieved. This indicates that coordination level matching for the filter matching, works well for initial precision, but is not as useful at higher recall levels.

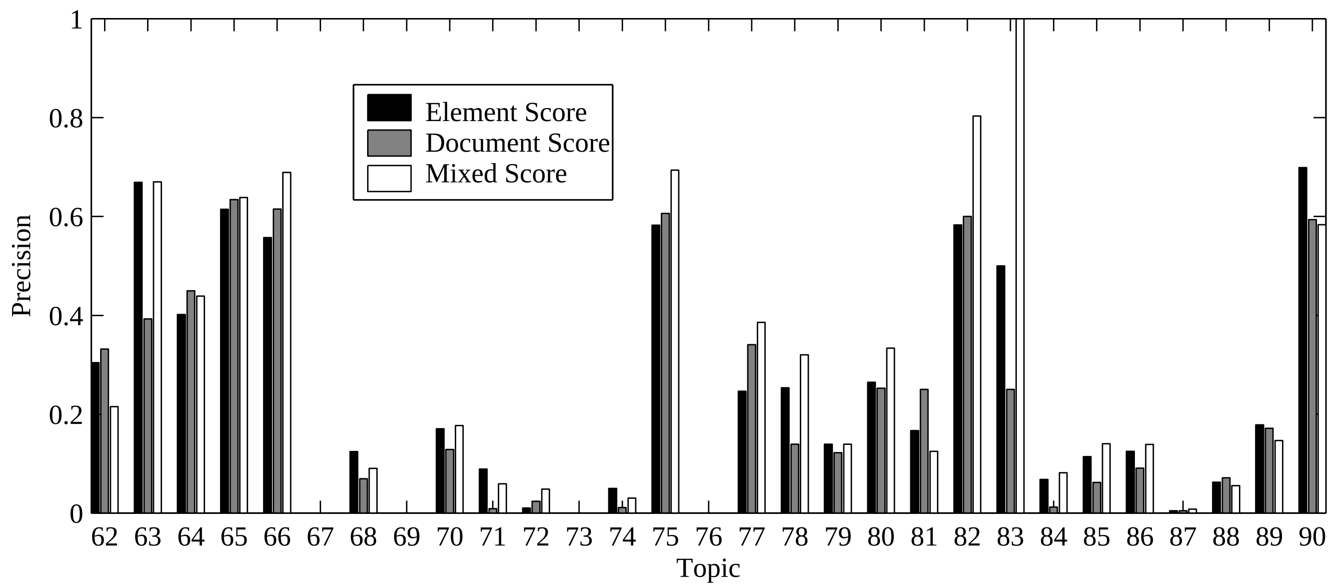

Figure 7: Precision for each of the SCAS topics. Topics 61, 67, 69, 73, and 76 have no strict judgments.

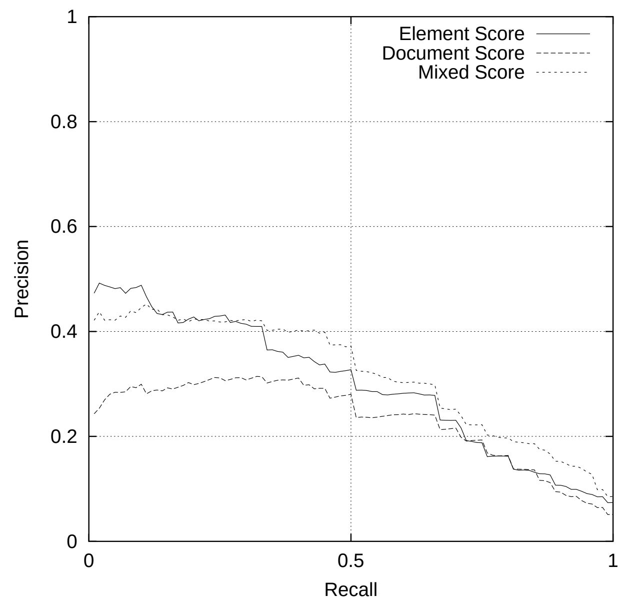

Figure 6: Precision-recall curves for our SCAS submissions, using the strict evaluation

Let us now try to analyze individual topics and topic groups. Figure 7 shows the average precision for our SCAS runs, individually for each topic. We see that the our performance is topic dependent. For this task, we do not see as clear correlation between precision and total number of relevant elements, as we saw for the content-only task. Since the target element is usually specified, this is less of a needle-in-the-haystack problem. To try to understand this better we look at performance over three different classes of topics.

Table 4 shows mean average precision for three different classes of target elements. First we look at the class of topics where the target is ⟨article⟩, then we look at the class where the target is ⟨sec⟩, and finally we look at the class of other topics (where the target is either *, ⟨abs⟩, ⟨p⟩, ⟨vt⟩ or ⟨bb⟩). The second column in the table shows how many topics there are in each class. The remaining columns show the performance of each run. The difference of each run is calculated using the overall performance of that run as baseline. Before we continue it must be said that the results must be taken with a grain of salt; they are based on very few topics, the classes only contain 10, 8 and 7 topics respectively.

Target	#	elem.-based		doc.-based		mixed	
article	10	0.3298	+10%	0.3142	+36%	0.3526	+11%
sec	8	0.2354	-21%	0.2364	+2.2%	0.2810	-13%
other	7	0.2569	-14%	0.1712	-26%	0.3199	+0.53%

Table 4: Average precision of our runs for the SCAS topics, clustered by tag name of the target element

For the class of topics where the target is an article, all runs perform well relative their overall performance. Compared to each other, the element-based run and document-based run perform similarly. The only difference is the value chosen for the smoothing parameter λ. For this class, the mixed run scores better than the other two runs, giving further evidence of how structure can help improve article retrieval [11].

For the class of topics where sections are the target, the performance of the document-based run is similar to it's overall performance. The element-based run and the mixed run perform poorly relative to their overall performance. Compared to each other, the mixed run still performs somewhat better than the other two runs. Again there is not much difference between the element-based run and the document-based run. This is surprising since one would have guessed that the element-based run would perform better.

For the class of the remaining topics, the performance of the mixed run is similar to it's overall performance. The other two runs perform poorly relative to their overall performance. Compared to each other, the mixed run is still better than the other two. Now the element-based run is clearly better than the document-based run.

Overall we can say safely that, our runs perform better on topics where the target element is an article, compared to the performance for other target-type classes. When the different runs are compared to each other, the mixed run performed consistently better than the other two. The element-based run only differentiated itself from the document-based run when the task was to find the smaller elements such as paragraphs and abstracts.

4.3 Vague Content-And-Structure task

At the time of writing the evaluation metric of the Vague Content-And-Structure task had not been released. Hence there are no results to discuss for this task.

5. CONCLUSIONS

This paper described our official runs for the INEX 2003 evaluation campaign. Our main research question was to further investigate the appropriate unit of retrieval. Although this problem is most visible for INEX's CO task, it also plays a role in the element and filter base runs for the CAS topics. With default adhoc retrieval settings, small XML elements dominate the ranks of retrieved elements. We conducted experiments with a number of approaches that aim to retrieve XML elements similar to those receiving relevance in the eyes of the human assessors. First, we experimented with a uniform length prior, ensuring the retrieval of larger sized XML elements [6]. Second, we experimented with Rocchio blind feedback, resulting in longer expanded queries that turn out to favor larger XML elements than the original queries. Third, we experimented with size cut-off, only indexing the element that contain at least 20 words. Fourth, we experimented with an element filter, ignoring elements occurring in the front and back matter of articles. Fifth, we experimented with smoothing settings, where the increase of the term importance weight leads to the retrieval of larger elements [4]. Finally, we combined approaches in various ways to obtain the official run submission.

Our future research focuses on the question of what is the appropriate statistical model for XML retrieval. In principle, we could estimate language models from the statistics of the article index similar to standard document retrieval. An alternative is to estimate them from the statistics of the element index, or from a particular subset of the full element index. In particular, we smooth our element language model with collection statistics from the overlapping element index. Arguably, this may introduce biases in the word frequency and document frequency statistics. Each term appearing in an article usually creates several entries in the index. The overall collection statistics from the index may not be the best estimator for the language models. In our current research we investigate the various statistics from which the language models can be estimated.

6. ACKNOWLEDGMENTS

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HyREX at INEX 2003

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ABSTRACT

Abstract: In this paper, we describe two new approaches for processing INEX queries. For CO queries, we adopt Amati's divergence from randomness approach (aka language model) and extend it by an additional factor for considering the hierarchical level of the element to be retrieved. For CAS queries, we investigate several mappings from INEX queries to our query language XIRQL, where we tried to introduce different degrees of vagueness. Both approaches yield good retrieval results, but still leave room for improvement.

1. INTRODUCTION

The HyREX (Hypermedia Retrieval Engine for XML) system developed by our group [Fuhr & Großjohann 01], [Fuhr & Großjohann 04], [Fuhr et al. 02] supports document ranking based on index term weighting, specificity-oriented search for retrieving the most relevant parts of documents, data types with vague predicates for dealing with specific types of content and structural vagueness for vague interpretation of structural query conditions. In INEX 2002, HyREX performed very well for content-only (CO) queries, but only poorly for content-and-structure(CAS) queries (although this was due to a bug in the implementation).
In this paper, we describe a new retrieval model for CO queries based on Amati's divergence from randomness (DFR) approach. For the CAS queries, we investigated several methods for transforming INEX topics into our own query language XIRQL [Fuhr & Großjohann 01].

2. CONTENT-ONLY QUERIES

In [Fuhr & Großjohann 01], we proposed the *augmentation* method for processing content-only queries. This method gave very good results in INEX 2002. In the augmentation approach, standard term weighting formulas (we were using the BM25 formula [Robertson et al. 95] for this purpose) are used for indexing the leave nodes of the document tree. For computing the indexing weights of inner nodes, the weights from the leaves are propagated towards the inner nodes. During propagation, however, the weights are down-weighted by multiplying them with a so-called augmentation factor. This down-weighting happens whenever the indexing weight is propagated from an element that belongs to a predefined set of so-called index node root elements to its parent element. In case a term at an inner note receives propagated weights from several leaves, we compute the overall term weight by assuming a probabilistic disjunction of the leaf term weights. This way, more specific elements are preferred during retrieval

This year, we were trying to adopt the DFR approach, which is a kind of language model. Here we give only a brief description of the application of this approach to XML retrieval. A more detailed presentation can be found in [Abolhassani & Fuhr 04].

2.1 The DFR approach

[Amati & Rijsbergen 02] introduce a framework for deriving probabilistic models of IR. These models are non-parametric models of IR as obtained in the *language model* approach. The term weighting models are derived by measuring the divergence of the actual term distribution from that obtained under a random process.
In this framework, the weighting formula for a term in a document is the product of the following two factors:

1. $Prob_1$ is used for measuring the *information content* of the term in a document, and $(-\log_2 Prob_1)$ gives the corresponding amount of information.

2. $Prob_2$ is used for measuring the *information gain* of the term with respect to its 'elite' set (the set of all documents in which the term occurs). The less the term is expected in a document with respect to its frequency in the elite set (measured by the counter-probability $(1 - Prob_2)$), the more the amount of information is gained with this term.

Then the weight of a term in a document is defined as:

$$w = (1 - Prob_2) \cdot (-\log_2 Prob_1) = Inf_2 \cdot Inf_1 \qquad (1)$$

For computing the two probabilities, the following parameters are used:

N number of documents in the collection,

tf term frequency within the document (since different normalisations are applied to the term frequency, we use tf_1 and tf_2 in the following formulas),

n size of the elite set of the term,

F term frequency in elite set.

Furthermore, let $\lambda = F/N$ in the following.
As probability distribution for estimating $Prob_1$, different probabilistic models are regarded in [Amati & Rijsbergen 02]. In this paper, we use only two of them:

- The **binomial** model assumes that the F term occurrences are distributed independently over the N document; thus, we have a binomial distribution with $p = 1/N$. Approximating the binomial formula with the divergence yields:

$$Inf_1 = tf_1 \cdot \log_2 \frac{tf_1}{\lambda} + \left(\lambda + \frac{1}{12tf_1} - tf_1\right)$$

Table 1: Results from direct application vs. augmentation approach

document length	Dynamic		Fixed	
	B Norm.	L Norm.	B Norm.	L Norm.
Binomial	0.0109	0.0356	0.0640	0.0717
Bose-Einstein	0.0214	0.0338	0.0468	0.0606
Augmentation	0.1120			

Table 2: Results from 2nd normalisation with two basic values for β

	$\beta = 0$		$\beta = -1$	
	B Norm.	L Norm.	B Norm.	L Norm.
Binomial	0.0391	0.0586	0.0640	0.0900
Bose-Einstein	0.0376	0.0609	0.0376	0.0651

$$\cdot \log_2 e + 0.5 \log_2(2\pi \cdot tf_1) \qquad (2)$$

- The **Bose-Einstein** model considers all possible distributions of the F term occurrences within the N documents and then considers all those events where the current document has tf_1 occurrences. The Geometric as limiting form of the Bose-Einstein model yields:

$$Inf_1 = -log_2 \frac{1}{1+\lambda} - tf_1 \cdot \log_2 \frac{\lambda}{1+\lambda} \qquad (3)$$

For the parameter $Inf_2 = (1 - Prob_2)$ (which is also called *first normalisation*), $Prob_2$ is defined as the probability of observing another occurrence of the term in the document, given that we have seen already tf occurrences. For this purpose, Amati regards two approaches:

L Based on Laplace's law of succession, he gets

$$Inf_2 = \frac{1}{tf_2 + 1} \qquad (4)$$

B Regarding the ratio of two Bernoulli processes yields

$$Inf_2 = \frac{F+1}{n \cdot (tf_2 + 1)} \qquad (5)$$

These parameters do not yet consider the length of the document to be indexed. For the relationship between document length and term frequency, we apply the following formula:

$$\rho(l) = c \cdot l^{\beta} \qquad (6)$$

where l is the document length, $\rho(l)$ is the density function of the term frequency in the document, c is a constant and β is a parameter to be chosen.
In order to consider length normalisation, Amati maps the tf frequency onto a normalised frequency tfn computed in the following way: Let $l(d)$ denote the length of document d and avl is the average length of a document in the collection. Then tfn is defined as:

$$tfn = \int_{l(d)}^{l(d)+avl} \rho(l) dl \qquad (7)$$

Thus, the normalised term frequency tfn is computed by assuming that there would be a document of average length appended to the actual document, and that we estimate the number of term occurrences within this hypothetical document (based on the term density function $\rho(l)$).

For considering these normalisations, Amati sets $tf_1 = tf_2 = tfn$ in formulas 2–5 and then computes the term weight according to eqn 1.
For retrieval, the query term weight qtf is set to the number of occurrences of the term in the query. Then a linear retrieval function is applied:

$$R(q,d) = \sum_{t \in q} qtf \cdot Inf_2(tf_2) \cdot Inf_1(tf_1) \qquad (8)$$

In [Amati & Rijsbergen 02], DFR evaluation results for different parts of the TREC collection are reported. In many cases, DFR variants give better results than the BM25 formula[1], and in some cases even yield the best overall results. Thus the DFR approach offers both a solid theoretical foundation an a high retrieval quality.

2.2 Applying divergence from randomness to XML documents

2.2.1 Direct application of Amati's model

In Section 2.1, we have described the basic model along with a subset of the weighting functions proposed by Amati. Given that we have two different formulas for computing Inf_1 as well as two different ways for computing Inf_2, we have four basic weighting formulas which we are considering in the following.
In a first round of experiments, we tried to apply Amati's model without major changes. However, whereas Amati's model was defined for a set of atomic documents, CO retrieval is searching for so-called *index nodes*, i.e. XML elements that are meaningful units for being returned as retrieval answer.
As starting point, we assumed that the complete collection consists of the concatenation of all XML documents. When we regard a single index node, we assume that the complete collection consists of documents having the same size as our current node. Let L denote the total length of the collection and $l(d)$ the length of the current node (as above), then we compute the number of hypothetical documents as $N = L/l(d)$. Since we assume that all documents are of equal length, no document length normalisation (eqn. 7) is necessary in this case; instead, we have an implicit consideration of document length via modifying N, which, in turn, affects λ in eqn. (2) and (3).
Table 1 shows the experimental results. The first two result columns list the average precision values for this setting when applying the four different weighting functions. We suspect that the poor performance is due to the fact that the weights derived from different doc-

[1]In [Amati & Rijsbergen 02], it is shown that BM25 actually is an approximation of one of the DFR formulas.

Table 3: Results from 2nd normalisation with two other values for β

	$\beta = -0.75$		$\beta = -0.80$	
	B Norm.	L Norm.	B Norm.	L Norm.
Binomial	0.0799	0.1026	0.0768	0.1005
Bose-Einstein	0.0453	0.0653	0.0448	0.0654

Table 4: Average precision for the Bose-Einstein L Norm combination with various values of α

α	2	4	9	16	20	32	64	96	104	116	128
prec.	0.0726	0.0865	0.0989	0.1059	0.1077	0.1083	0.1089	0.1094	0.1087	0.1081	0.1077

ument lengths are not comparable, i.e. that our 'implicit' document length normalisation via modifying the hypothetical total number of documents N is not feasible.
As an alternative method, we computed the average size of an index node. The two last columns in table 1 show a much better retrieval quality for this case.
In the subsequent experiments, we focused on the second approach. By referring to the average size of an index node we were also able to apply document length normalisation according to Equation 6. Table 2 shows the corresponding results for $\beta = 0$ and $\beta = -1$. The results show that length normalisation with $\beta = -1$ improves retrieval quality in most cases. These results were also in conformance with Amati's findings that $\beta = -1$ gives better results than $\beta = 0$.
Subsequently we tried some other values for β. Table 3 shows the corresponding results for $\beta = -0.75$ and $\beta = -0.80$, with which we got better results.
Overall, using a fixed average document length, and length normalisation, gave better results than those achieved in the first round. However, the resulting retrieval quality was still lower than that of the augmentation approach (see table 1). Thus, in order to arrive at a better retrieval quality, we investigated other ways than straightforward application of Amati's model.

2.2.2 *Considering the hierarchical structure of XML documents*

In order to consider the hierarchical structure of XML documents, we investigated different ways for incorporating structural parameters within the weighting formula. Regarding the basic ideas, as described in Section 2.1, the most appropriate way seemed to be the modification of the Inf_2 parameter, which refers to the 'elite' set. Therefore, we computed Inf_1 as above, by performing document length normalisation with respect to the average size of an index node.
For computing Inf_2, we also applied document length normalisation first, thus yielding a normalised term frequency tfn. Then we investigated several methods for 'normalising' this factor with respect to the hierarchical document structure; we call this process *third normalisation*. For this purpose, we introduced an additional parameter $h(d)$ specifying the height (or level) of an index node relative to the root node (which has $h = 1$).
Using the level information, we first tried several heuristic formulas like $tf_2 = tfn \cdot h(d)^\alpha$ and $tf_2 = tfn \cdot h(d)^{-\alpha}$, which, however, did not result in any improvements. Finally, we came up with the following formula:

$$tf_2 = tfn \cdot (h(d)/\alpha) \qquad (9)$$

Here α is a constant to be chosen, for which we tried several values. However, the experiments showed that the choice of α is not critical. This weighting formula gives higher weights to terms occurring in deeper elements of the document tree. This way, we try to achieve the INEX CO goal of retrieving the most specific elements answering the query.
Table 4 shows the results for the combination of Bose-Einstein and Laplace normalisation, for which we got significant improvements. This variant also gave better results in Amati's experiments. In further experiments not listed here we tried to combine 3rd normalisation with the binomial model; however, this resulted in a decrease of retrieval quality.

3. CONTENT-AND STRUCTURE(CAS) TOPICS

The query language XIRQL of our retrieval system HyREX is very similar to the INEX CAS topic specification. However, our experience from INEX 2002 has shown that a 'literal' interpretation of the CAS queries does not lead to good retrieval results. Thus, we were looking for 'vague' interpretations of the INEX topics. Since XIRQL has a high expressiveness, we did not want to change the semantics of XIRQL (by introducing vague interpretations of the different language elements). Instead, we focused on the transformation from the INEX topic specification into XIRQL.
XIRQL is an extension of XPath [Clark & DeRose 99] by IR concepts. We assume that XML document elements have specific data types, like e.g. person names, dates, technical measurement values and names of geographic regions. For each data type, there are specific search predicates, most of which are vague (e.g. phonetic similarity of names, approximate matching of dates and closeness of geographic regions). In addition to Boolean connectors, there also is a weighted sum operator for computing the scalar product between query and document term weights.
The general format of a of an INEX query is
//TE[filter] or
//CE[filter]//TE[filter]
Where TE stands for Target Element and CE stands for Context Element.
In XIRQL, single query conditions can be combined in the following way:

Conjunctions(and) Filter conditions(conditions within [..]) can be combined by the and operator

Disjunctions(or) Filter conditions can be combined by the or operator.

Weighted Sum (wsum) and Precedence Weighted sum notation can be used to indicate the importance of a query term, e.g.

```
//article[wsum(
0.7,.//atl//#PCDATA $stem$ "image",
0.3,.//atl//#PCDATA $stem$ "retrieval"
)]
```

Phrases Since HyREX has no specific phrase operator (yet), we represented phrases as conjunctions of the single words, e.g.

```
//article[wsum(
1.0,.//atl//#PCDATA [. $stem$ "image"
$and$ . $stem$ "retrieval"],
1.0,. $stem$ "colour")]
```

3.1 Experimentation

In order to search for better transformations from INEX CAS topics into XIRQL, we performed a number of experiments using the INEX 2002 topics (which we transformed into the 2003 format). For generating our XIRQL queries, we used only titles and keywords of the topics. In the following we briefly characterise the different kinds of transformations investigated. We illustrate each method by showing the resulting XIRQL expression for the following INEX topic(articles about image retrieval methods based on colour, contour, shape, texture and semantics):

```
//article[about(.//atl,'image retrieval'
) and about(.,'image retrieval colour
shape texture')]
```

3.1.1 CAS-I

The first transformation assumes a very strict interpretation of the INEX query. Except for the query terms, we always assume a conjunction of conditions:

1. Only query title is used.
2. Phrases are represented using conjunctions.
3. Query terms are represented using disjunctions
4. Mandatory ('+' prefixed) terms are handled by conjunctions

```
//article[(.//atl//#PCDATA[
. $stem$ "image" $and$
. $stem$ "retrieval"]) $and$
(.//#PCDATA[ . $stem$ "image"] $or$
 .//#PCDATA[ . $stem$ "retrieval"]
 $or$ .//#PCDATA[ . $stem$ "colour"]
 $or$ .//#PCDATA[ . $stem$ "shape"]
 $or$ .//#PCDATA[ . $stem$ "texture"]
 )]
```

3.1.2 CAS-II

Here we tried a vague interpretation of the query, by combining the different conditions via weighted sum, and mandatory terms just get higher weights.

1. Only query title is used.
2. Phrases are represented using conjunctions.
3. Terms are represented using weighted sum notation and assigned weight 1.
4. Mandatory terms are assigned higher weights.

```
/article[ wsum(1.0,.//atl//#PCDATA[
. $stem$ "image" $and$
. $stem$ "retrieval"],
 1.0, ... $stem$ "image",
 1.0, ... $stem$ "retrieval",
 1.0, ... $stem$ "colour",
 1.0, ... $stem$ "shape",
 1.0, ... $stem$ "texture")]
```

3.1.3 CAS-III

This variant is is a combination of CAS-I and CAS-II:

1. Only query title is used.
2. Phrases are represented using conjunctions.
3. Terms are represented using weighted sum notation and XPath notations. These two notations are joined with or operator.
4. '+' prefixed terms are assigned higher weight 5 and also represented as phrases.

```
//article[(.//atl//#PCDATA[
. $stem$ "image" $and$
. $stem$ "retrieval"])
$and$
(.//#PCDATA[ . $stem$ "image"] $or$
 .//#PCDATA[ . $stem$ "retrieval"] $or$
 .//#PCDATA[ . $stem$ "colour"] $or$
 .//#PCDATA[ . $stem$ "shape"] $or$
 .//#PCDATA[ . $stem$ "texture"]) $or$
 wsum(1.0,.//atl//#PCDATA $stem$ "image",
  1.0,.//atl//#PCDATA $stem$ "retrieval",
  1.0, ... $stem$ "image",
  1.0, ... $stem$ "retrieval",
  1.0, ... $stem$ "colour",
  1.0, ... $stem$ "shape",
  1.0, ... $stem$ "texture")]
```

3.1.4 CAS-IV

This variant is similar to CAS-I, but considers terms from both the title and the keywords.

1. Query titles and keywords are used. Keywords are considered in case there are less than 3 query terms in the title.
2. Phrases are represented using conjunctions.
3. Terms are represented using disjunctions
4. '+' prefixed terms are handled as phrases.

```
//article[  (  .//atl//#PCDATA[
. $stem$ "image" $and$
. $stem$ "retrieval"]) $and$
 (.//#PCDATA[ . $stem$ "image"] $or$
  .//#PCDATA[ . $stem$ "retrieval"]
  $or$ .//#PCDATA[ . $stem$ "colour"]
  $or$ .//#PCDATA[ . $stem$ "shape"]
  $or$ .//#PCDATA[ . $stem$ "texture"
  ])]
```

3.1.5 CAS-V

This is a more vague variant of CAS-II, where we combine even the components of a phrase via wsum.

1. Only query title is used.
2. Phrases are also handled as terms and assigned weight 1.0.
3. Terms are combined by wsum operator.
4. Higher weight (5) is assigned to terms prefixed with '+'.

Table 5: Query variations summary

	query part	notation	terms	phrases	+prefixed terms
CAS-I	title	XPath	or	and	and
CAS-II	title	wsum	weight 1.0	and	weight 5.0
CAS-III	title	XPath & wsum	or & weight 1.0	and	and & weight 5.0
CAS-IV	title & keywords	XPath	or	and	and
CAS-V	title	wsum	weight 1.0	weight 1.0	weight 5.0

Table 6: Results:Experimentation with INEX 2002 CAS topics

Query Variation	Average Precision			
	ignore empty		consider empty	
	strict	generalised	strict	generalised
CAS-I	0.2640	0.2338	0.1692	0.1508
CAS-II	0.1325	0.1215	0.0859	0.0798
CAS-III	0.1724	0.1415	0.1045	0.0916
CAS-IV	0.1297	0.1179	0.0959	0.0877
CAS-V	0.1327	0.1077	0.0806	0.0872

```
//article[
wsum( 1.0,.//atl//#PCDATA $stem$ "image",
 1.0,.//atl//#PCDATA $stem$ "retrieval",
 1.0, ... $stem$ "image",
 1.0, ... $stem$ "retrieval",
 1.0, ... $stem$ "colour",
 1.0, ... $stem$ "shape",
 1.0, ... $stem$ "texture")
]
```

3.1.6 *Evaluation*

Using the two strict and the generalised variants of the INEX evaluation metrics [Gövert & Kazai 03], we got the results shown in table 8. Depending on the query complexity, some of the queries could not be processed by HyREX; columns headed by 'ignore empty' give performance figures where these queries are ignored, whereas 'consider empty' means that these queries are considered with zero precision. One can see that the strict interpretation CAS-I yields the best results, whereas all vague interpretations lead to a lower retrieval quality. We conclude that — at least for the strict interpretation of the CAS queries — vague interpretations of the query logic by replacing conjunctions with disjunctions or weighted sums do improve results, they lead to a lower retrieval quality.

4. INEX 2003 SUBMISSIONS & RESULTS

Our CO submissions in INEX 2003 include:

- factor 0.5
- factor 0.2
- difra_sequential

The first two submissions use the "augmentation" method (the same as in our 2002 INEX submission) with 0.5 and 0.2 as "augmentation facto", respectively. The third submission is based on the "DFR" method. Here, we chose the best configuration according to our experiments results, i.e. Bose-Einstein and L Normalisation with the parameters $\alpha = 96$ and $\beta = -0.80$.
Table 7 lists the evaluation results of our submissions, based on different metrics, in INEX 2003. The results show that the latter two submissions both performed well, with the augmentation method still slightly better than the DFR approach.
For the CAS topics, two subtasks were defined in INEX: strict CAS(SCAS) and vague CAS (VCAS). SCAS enforces the strict interpretation of CAS topics while in case of VCAS, query conditions can be treated vaguely. For the latter also a list of equivalent tags was defined.; as long as the retrieved component is structurally similar to the user's interest (target element), it is considered to be correct.
With regard to these two subtasks, we submitted three runs based on the query transformation CAS-I ... III for the SCAS task as SCAS03-I ... III, while the other two transformations CAS-IV and CAS-V were used as VCAS submissions VCAS03-I and VCAS03-II, respectively. Since our system could not process all transformations with the alias list of element names (leading to the corresponding disjunction of structural conditions), the alias list was not applied for two of the submissions:

- SCAS03-I-alias
- SCAS03-II-alias
- SCAS03-III-noalias
- VCAS03-I-alias
- VCAS03-II-alias
- VCAS03-I-noalias

Table 8 shows the evaluation results of our submissions in INEX 2003. The results confirm the outcome of our own experiments. SCAS03-I-alias is the best of our submitted runs and performed quite well(ranked at 5th and 9th out of 38 for strict and generalised quantisations respectively) in comparison to other approaches.

5. CONCLUSIONS

The results from INEX 2003 show that HyREX yields good retrieval performance both for CO and CAS queries. For the CO queries, our extension to the basic DFR approach takes into account only the level of a retrieved element (via third normalisation). However, there are numerous other parameters that could considered, such as e.g. element names, element-specific node length, or

Table 7: Average precision for our CO submissions in INEX 2003

Submission	Average Precision					
	inex_eval		inex_eval_ng			
			consider overlap		ignore overlap	
	strict	generalised	strict	generalised	strict	generalised
factor 0.5	0.0703	0.0475	0.1025	0.0623	0.0806	0.0590
factor 0.2	0.1010	0.0702	0.1409	0.0903	0.1219	0.0964
difra_sequential	0.0906	0.0688	0.1354	0.0774	0.1217	0.0920

Table 8: Average precision for our CAS submissions in INEX 2003

Submission	Average Precision & Ranking			
	strict		generalised	
	avg. precision	ranking	avg.precision	ranking
SCAS-I-alias	0.2594	5	0.2037	9
SCAS-II-alias	0.2213	18	0.1744	18
SCAS-III-noalias	0.2034	19	0.1707	18

element specific prior probabilities. By investigating the influence of these factors, we will continue our work on the DFR approach towards a full-fledged language model for XML retrieval. On the CAS side, besides dealing with some weaknesses of the current implementation, we will investigate further methods for 'vague' interpretations of this type of queries, especially with regard to structural conditions.

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Bayesian Networks and INEX'03

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ABSTRACT

We present a Bayesian framework for XML document retrieval. This framework allows us to consider *content-only* (CO) queries. We perform the retrieval task using inference in our network. The proposed model can adapt to a specific corpus through parameter learning and it uses a grammar to speed up the retrieval process in large or distributed databases. We also experimented list filtering to avoid overlap in the retrieved element list.

Keywords
Bayesian networks, INEX, XML, Focused retrieval, Structured document retrieval

1. INTRODUCTION

The goal of our model is to provide a generic system for performing different Information Retrieval (IR) tasks on collections of structured documents. We take an IR approach to this problem. We want to retrieve specific relevant elements from the collection as an answer to a query. The elements may be any document or document part (full document, section(s), paragraph(s), etc.) indexed from the structural description of the collection. We consider the task as a *focused retrieval*, first described in [1, 7].

This year, we focused on *content only* (CO) queries since many research questions still remain open for this specific task. The Bayesian Network (BN) model is briefly described in section 2.1. We also present modifications with respect to the model presented last year.

2. MODELS

The generic BN model used for the CO task was described in the last proceedings [8]. We only give here the main model characteristics. Our work is an attempt to develop a formal model for structured document access. Our model relies on Bayesian networks and provides an alternative to other specific approaches for handling structured documents [6, 3, 4]. BN offer a general framework for taking into account relation dependencies between different structural elements. Those elements, which we call *doxels* (for Document Element) will be random variables in our BN.

We believe that this approach allows casting different access information tasks into a unique formalism, and that these models allow performing sophisticated inferences, e.g. they allow to compute the relevance of different document parts in the presence of missing or uncertain information. Compared to other approaches based on BN, we propose a general framework which should adapt to different types of structured documents or collections. Another original aspect of our work is that model parameters are learnt from data. This allows to rapidly adapt the model to different document collections and IR tasks.

We have made the following additions to the model presented last year :

- We experimented with different weighting schemes for terms in the different doxels. Weight importance may be relative to the whole corpus of documents, to doxels labelled with the same tag, etc. ;
- We introduced a grammar for modelling different constraints on the possible relevance values of doxels knowing its parent relevance value ;
- To limit the overlap (e.g. return a section and one of its paragraph) of retrieved doxels, we introduced simple filtering techniques.

2.1 Bayesian networks

The BN structure we used directly reflects the document hierarchy, *i.e.* we consider that each structural part within that hierarchy has an associated random variable. The root of the BN is thus a "corpus" variable, its children the "journal collection" variables, etc. In this model, due to the conditional independence property of the BN variables, relevance is a local property in the following sense: if we know the relevance of a journal, the relevance value of the journal collection will not bring any new information on the relevance of one article of this journal (figure 1).

In our model, the random variable associated to a structural element can take three different values in the set $V = \{N, G, E\}$ which is related to the *specificity* dimension of the INEX'03 assessment scale:

N (for Not relevant) when the element is not relevant;

G (for too biG) when the element is marginally or fairly specific;

E (for Exact) when the element has a high specificity.

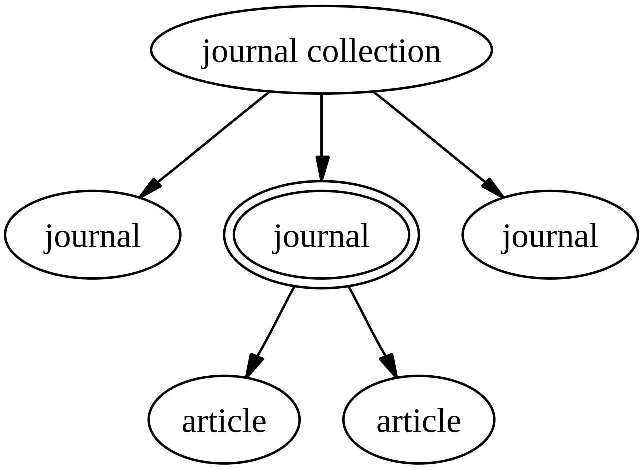

Figure 1: Independence in the BN. When we know the relevance of a journal, the relevance of the journal collection have no influence on the articles within this journal.

For any doxel e and for a given query, the probability $P(e = E|\text{query})$ gives us the *final* Retrieval Status Value (RSV) of this element. This value is used for the ranking of the different doxels with respect to the query.

We considered *two* other types of random variables. The first one is the query that is described as a vector of word frequencies. Note that this random variable is always observed (known). The second one is associated to *baseline* models and can take only two values: *relevant* and *not relevant.*

For a given query, a local relevance score is computed for each doxel via the baseline score models. This score only depends on the query and the doxel content. Based on these local scores and on parameters, BN inference is then used to combine evidence and scores for different doxels in the document model. For computing the local score, different models could be used. We used in our experiments simple retrieval methods and classical ones such as Okapi. The first one (*ratio*) computes for each element the value S_1:

$$S_1(\text{element}) = \frac{\sum_{\text{term}t} tf_{\text{query}}(t) \frac{tf_{\text{element}}(t)}{tf_{\text{parent}}(t)}}{\sum_{\text{term}t} tf_{\text{query}}(t)}$$

where tf_{parent} denotes the term frequency in the parent of the element, tf_{element} the term frequency within the element and tf_{query} within the query. The second one (*weight ratio*) is simply S_1 divided by a decreasing function of the element length:

$$S_2(\text{element}) = \frac{S_1(\text{element})}{\log(20 + \text{length}(\text{element}))}$$

where the length of the element is number of words that this element and its descendants contain. All those formulas and coefficient were determined empirically. The main advantages of these formulas are that they give scores that are naturally bounded (between 0 and 1) and that they can be computed *locally.* We can then define the probability that an element is relevant (R) for the first (resp. second) model M_1 (M_2) by:

$$P(M_i = R|\text{query}, \text{element content}) = S_i \text{ with } i \in \{1, 2\}$$

We also tried to add the classical Okapi model, but as its RSV are harder to normalise, we were not able to integrate it with success into our BN framework. We will try to use the normalisation proposed by Robertson [9] next year: our goal was to prove BN can perform better than its baseline models.

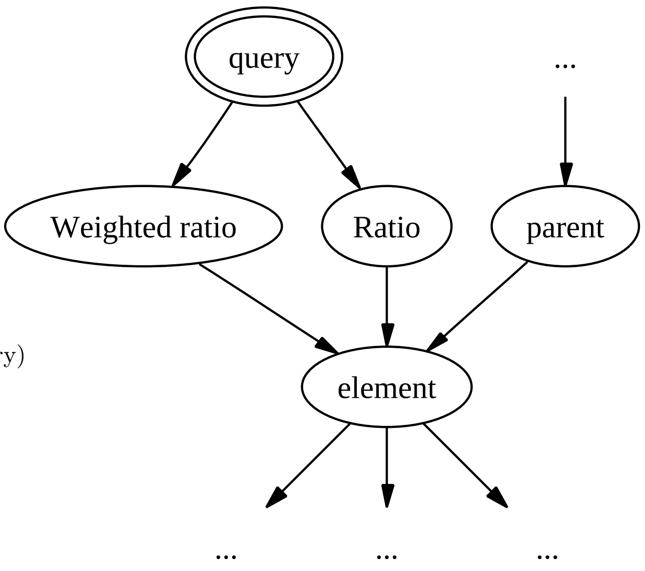

Figure 2: Bayesian Network model (detail view). The element state depends on the parent state and on the relevance of the element for the model *ratio* (M_1) and *weighted ratio* (M_2)

In our model, the probability that an element is in the state N, G or E depends on the parent state and on the fact that M_i has judged the element as relevant or not relevant (figure 2). We can then compute the probability using this formula for any element e and any state $v \in V$:

$$\begin{aligned} P(e = v|\text{query}) = \sum_{\substack{v_p \in V \\ r_1, r_2 \in \{R, \neg R\}}} & \theta_{c(e),v,v_p,r_1,r_2} \\ & \times P(e \text{ parent} = v_p) \\ & \times P(M_1 = r_1|\text{query}) \\ & \times P(M_2 = r_2|\text{query}) \end{aligned}$$

where θ is a learnt parameter that depends on the different states of the four random variables (element state, parent state, baseline model 1 and 2 relevance) and on the category $c(e)$ of the element. The categories used in our experiment are shown in table 1. In our BN, scores are computed recursively with the above formula: we begin by the biggest doxels (INEX volumes) and then we compute scores while going deeper and deeper in the document tree (article, body, paragraph and so on).

tags	category $c(e)$
ss, ss1, sec1	section
bib, bibl, ack, reviewers	misc
ip, ip1, ip2, ip3, bb, app, p1, p2	paragraph
figw, fig	figure
l1, l2, l3, l4, l5, l6, l7, l8, l9, la, lb, lc, ld, le, numeric-list, numeric-rbrace, bullet-list, index	list
index-entry, item-none, item-bold, item-both, item-bullet, item-diamond, item-letpara, item-mdash, item-numpara, item-roman, item-text	item
hdr, hdr2, hdr1, h3, h2, h2a, h1a, h1, h	header
bdy, article	container
* (any other tag)	other

Table 1: Element categories

Adding a grammar to the BN

We used a grammar in order to add some constraint on the retrieval inference process. That grammar enables us to express coherence rules on scored doxels within the same document path:

- A non relevant element *may not* have a relevant descendant:
$$\forall c, r_1, r_2, \theta_{c,v,N,r_1,r_2} = 0 \text{ if } v \in \{G, E\}$$
- An exact doxel (E) can not have a child which is "too big" (G).
$$\forall c, r_1, r_2, \theta_{c,G,E,r_1,r_2} = 0$$

The main interest of this grammar is to provide us a way to make a decision about whether we can find an element which has a higher RSV in the set of descendants of a given element. Indeed, we can show that:

$$P(e = E|\text{query}) \leq P(p = E|\text{query}) + P(p = G|\text{query}) \quad (1)$$

where p is the parent of the doxel e.

Learning parameters

In order to fit a specific corpus, parameters are learnt from observations using the Expectation Maximization (EM) algorithm. An observation $O^{(i)}$ is a query with its associated relevance assessments (document/part is relevant or not relevant to the query). EM [2] optimises the model parameters Θ with respect to the likelihood $\mathcal{L}$ of the observed data:

$$\mathcal{L}(O, \Theta) = \log P(O|\Theta)$$

where $O = \left\{O^{(1)}, \ldots, O^{(|O|)}\right\}$ are the N observations. Observations may or may not be *complete*, *i.e.* relevance assessments need not to be known for each structural element in the BN in order to learn the parameters. Each observation O_i can be decomposed into E_i and H_i where E_i corresponds to structural entities for which we know whether they are relevant or not, i.e. structural parts for which we have a relevance assessment. E_i is called the evidence. H_i corresponds to hidden observations, i.e. all other nodes of the BN.

In our experiment, we used for learning the 30 CO queries from INEX'02 and their associated relevance assessments.

2.2 Filtering

A Structured IR system has to cope with overlapping doxels, as it may for example return a section and its paragraph. In order to avoid duplicate information, it might be interesting to filter out the returned result in order to choose between different levels of granularity. We thus developed a simple filtering algorithm which we describe below. The basic idea is to remove an element when another element in the retrieved list contains or is contained by the element. For INEX'03, we chose a very simple filtering mainly motivated by intuition.

The filtering we chose removes some of the retrieved doxels in the list while preserving the relative ranking of other document components. Kazai et al. [5] had this idea with the BEP[1]. We can consider our filtering step as an instance of BEP which does not take into account hyperlinks. Filtering is a necessary step for improving the effectiveness of Structured IR systems.

We tried the three following strategies:

Root oriented If a doxel appears on the retrieved list, its descendants in the document tree will not give any new information when they appear later. We thus remove any element in the ranked list if an ancestor is higher in the list. This simple method favours large doxels which is in conflict with the CO objective (retrieve the most specific doxels as possible).

Leaf oriented This is the inverse of the previous approach. We remove an element from the list when there is a descendant higher. The limit of this method is that when the latter is not relevant, then all the other informations brought by the ancestor are lost for the user.

BEP BEP strategy cumulates root and leaf oriented filtering. That is, an element is kept only if there is neither descendant nor ancestor higher in the retrieved list.

We chose the "Root oriented" strategy for two official submissions for INEX'03. This strategy gave the best results with the INEX'02 collection.

3. EXPERIMENTS

Three official runs were submitted to INEX'03:

okapi-1 In this run, we used the Okapi weighting scheme; every volume (and not every doxel) in the INEX corpus was considered as a document while the average document length used in the Okapi formula was local: for every doxel, the average document length was the average length of the doxel and its siblings. Results were filtered with "root oriented" strategy.

[1]Best Entry Point

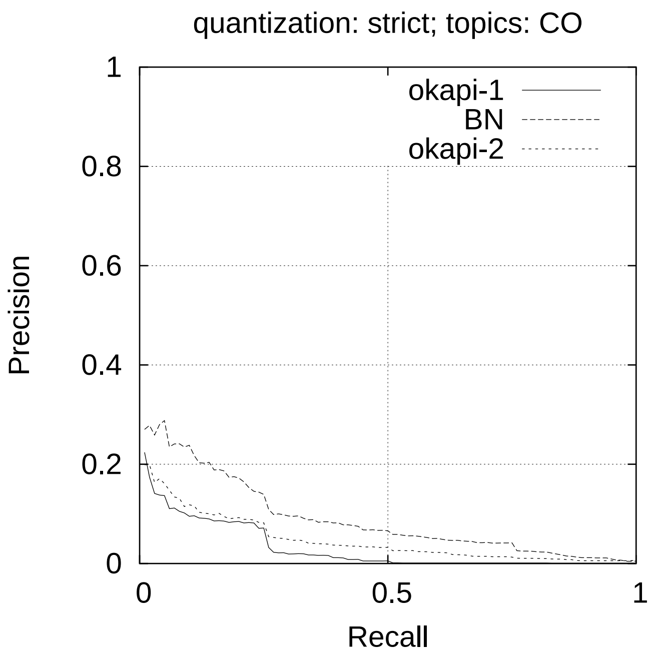

Figure 3: Official runs (strict quantisation)

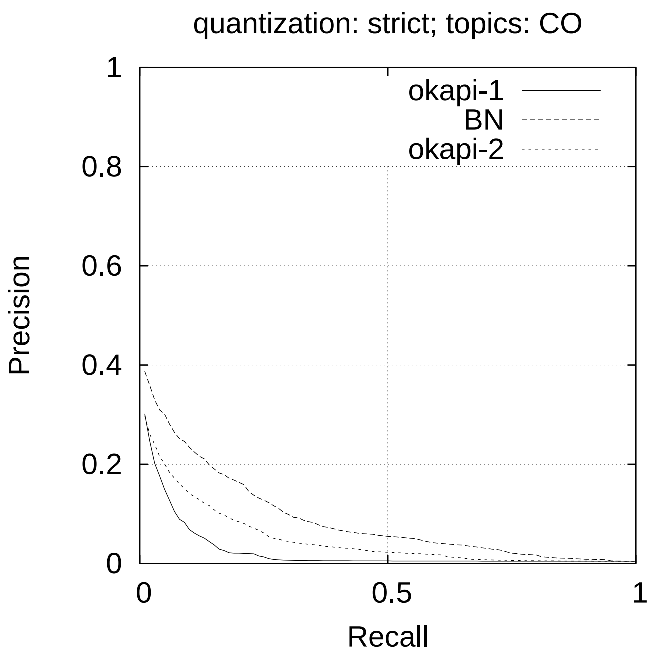

Figure 4: Official runs (generalised quantisation)

BN In this run, we submitted the doxel retrieved with the BN which is described in section 2.1. Results were filtered with the "root oriented" strategy.

okapi-2 In this run, we used the Okapi weighting scheme; every article (and not every doxel) in the INEX corpus was considered as a document while the average document length was the same as for okapi-1.

	average precision	rank
okapi-1	0.030 / 0.024	35 / 36
bn	0.046 / 0.048	19 / 18
okapi-2	0.089 / 0.087	7 / 5

Table 2: Results: in each cell, the first number is the strict quantisation, the second one the generalised.

The results are summarised in figures (3,4) and table 2. There is a gap between the model okapi-2 and the two other ones BN and okapi-1. The BN model is limited by its two baseline models that have performances that are a little below the BN results – these results are not shown here but are based on experiments with the INEX'02 dataset. The best performances are thus reached by a model which is very close to the standard Okapi (term weight are computed on an article basis): the only change is the length normalisation, which is local. Some preliminary experiments have shown this kind of normalisation gives the best results.

The main results we obtained are twofold. Firstly, with respect to last year, BN have shown they are able to perform reasonably well with respect to the baseline models performances. Secondly, using classical models as Okapi can help to improve significantly the BN performances as they perform much better than other models we have experimented. We still need to investigate further the filtering process, as we believe this is a key issue in XML retrieval.

4. CONCLUSION

We have described a new model for performing IR on structured documents. It is based on BN whose conditional probability functions are learnt from the data via EM. This model uses a grammar for restricting the allowed state of a doxel in our BN knowing the state of its parent. The BN framework has thus three advantages:

1. it can be used in distributed IR, as we only need the score of the parent element in order to compute the score of any its descendants;
2. it can use simultaneously different baseline models: we can therefore use specific models for non textual media (image, sound, etc.) as another source of evidence;
3. whole parts of the corpus can be ignored when retrieving doxels using inequality (1).

The model has still to be improved, tuned and developed, and several limitations have still to be overcome in order to obtain an operational structured information retrieval system. In particular, we should improve the baseline models and further experiments are thus needed for tuning the learning algorithms and for filtering.

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Cheshire II at INEX ’03: Component and Algorithm Fusion for XML Retrieval

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ABSTRACT
This paper describes the retrieval approach that UC Berkeley used in the 2003 INEX evaluation, and the subsequent analysis and correction of search failures in the “official runs”. As in last year’s INEX, our primary approach is a combination of probabilistic methods using a Logistic Regression (LR) algorithm for estimation of document (article) relevance and/or element relevance, along with Boolean constraints. This year we also used data fusion techniques to combine results from multiple probabilistic retrieval algorithms, specifically the Okapi BM-25 algorithm, and multiple search elements for any given query.

1. INTRODUCTION
Early in the TREC evaluations a number of participating groups found that fusion of multiple retrieval algorithms provided an improvement over a single search algorithm[13, 2]. With ongoing improvements of the algorithms used in the TREC main (i.e., ad hoc retrieval) task, later analyses[9, 1] found that the greatest effectiveness improvements appeared to occur between relatively ineffective individual methods, and the fusion of ineffective techniques, while often approaching the effectiveness of the best single IR algorithms, seldom exceeded them for individual queries and never exceeded their average performance.

Our approach to XML retrieval in last year’s INEX, as reported in our 2002 INEX paper[6], was to use a “Fusion Search” facility in the Cheshire II system that merged the result sets from multiple searches. For the majority of the content-only and content and structure queries separate searches from different indexes and different elements of the collection were merged into a single integrated result set. This facility was developed originally to support combination of results from distributed searches, but has proved to be quite valuable when applied to the differing elements of a single collection as well.

One of the main questions we were investigating in the 2002 INEX was how to take advantage of more precise search matches (e.g. Boolean title searches) when they are possible for a given query, yet to permit the enhanced recall that probabilistic queries can provide. We found in subsequent analysis of the INEX 2002 results, that our implementation of this approach suffered significantly from a number of bugs. As noted in the final INEX 2002 paper, some of the bugs were found in the script that converted the results to the INEX submission format, not in retrieval itself, where only the first occurrence of component in a document was converted to an entry for the submission (this was most signicant in one query where all of the relevant components were in a single article).

We also discovered in analysis of the results from last year that Fusion Searches were not correctly accumulating scores for each component search in some cases. This turned out to be a particularly costly bug (in terms of the INEX performance measures) caused by a failure to sort some of the intermediate resultsets in searches before they were merged, leading to an incorrect ranking sequence in the final resultsets, and in some particularly pathological situations resulting in the effective reversal of the correct ranking sequence.

For the official INEX 2003 runs, the bugs noted above were corrected. But, unfortunately, others were discovered rather late in the evaluation process, which led to the worse-than-expected results obtained for the official runs (these bugs are described below in the discussion of retrieval score normalization in combining results from different indexes and algorithms). We now believe that most of the bugs have been corrected, which has led to significant improvements in the performance of both CO and SCAS searches in our “post-INEX” experiments.

Our principle approach this year was to expand on the basic fusion approach used last year, using a combination of new implementations of additional algorithms, and new operators for merging intermediate results from different algorithms and search elements. The major addition this year is that we have implemented, and employed, a version of the Okapi BM-25 algorithm. The remainder of this paper describes the retrieval algorithms, new methods for combining results for different elements, and discusses the comparative results for the different official runs and our subsequent runs with bugs corrected.

2. THE RETRIEVAL ALGORITHMS AND OPERATORS
The original design rationale and features of the Cheshire II search engine have been discussed elsewhere [8, 7] and will only be briefly repeated here with an emphasis on those features that were applied in the INEX evaluation. We will also describe our newly implemented algorithms and operators used in the official and subsequent runs.

2.1 Original Probabilistic and Boolean Operations

The Cheshire II search engine supports various methods for translating a searcher's query into the terms used in indexing the database. These methods include elimination of "noise" words using stopword lists (which can be different for each index and field of the data), particular field-specific query-to-key conversion or "normalization" functions, standard stemming algorithms (a modified version of the Porter stemmer) and support for mapping database and query text words to single forms based on the WordNet dictionary and thesaurus using a adaption of the WordNet "Morphing" algorithm and exception dictionary.

In his analysis of fusion approaches to improving retrieval performance, Lee[9] found that the best results were obtained by combining algorithms where similar sets of relevant documents were returned but that retrieved different sets of non-relevant documents. With this in mind, we chose for this research two probabilistic algorithms that at least partially fulfill this criteria. The first algorithm is based on logistic regression and the second is the well-known Okapi BM-25 algorithm. In this section we describe each algorithm as it was implemented for this evaluation.

2.2 Logistic Regression Algorithm

The *logistic regression* (LR) algorithm used in this study was originally developed at Berkeley by Cooper, et al.[4] and shown to provide good full-text retrieval performance in the TREC ad hoc task. As originally formulated, the LR model of probabilistic IR attempts to estimate the probability of relevance for each document based on a set of statistics about a document collection and a set of queries in combination with a set of weighting coefficients for those statistics. The statistics to be used and the values of the coefficients are obtained from regression analysis of a sample of a collection (or similar test collection) for some set of queries where relevance and non-relevance has been determined. More formally, given a particular query and a particular document in a collection $P(R \mid Q, D)$ is calculated and the documents or components are presented to the user ranked in order of decreasing values of that probability. To avoid invalid probability values, the usual calculation of $P(R \mid Q, D)$ uses the "log odds" of relevance given a set of S statistics, s_i, derived from the query and database, such that:

$$\log O(R \mid Q, D) = b_0 + \sum_{i=1}^{S} b_i s_i \tag{1}$$

where b_0 is the intercept term and the b_i are the coefficients obtained from the regression analysis of the sample collection and relevance judgements.

Based on the structure of XML documents as a tree of XML elements, we define a "document component" as an XML subtree that may include zero or more subordinate elements or subtrees with text as the leaf nodes of the tree. Naturally, a full XML document may also be considered a document component. As discussed below, the indexing and retrieval methods used in this research take into account a selected set of document components for generating the statistics used in the search process and for extraction of the parts of a document to be returned in response to a query. Because we are dealing with not only full documents, but also document components (such as sections and paragraphs or similar structures) derived from the documents, we will use C to represent document components in place of D. Therefore, the full equation describing the LR algorithm used in these experiments is:

$$\begin{aligned}
\log O(R \mid Q, C) \quad = & \\
& -3.70 + \left(1.269 \cdot \left(\frac{1}{|Q_c|}\sum_{j=1}^{|Q_c|} \log qtf_j\right)\right) \\
+ & \left(-0.310 \cdot \sqrt{|Q|}\right) \\
+ & \left(0.679 \cdot \left(\frac{1}{|Q_c|}\sum_{j=1}^{|Q_c|} \log tf_j\right)\right) \\
+ & \left(-0.0674 \cdot \sqrt{cl}\right) \\
+ & \left(0.223 \cdot \left(\frac{1}{|Q_c|}\sum_{j=1}^{|Q_c|} \log \frac{N - n_{t_j}}{n_{t_j}}\right)\right) \\
+ & \left(2.01 \cdot \log |Q_d|\right)
\end{aligned} \tag{2}$$

Where:

Q is a query containing terms T,

$|Q|$ is the total number of terms in Q,

$|Q_c|$ is the number of terms in Q that also occur in the document component,

tf_j is the frequency of the jth term in a specific document component,

qtf_j is the frequency of the jth term in Q,

n_{t_j} is the number of components (of a given type) containing the jth term,

cl is the document component length measured in bytes. and

N is the number of components of a given type in the collection.

This equation, used in estimating the probability of relevance in this research, is essentially the same as that used in [3]. The coefficients were estimated using relevance judgements and statistics from the TREC/TIPSTER test collection. In this evaluation we used the same coeffients for each of the main document components used. This means that we are treating all components smaller than a full document as if they were, in effect, small documents.

2.3 Okapi BM-25 Algorithm

The version of the Okapi BM-25 algorithm used in these experiments is based on the description of the algorithm in Robertson[11], and in TREC notebook proceedings[12]. As with the LR algorithm, we have adapted the Okapi BM-25 algorithm to deal with document components :

$$\sum_{j=1}^{|Q_c|} w^{(1)} \frac{(k_1+1)tf_j}{K+tf_j} \frac{(k_3+1)qtf_j}{k_3+qtf_j} \qquad (3)$$

Where (in addition to the variables already defined):

K is $k_1((1-b)+b \cdot dl/avcl)$

k_1, b and k_3 are parameters , 1.5, 0.45 and 500, respectively, were used,

$avcl$ is the average component length measured in bytes

$w^{(1)}$ is the Robertson-Sparck Jones weight:

$$w^{(1)} = \log \frac{\left(\frac{r+0.5}{R-r+0.5}\right)}{\left(\frac{n_{t_j}-r+0.5}{N-n_{t_j}-R-r+0.5}\right)}$$

Where, for a given query and a given term:

r is the number of relevant components of a given type that contain a given term,

R is the total number of relevant components of a given type for the query. (Note that these statistics do not take into account nested components.)

Our current implementation uses only the *a priori* version (i.e., without relevance information) of the Robertson-Sparck Jones weights, and therefore the $w^{(1)}$ value is effectively just an IDF weighting. The results of searches using our implementation of Okapi BM-25 and the LR algorithm seemed sufficiently different to offer the kind of conditions where data fusion has been shown to be most effective [9].

2.4 Boolean Operators

The Cheshire II system used in the evaluation supports searches combining probabilistic and (strict) Boolean elements, as well as operators to support various merging operations for both types of intermediate result sets. Although strict Boolean operators and probabilistic searches are implemented within a single process, using the same inverted file structures, they really function as two parallel *logical* search engines. Each logical search engine produces a set of retrieved documents. When a single search strategy is used the result is either a probabilistically ranked set or an unranked Boolean result set. When both are used within in a single query, combined probabilistic and Boolean search results are evaluated using the assumption that the Boolean retrieved set has an estimated $P(R \mid Q_{bool}, C) = 1.0$ for each document component in the set, and 0 for the rest of the collection. The final estimate for the probability of relevance used for ranking the results of a search combining strict Boolean and probabilistic strategies is simply:

$$P(R \mid Q, C) = P(R \mid Q_{bool}, C) P(R \mid Q_{prob}, C)$$

where $P(R \mid Q_{prob}, C)$ is the probability of relevance estimate from the probabilistic portion of the search, and $P(R \mid Q_{bool}, C)$ is the Boolean. In practice the combination of strict Boolean "AND" and the probablistic approaches has the effect of restricting the results to those items that match the Boolean portion, with ranking based on the probabilistic portion. Boolean "NOT" provides a similar restriction of the probabilistic set by removing those document components that match the Boolean specification. When Boolean "OR" is used, the probabilistic and Boolean results are merged (however, items that only occur in the Boolean result, and not both, are reweighted as in the "fuzzy" and merger operations described below.

A special case of Boolean operator in the experimental system is that of proximity and phrase matching operations. In proximity and phrase matching the matching terms must also satisfy proximity constraints (both term order and adjacency in the case of phrases). Thus, proximity operations also result in Boolean intermediate result sets.

2.5 Result Combination Operators

Cheshire II provides a number of ways to using "FUZZY", "RESTRICT" and "MERGE" operators to combine intermediate results of a search from different components or indexes. With these operators we have available an entire spectrum of combination methods ranging from strict Boolean operations to fuzzy Boolean and normalized mean scores for probabilistic and Boolean results.

Fuzzy operators are versions of the Boolean operators that are less "strict" than the conventional Boolean operators, applied to weighted result lists. In place of Boolean AND, the "!FUZZY_AND" operator takes the mean of the two weights in the result sets for the same record (this differs from the conventional fuzzy AND that take the minimum of the two weight). The "!FUZZY_OR" takes the largest of the two weights for the same record. "!FUZZY_NOT" currently behaves the same way as strict Boolean "NOT". Otherwise these operators are used the same way as the strict Boolean operators.

The "!RESTRICT_TO" and "!RESTRICT_FROM" operators take either a component result and a document result, or two component results (where one component contains the other). As discussed in [6], "components" in the Cheshire II system can be the contents of any tag (or of a set of tags) that are treated as separate documents for the purposes of indexing and retrieval. In the case of component and document results the component list is restricted to components that are in the document result – the matching components only are returned retaining their weight from the original component result. When two nested component results are used with these operators the result is larger components that include one or more of the smaller components. (Note that with component and document results !RESTRICT_TO and !RESTRICT_FROM may be used interchangibly and the type of operation to be performed is determined by the nature of the result sets, but with two component results the nesting of the elements must be taken into account in constructing the query (i.e, Parent_set !RESTRICT_FROM Child_set or Child_set !RESTRICT_TO Parent_set). Naturally Parent and Child can be any sub-query that results in the appropriate kind of component.

The !MERGE_SUM operator combines the two resultsets (like a Boolean OR) but adds the weights (actually the resulting raw ranking adds 1.0 to the probabilistic result and sets 1.5 for Boolean results with matching document or component ids in both lists, and the original values for items found only in a single result). Note that !MERGE_SUM weights may exceed 1 and are not probabilities.

The !MERGE_MEAN operator combines the two resultsets (like a Boolean OR) but takes the MEAN (or average) of the weights from items in both lists and half of the weight of items in only a single list. This is the (currently) recommended operator for merging probabilistic resultsets.

The !MERGE_NORM operator combines the two resultsets (like !MERGE_MEAN) but it performs the min-max normalization of the weights suggested by Lee[9] before it takes the mean of the weights from items in both lists and half of the weight of items in only a single list. There was a bug in this process in the official runs, because items in only one of the two input lists were neither normalized nor divided in half. This effect of this bug was that items occurring in only a *single* result set, among the many partial results merged for each of the queries, were likely to receive *higher* weights in the final results than items occurring in many (or all) of the partial results.

The motivation for these new operators follows from the basic observation that has driven all research into data fusion methods in IR, that no single retrieval algorithm has been consistently proven to be better than any other algorithm for all types of searches. By providing a set of operators for combining the retrieved sets from different search strategies, we are hoping to capitalize the strengths of particular algorithms while reducing their limitations. In general, the assumption behind any implementation of data fusion is that the more evidence the system has about the relationship between a query and a document (including the sort of structural information about the documents found in the INEX queries), the more accurate it will be in predicting the probability that the document will satisfy the user's need. Other researchers have shown that additional information about the location and proximity of Boolean search terms can be used to provide a ranking score for a set of documents[5]. The inference net IR model has shown that the exact match Boolean retrieval status can be used as additional evidence of the probability of relevance in the context of a larger network of probabilistic evidence[14]. In the same way, we treat the set of documents resulting from the exact match Boolean query as a special case of a probabilistically ranked set, with each retrieved document having an equal rank.

3. INEX APPROACH

Our approach in INEX was to use all of the original and new features of the Cheshire II system in generating the results submitted for our official runs. This section will describe the indexing process and indexes used, and also discuss the scripts used for search processing. The basic database was unchanged from last year's. We did, however, create and use a number of additional indexes and performed a complete reindexing of the INEX document collection. This section will first describe the indexes and component definitions created for INEX 2003.

3.1 Indexing the INEX Database

All indexing in the Cheshire II system is controlled by an SGML Configuration file which describes the database to be created. This configuration file is subsequently used in search processing to control the mapping of search command index names (or Z39.50 numeric attributes representing particular types of bibliographic data) to the physical index files used and also to associated component indexes with particular components and documents.

As noted above, any element or attribute may be indexed. In addition particular values for attributes of elements can be used to control selection of the elements to be added to the index. The configuration file entry for each index definition includes three attributes governing how the child text nodes of the (one or more) element paths specified for the index will be treated.

Each index can have its own specialized stopword list, so that, for example, corporate names have a different set of stopwords from document titles or personal names.

Most of the indexes used in INEX used keyword or keyword with proximity extraction and stemming of the keyword tokens. Exceptions to this general rule were date elements (which were extracted using date extraction of the year only) and the names of authors which were extracted without stemming or stoplists to retain the full name.

Other than the conversion of some indexes from keyword to keyword with proximity, the indexes and component elements for INEX 2003 were the same as those used in the 2002 evaluation[6].

Altogether, 27 separate indexes and 5 types of components (in addition to article-level) were used in search evaluation runs of the 2003 INEX topics. The official submitted runs in INEX are described in the next section.

3.2 INEX '03 Official Runs

Berkeley submitted six retrieval runs for INEX 2003, three CO runs and 3 SCAS runs. We did not submit any VCAS runs. This section describes the individual runs and general approach taken in creating the queries submitted against the INEX database and the scripts used to do the submission. All of the official runs were automatic, with queries generated by scripts that used title and keyword sections for the CO runs, and the title only for the SCAS runs. (The corrected runs described later also use automatic query generation with the same topic elements).

Berkeley_CO01: This run used LR ranking combined with Boolean phrase matching and MERGE_MEAN partial result combinations. Only article level results are returned in this run.

Berkeley_CO_Okapi: This run employed the Okapi BM-25 algorithm for ranked search components, combined with Boolean elements for proximity and term restrictions. Results from multiple components where combined using MERGE_MEAN merging of results. RSV scores were normalized and multiple result sets combined to include Article-level, section-level and paragraph-level results.

Berkeley_CO_MergePrOk: This run was a fusion of LR and Okapi algorithms using a score-normalized merging algorithm (MERGE_NORM). Results from multiple components where combined using MERGE_MEAN and MERGE_NORM merging of results. Separate retrieval of Articles, Sections and paragraphs were combined using score normalized merges of these results.

Berkeley_SCAS01: Used LR ranking combined with Boolean phrase matching and MERGE_MEAN partial result combinations. FUZZY_AND and FUZZY_OR operators were used in combining AND and OR elements within an "about" predicate.

Berkeley_SCAS_Okapi: Used the Okapi BM-25 ranking instead of LR and used normalized scores in merging results from different aspects of the queries. Results from multiple components used the MERGE_NORM operator for merging of results.

Berkeley_SCAS_Okapi2: Was similar to the above run, except for the use of some different indexes (including more of the document text).

4. EVALUATION

The summary average precision results for the official runs described above are shown in Table 1.

Run Name	Short name	Avg Prec (strict)	Avg Prec (gen.)
Berkeley_CO01	Prob	0.0467	0.0175
Berkeley_CO_Okapi	Okapi	0.0318	0.0314
Berkeley_CO_MergePrOk	MergePrOK	0.0546	0.0557
Berkeley_SCAS01	Prob_SCAS	0.1970	0.1545
Berkeley_SCAS_Okapi	Okapi_SCAS	0.0865	0.0682
Berkeley_SCAS_Okapi2	Okapi2_SCAS	0.0869	0.0687

Table 1: Cheshire Official Runs for INEX 2003

Figures 1 and 2 show, respectively, the Recall/Precision curves for generalized quantization of each the SCAS and CO results of the officially submitted Berkeley runs. None of Berkeley runs appeared in the top ten for all submitted runs. The results, as discussed above, particularly for the the Okapi-based runs have relatively poor results due to implementation errors. It is, however, worth noting that the fusion results (MergePrOk) did perform better than either the probabilistic or (flawed) Okapi runs for the CO task. Thus, the issue that we were seeking to investigate (whether XML retrieval would benefit from data fusion methods operating across both elements and algoritms, had some cautious confirmation from the official runs. The MergePrOK run which combined results for both LR and Okapi algorithms showed a marked improvement over the Okapi run alone. However The high-end precision in that run was less than in the Prob run, this may however be due to the bug described previously. In addition, it is likely that if the logistic regress algorithm run (Prob) had included section and paragraph elements, it would probably have had much better overall performance.

4.1 Post-INEX CO Results

A large number of subsequent tests were run evaluate the causes of the relatively poor performance shown in the the official results, and to track down and correct the bugs discussed above. After correction of these problems, a number of tests were run to evaluate the corrected baseline performance for the LR and Okapi algorithms for the CO task. The result for these runs are shown in Tables 2 and 3. Run names that include "_full" in the name include expansions of the topic terms in the queries to include proximity-based search for quoted phrases, query term weight enhancements for "+" terms and Boolean NOT. Thus, "prob_full" and "okapi_full" use the LR and Okapi algorithms, respectively, and include the full expansion. Run names with "_base" use just the particular algorithm with no term expansions or reweighting.

For fusion operations between different indexes for a particular document component, the MERGE_NORM operator was used to combine the sub-query results. In Tables 2 and 3 "fusion_full" combines full queries of only the topic, sec_words, and para_words indexes for both LR and Okapi, "fusion_t_full" combines both the topic, alltitles, sec_words, sec_title, and para_words, "fusion_ta_full" adds the abstract index to this. As in the preceding, "fusion_t_p_abs_full" and "fusion_t_p_abs_full" use the same indexes, but perform an additional LR search of the abstract and extract and merge the abstract in the final results used in evaluation.

The fusion approaches that we have been been exploring attempt to consider both the optimal combinations of search elements and algorithms that should used in the retrieval process. For this evaluation we have not re-estimated the logistic reression parameters or examined the possibility of differential weightings that could be applied to the search elements to best estimate the probability of relevance for a given query and document element, or combination of elements.

The summary average precision results for the runs described above are shown in Tables 2 and 3 for the strict and generalized quantization of the INEX evaluation metrics. In these tables ΔP shows the percentage difference for the test from the "prob_base" baseline and 'ΔO shows the difference from "okapi_base".

Figures 3 and 4 show the Recall/Precision curves for generalized quantization of the base algorithms (prob_base and okapi_base) in combination with the full expanded queries (Figure 3) or the best performing fusion query (fusion_t_full).

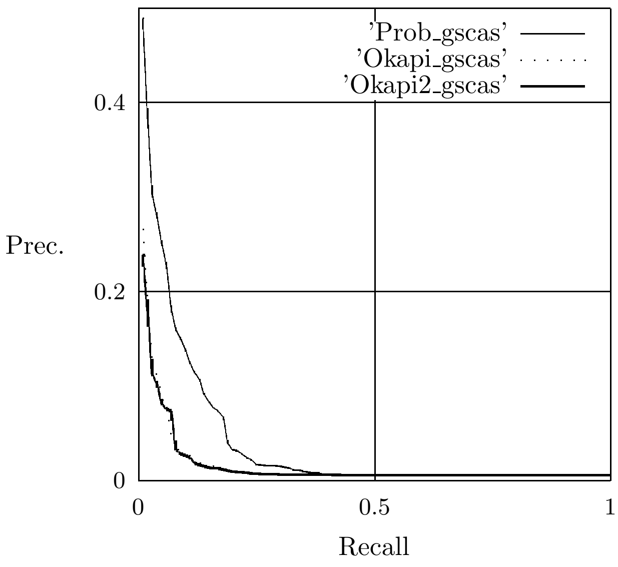

Figure 1: Official SCAS Runs (generalized)

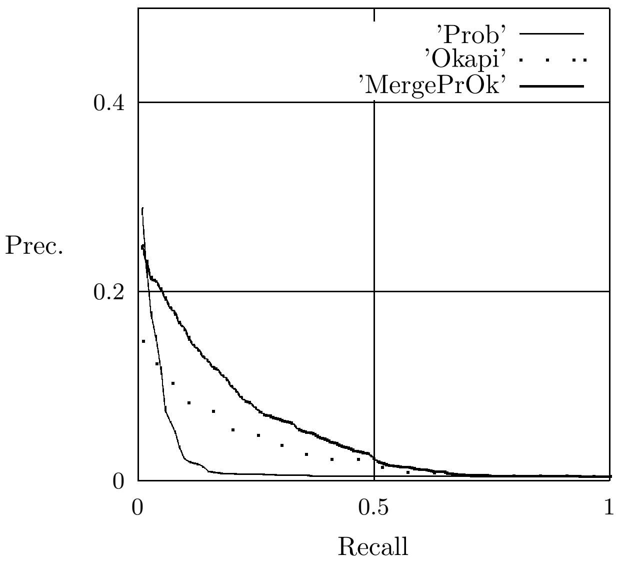

Figure 2: Official CO Runs (generalized)

Run Name	MAP	Δ P	Δ O
fusion_t_full	0.0690	22.97	18.99
fusion_t_p_abs_full	0.0635	16.26	11.94
fusion_ta_full	0.0632	15.89	11.55
fusion_full	0.0600	11.37	6.80
prob_full	0.0589	9.72	5.07
fusion_ta_p_abs_full	0.0584	9.00	4.30
okapi_full	0.0563	5.51	0.63
okapi_base	0.0559	4.90	0.00
prob_base	0.0532	0.00	-5.16

Table 2: Post Evaluation of CO Queries: Mean Average Precision of different algorithms and search element combinations (strict)

Run Name	MAP	Δ P	Δ O
fusion_t_full	0.0741	15.89	4.85
fusion_full	0.0739	15.61	4.53
okapi_full	0.0730	14.58	3.37
fusion_ta_full	0.0725	14.07	2.79
fusion_t_p_abs_full	0.0712	12.49	1.01
okapi_base	0.0705	11.60	0.00
fusion_ta_p_abs_full	0.0698	10.75	-0.96
prob_full	0.0690	9.70	-2.15
prob_base	0.0623	0.00	-13.12

Table 3: Post Evaluation of CO Queries: Mean Average Precision of different algorithms and search element combinations (generalized)

As Tables 2 and 3 indicate, the use of query expansion, as discussed in section 3.2, appears to offer some benefit of the unexpanded query for both quantizations, prob_full shows improvement over prob_base and okapi_full shows improvement over okapi_base. What is somewhat more interesting is that under strict quantization the LR approach in prob_full performs better than either okapi test, but for generalized quantization both Okapi tests perform better than either LR test (and indeed better than some of the fusion approaches. This implies that the Okapi algorithm is better at identifying a wider range of degrees of perceived relevance, while the LR algorithm is better at identifying the highly relevant items.

When the two algorithms are combined (with only topic and word searches in fusion_full) the results for both the strict and generalized measures are better than any of the single algorithms. This is different from the kind of results reported in [1], and seems to confirm the improvements from data fusion reported by Lee[9]. When the searches include a separate ranking of title searches merged with the topic searches the performance is further improved and performs the best for both quantizations of all of the query forms examined here. However, it appears that element indexes cannot be arbitrarily combined in attempting to improve performance, adding the abstract index results in reduced performance relative to topic and titles alone.

4.2 Post-INEX SCAS Results

Some of the subsequent SCAS runs are shown in Table 4. The table shows that the LR-based queries (indicated by "scas.p" in the names) seem to be generally less effective than the Okapi-based queries (including "scas.o" in the run names). Of course, the SCAS queries are in general more complex than the CO queries, and make use of many additional merging operations (such as the "RESTRICT" operators) driven by the individual Xpath queries. The runs with the same number, used the same combinations of merge operators and differ only in the ranking algorithm employed. The Fusion runs (indicated by name with "scas.fus" each combine results from different runs, those with numbers only in the last part of the name are Okapi only runs, and

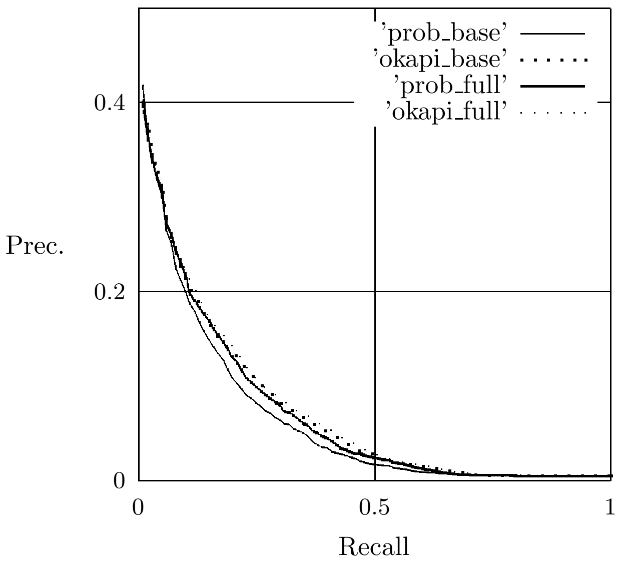

Figure 3: Recall-Precision of LR and Okapi retrieval algorithms for CO (generalized quantization)

Run Name	Avg Prec (gen.)	Avg Prec (strict)
scas.fus.258	0.2107	0.2403
scas.fus.78	0.2075	0.2395
scas.fus.p28o8	0.1985	0.2304
scas.fus.p8o87	0.2020	**0.2444**
scas.o.2	0.2010	0.2205
scas.o.7	0.1996	0.2247
scas.o.8	**0.2120**	0.2308
scas.p.2	0.1877	0.2092
scas.p.8	0.1948	0.2174

Table 4: Post Evaluation of SCAS Queries: Mean Average Precision of different algorithms and search element combinations

the others mix LR and Okapi runs. The best performing SCAS run for the generalized evaluation metrics was an Okapi run that used the "MERGE_NORM" operator when a "AND" was used in an "about" clause in a query, and "MERGE_SUM" was used for "OR". For Xpath expression with separate "about" clauses in nodes on different levels in the document tree, the "RESTRICT_FROM" operators were used. Terms with "+", "-", and quotes were handled the same way as in the CO runs, with added search elements for exact phrase matching, additional query term weighting for "+" and use of Boolean "NOT" for "-".

Figures 5 and 6 show the generalized recall-precision metrics for the SCAS runs above. Figure 5 shows the LR and Okapi results and Figure 6 shows the different fusion results.

5. CONCLUSIONS

The results reported here are the first evaluation of the new fusion and resultset merging operators in the Cheshire II

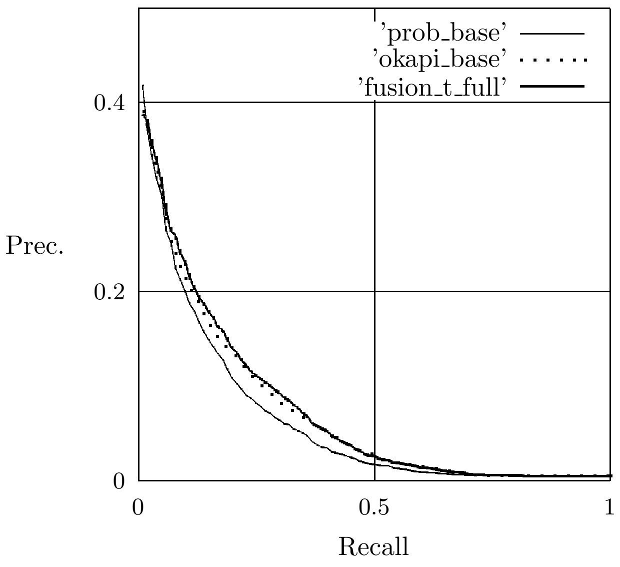

Figure 4: Recall-Precision of the best fusion method compared to algorithm baselines for CO (generalized quantization)

system. In exploring the fusion of different algorithms and document components in content-oriented and structured XML retrieval we have obtained some encouraging results. The results indicate that several of the fusion approaches that we tested do perform better than the individual algorithms, and that some Boolean constraints seem to be beneficial for XML retrieval. This is different from most studies of fusion methods, where the fusion is of different algorithms for the same collection of full documents [1, 10]. Because we are combining not only full document results, but also component elements of documents, we believe that the results benefit from the differing selectivity of different document components, when those can be merged into a single ranked list.

However, there is much room for further study, in particular this study did not include language models of XML, which have proved to be highly effective in the INEX evaluations. Future work will extend the Cheshire II system to include language model-based XML retrieval algorithms and test it in combination with the logistic regression and Okapi algorithms tested here.

When using the LR algorithms, as described above, the *same* weighting coefficients were applied to the statistics from *all* components ranging from full documents to paragraphs and titles. We plan to investigate a new implementation of the logistic regression algorithm where these coefficients will be estimated for each component type using a training sample of those components and their matching relevance judgements. Thus, the weighting coefficients applied to component length, for example, might be quite different depending on the component type. This can be expected to provide better tuned weighting coefficients and hence ranking values for the individual components and should, in turn, improve

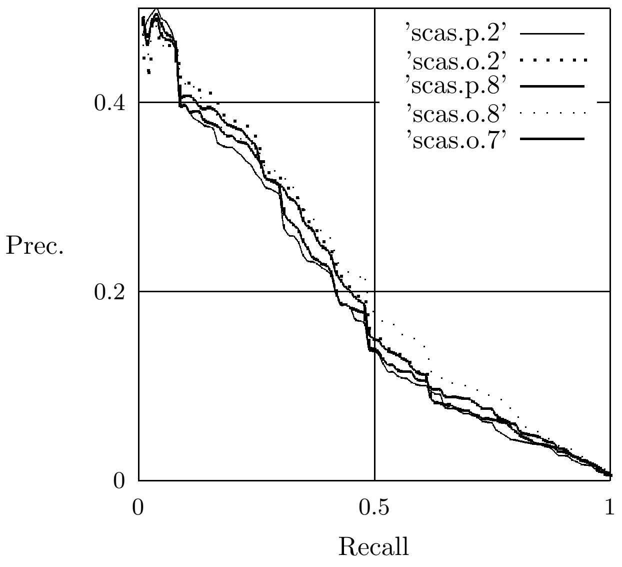

Figure 5: Recall-Precision of LR and Okapi retrieval algorithms for SCAS (generalized quantization)

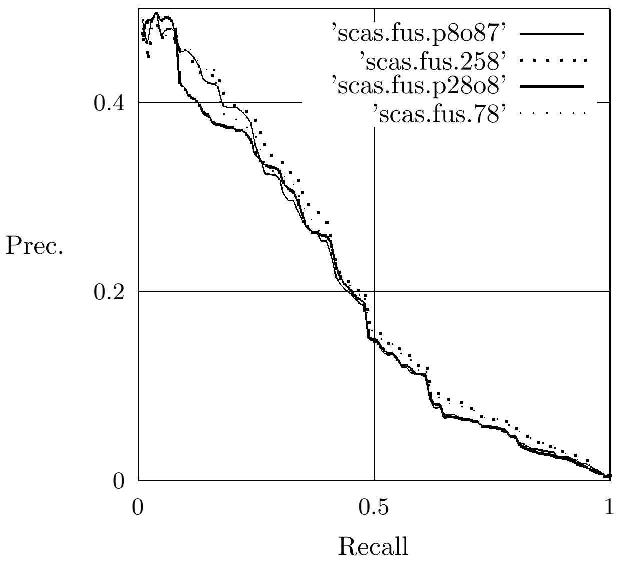

Figure 6: Recall-Precision of fusion approaches for SCAS (generalized quantization)

the fusion of components.

6. ACKNOWLEDGMENTS

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Searching in an XML Corpus Using Content and Structure[*]

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ABSTRACT
This paper presents a system for XML retrieval. The approach consists of a variety of Information Retrieval techniques augmented with the ability to give weights to different fragments of a document, based on the tags. Specifically, term frequencies, inverse document frequencies, proximity among occurrences of keywords, and similarity between keywords and words from the given document, are used. Each technique has been implemented as a separate ranker and the final ranking is done by merging the results of the various rankers.

1. INTRODUCTION
An XML document has a structure in addition to content, and an XML search engine should be capable of taking advantage of the structure in order to improve the quality (i.e., precision and recall) of the results. The structure may also be incorporated into the topic (i.e., query) in two ways. First, the topic may include conditions that relate content to structure (e.g., some keyword should appear in the title of the document). Second, the topic may specify the exact fragment of the document that should be returned as an answer. Even if the topic does not have any hint about the structure, the search engine should still be able to find not just the relevant documents, but also the most relevant fragment (or fragments) within each document.

Several different paradigms have been proposed recently for searching XML documents. In XRANK [7], the main idea is a generalization of the Page-Rank [4] technique of Google [1]. In XSEarch [6], the emphasis is on retrieving only those answers that consist of *semantically related* nodes. Neither one of these approaches is suitable for the INEX corpus, which consists of articles from the IEEE digital library. The XRANK approach is not directly applicable to INEX, since the XML documents of INEX do not have cross references in the form of IDREFs or XLinks. The XSEarch approach is irrelevant to INEX, since all the nodes of any single XML document are deemed semantically related.

Our approach consists of a variety of Information Retrieval techniques augmented with the ability to give weights to different fragments of a document, based on the tags. Specifically, we use term frequencies, inverse document frequencies, proximity among occurrences of keywords, and similarity between keywords and words from the given document. Each technique has been implemented as a separate ranker and the final ranking is done by merging the results of the various rankers.

2. TOPIC SEMANTICS AND SYNTAX
The query language of a standard search engine is simply a list of keywords, optionally preceded by the + or − sign. In the context of XML, the query language can also contain information about the structure, in the form of path expressions that describe specific parts of a document where the keywords should appear.

In INEX'03 [9], a query is called a *topic* and comprises four parts: (1) *title:* this part describes the topic in a formal syntax, (2) *description:* a description in a natural language of the information that is needed, (3) *narrative:* a more detailed description, and (4) *keywords:* a set of comma-separated *terms,* where a term is a single keyword or a phrase encapsulated in double quotes. Our system uses only the title.

A topic can be either *content only* (abbr. CO) or *content and structure* (abbr. CAS). In a CO topic, the title contains only content-related conditions; it is a set of space-separated terms, optionally preceded by the + or the − sign. For example,

```
+database +‘‘java programming’’
```

[*]This research was supported by The Israel Science Foundation (Grant 96/01).

is a CO topic about "database" and "java programming."

In a CAS topic, the title relates terms to specific locations in documents. The general form of the title is
`CE[filter] CE[filter] ... CE[filter]`,
where each `CE` is a *context element* that specifies a path in the document (using XPath syntax). A `filter` is a Boolean combination of XPath predicates (e.g., a comparison between a path expression and a constant) and predicates of the form `about(path,string)`, where `path` is an XPath expression and `string` is a quoted string of terms (each term could be preceded by a $+$ or $-$). For example,

```
//article[.//@yr > '2000']
  //sec[about(.,'+''java programming''')]
```

specifies that sections about "java programming" from articles written after 2000 should be retrieved.

We use T to denote a CO or a CAS topic. By a slight abuse of notation, T also denotes the list of all stemmed terms appearing in the title of T. Stop words are eliminated. T_+ denotes the list of terms in T that are preceeded by a $+$ sign, T_- denotes the list of terms that are preceded by a $-$ sign, and T_o is the list of all the remaining (i.e., optional) terms in T.

3. AN OVERVIEW OF THE SYSTEM

The design of our system was influenced by two major considerations. First, our goal was to build an extensible system so that various information-retrieval techniques could be combined in different ways and new techniques could be easily added. Second, the system had to be developed in a very short time.

The first consideration led to the decision to implement each information-retrieval technique as a separate ranker and to implement a merger that would merge the results of the individual rankers.

The second consideration influenced the implementation of the topic (i.e., query) processor. In INEX, a topic may include expressions in XPath (augmented with the "about" function) that refer to the structure of the documents to be retrieved. Thus, an XPath processor is needed in order to evaluate a given topic. However, any existing XPath processor cannot be applied to the complete description of a topic that is written in the formal syntax of INEX; instead, it can only be applied separately to each XPath expression that is embedded inside the topic. This is not sufficient for an accurate processing of CAS (content and structure) topics, since when different XPath expressions from the same topic are evaluated separately, it is impossible to tell how to combine their results correctly. So, it seemed that the topic processor would require a complete implementation of an XPath parser (and that would be time consuming). Instead, we implemented (in Java) a parser for INEX topics that creates an XSL stylesheet (i.e., a program written in XSL). Since XPath is included in XSL, we circumvented the need to implement an XPath parser as a part of our topic processor.

Figure 3 depicts the main components of the system. The first step is building the indices, which are described in detail in Section 4. Given a topic, the indices are used to filter the whole corpus in order to retrieve the documents that contain all the required keywords (i.e., keywords preceded by $+$). Documents that pass through the filtering phase are processed by an XSL stylesheet that is generated from the topic. The XSL stylesheet retrieves from each document all the fragments that are relevant to the processing of the given topic. The retrieved fragments are produced as an XML file (one per document) in a manner that preserves the original hierarchy among these fragments. In the next step, each ranker processes all the XML files and creates a new XML file of the ranked results. In the final steps, the results of the various rankers are merged into a single XML file.

4. INDEXING

The system uses several indices when processing topics (i.e., queries). The creation of the indexes is done as a preprocessing step by the *indexer*. The indices are described below.

Document-Location Array

The system assigns a unique *document identifier* (also called *did*) to each document. The *document-location array* is used to associate each *did* with the physical location, in the file system, of the corresponding document.

Inverted Keyword Index

The *inverted keyword index* associates each keyword with the list of documents that contain it. Stop words, i.e., words that are used very frequently in English (e.g., "in," "to," "the," etc.) do not appear in the index. Also, regular stemming, using the Porter's stemmer [12], is done in order to achieve a higher flexibility when searching for a particular keyword. The inverted-keyword index stores stems of words. For each stem w, there is a *posting list* of the *did*'s of all the documents that contain some keyword with stem w.

Keyword-Distance Index

The *keyword-distance index* stores information about proximity of keywords in the corpus. For each pair of keywords, the system computes a score and the keyword-distance index holds this score. The score reflects the number of occurrences of that pair of keywords in any single sentence. It also reflect the distance between the two keywords when they appear in the same sentence. The score for a given pair of keywords is the sum of the inverse of the distance between the two keywords over all the sentences in all the documents of the corpus. Formally, the score of the pair (w_i, w_j) is

$$D(w_i, w_j) = \sum_{d \in \mathcal{D}} \sum_{s \in d} \sum_{(w_i, w_j) \in s} \frac{1}{distance(w_i, w_j)}$$

where $\mathcal{D}$ is the set of all the documents in the corpus, d is a document, s is a sentence, and $distance(w_i, w_j)$ is the number of words separating w_i and w_j. Scores are normalized and $D(w, w)$ is defined to be 1 (the maximum). The keyword-distance index actually stores the scores for pairs of stems rather than complete keywords.

Tag Index

Tags are given weights according to their importance. The weight of each tag is a parameter that can be easily modified

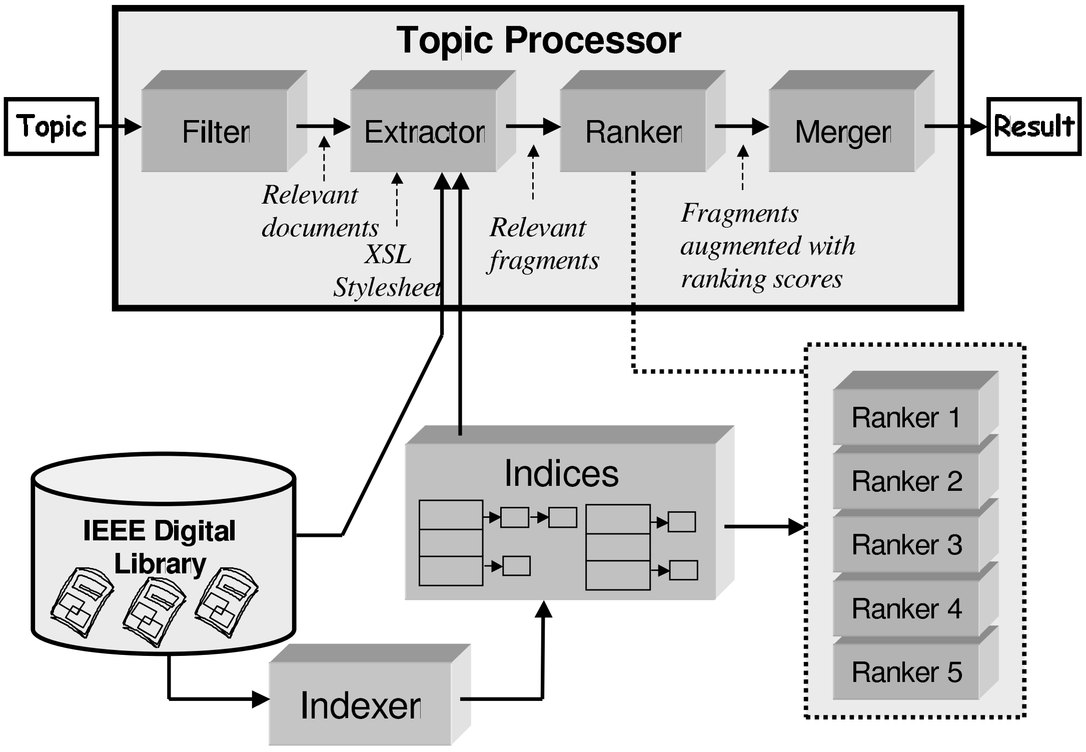

Figure 1: Overall Architecture

by anyone who uses the system. A Java property file stores the weight $tw(t)$ of each tag t.

Inverse-Document-Frequency (idf) Index

The *document frequency* of a keyword k is the number of documents that contain k, divided by the total number of documents in the corpus. The *inverse document frequency* is defined as follows:

$$idf(k) := \log\left(1 + \frac{|\mathcal{D}|}{|\{d \mid d \in \mathcal{D} \text{ and } k \in d\}|}\right)$$

where $\mathcal{D}$ is the set of all the documents in the corpus. The *inverse-document-frequency index* is a hash table that holds the inverse document frequency for the stem k of each keyword.

5. TOPIC PROCESSING

The processing of a topic T is done in four phases. In the *filtering phase,* the documents that contain all the keywords in T_+ are retrieved from the corpus. In the *extraction phase,* the relevant fragments are extracted from each document. In the *ranking phase,* the fragments from the previous phase are ranked by each ranker. In the *merging phase,* the results of the various rankers are merged together. Next, we describe each phase in detail.

In the filtering phase, for each keyword $k \in T_+$, the posting list L_k of the stem of k is extracted from the inverted keyword index. The intersection $L_T = \cap_{k \in T_+} L_k$ is computed and the result is an XML document that contains a list of all the *did*'s of the documents in L_T.

In the extracting phase, an XSL stylesheet is generated from the title of the topic. This stylesheet extracts the relevant fragments from each document that passed the filtering phase. For CAS topics, the relevant fragments are determined by the title. For CO topics, the system has to determine which fragments are relevant. In our system, the fragments that could be returned are determined in advance; this policy was proposed by [3] and is also used in XRANK [7]. Specifically, these fragments are either the whole document, the front matter, the abstract, any section or any subsection.

A potentially relevant fragment must also satisfy some conditions. First, it must include all the terms that are preceded by +. Moreover, it may have to satisfy some predicates, e.g., `.//@yr > '2000'`. Thus, extracting the relevant fragments requires a processor that is capable of parsing titles of CO and CAS topics. An XPath processor is not suitable for the job, since the syntax of titles is more general than that of XPath. In our system, a Java program parses the title and generates an XSL stylesheet that does the extraction. Since XPath is included in XSL, portions of the title that adhere to the XPath syntax can be transplanted into the stylesheet. This lead to a fast implementation of the topic processor.

In the title of a CAS topic, there is a *core path expression* that consists of the concatenation of all the context elements.

There are also several *filter path expressions,* where each one is a path expression that appears in some filter concatenated with all the context elements that precede it. The last element of the core path expression and the last element on any filter path expression are called *target elements.* For example, consider the following CAS title:

```
//a[about(.//b, ‘...’)]//c[about(.//d, ‘...’)]
```

The core path expression is `//a//c`. The fragments that eventually will be returned as answers for this title are `c` elements. The filter path expressions are `//a//b` and `//a//c//d`. Fragments that are `b` and `d` elements should be extracted in order to check the conditions that are specified in the `about` clauses.

Extracting fragments for the path expressions and checking that each one satisfies its corresponding condition is not quite enough. In order for the rankers to work correctly, it is important to know whether a fragment extracted for a `b` element is related to a fragment extracted for a `d` element, in the sense that both have the same `a` element as an ancestor. Therefore, the XSL stylesheet extracts fragments in a manner that preserves the original hierarchy among these fragments. Essentially, the stylesheet has a sequence of nested loops. The nesting of the loops follows the hierarchy dictated by the the core and filter path expressions. Each loop extracts all the fragments for its corresponding element. Each extracted fragment is assigned a level number, which is the level of nesting of its corresponding loop. For example, in the above title, the extracted `d` elements are descendants of the extracted `c` elements and, hence, will have a larger level number. The XSL stylesheet is applied to all the documents that passed the filtering phase and it produces a new XML document, D_T, that contains for each extracted fragment *(1)* the URL of the parent document, *(2)* the path of the fragment in the document, *(3)* the stems of keywords from the title that appear in the fragment, *and (4)* the fragment itself. The XML file D_T is given to each ranker. Note that the `about` predicate can be evaluated by the rankers, since the relevant fragments are in D_T. The ranking of fragments and the final merging are explained in the next section.

6. RANKING THE RESULTS

We implemented five rankers, namely *word-number ranker*, *idf ranker*, *tf-idf ranker*, *proximity ranker* and *similarity ranker.* Each ranker gives scores to the fragments that are listed in the XML file D_T. This section describes the five rankers and how their results are merged.

6.1 Word-Number Ranker

Recall that T_o is the list of optional terms (i.e., not preceded by the $+$ or $-$ sign) from the title of a given topic T. Similarly, T_- is the list of terms that should not appear in the result (i.e., preceded by the $-$ sign). Given a fragment F, the number of optional terms that appear in F is $|T_o \cap F|$ and the number of unwanted terms in F is $|T_- \cap F|$. The score given to F by the word-number ranker is

$$|T_o \cap F| + 1 - \frac{\min(|T_- \cap F|, 10)}{10}.$$

Note that the score is increased when the number of optional terms appearing in the fragment F is increased and it is decreased when the number of unwanted terms in F is increased. Also note that the weight that is given to the appearance of a wanted term is an order of magnitude greater than the weight given to the appearance of an unwanted term. Moreover, there is a bound of 10 on the total number of unwanted terms that are taken into account.

6.2 Inverse-Document-Frequency (IDF) Ranker

We first give the intuition behind the idf ranker. Consider two fragments F_1 and F_2, such that $F_1 \cap T_+$ and $F_2 \cap T_+$ contain single keywords, w_1 and w_2, respectively. Also, assume that the intersection of F_1 and F_2 with T_- is empty. In this case, the word-number ranker returns the same score for F_1 and F_2. If, however, w_1 is a frequent word in the corpus and w_2 is a rare one, then F_2 should be given a higher score than F_1.

Let F be a given fragment. In the idf ranker, a rare keyword that appears in F has a greater effect on the score than a keyword that appears frequently in the corpus. The score of the idf ranker is the following sum of the idf values of the optional words and the unwanted words that appear in F.

$$\sum_{k \in \{T_o \cap F\}} idf(k) - \sum_{k \in \{T_- \cap F\}} idf(k)$$

Note that terms of T_+ are not considered by this ranker, since all the fragments contain them.

6.3 Tf-Idf Ranker

The tf-idf ranker uses a model similar to the vector-space model that is common in information retrieval [2]. We have modified the basic technique so that the weights given to tags will be incorporated in the computation of the ranker's score.

Let T be a given topic and let F be a fragment. We assume that all the words in T and in F are stemmed. We also assume that all the stop words are removed from F and T. The score given by the ranker to F with respect to T is computed using a variation of the standard *tfidf* (term frequency, inverse document frequency) method. Next, we briefly describe *tfidf* and how it is computed in our system.

Let k be a term. The *term frequency (tf)* of k in F is the number of occurrences of k in F (denoted as $occ(k, F)$), divided by the maximal number of occurrences in F of any term. That is,

$$tf(k, F) = \frac{occ(k, F)}{\max\{occ(k', F) \mid k' \in F\}}.$$

Note that a term is likely to have a larger term frequency in a small document than in a bigger one.

The inverse document frequency of k, $idf(k)$, was defined in Section 4. The *tfidf* of a term k w.r.t. a fragment F, denoted by $tfidf(k, F)$, is $tf(k, F) \times idf(k)$. Note that by taking a log in the *idf* factor, the overall importance of the *tf* factor in *tfidf* is increased.

In our system, each tag has a weight. The default weight is 1. A user can modify the weight of any tag. The *accumulated weight* of a word w in an XML file X is the multiplication of the weights of all the tags of the elements of X in which w is nested. That is, the accumulated weight of w is produced by multiplying all the weights of the tags of elements on the path from the root of X to w. The effect of the weight of tags on the computation of *tfidf* is as follows. For each occurrence of k in F, instead of increasing $occ(k, F)$ by 1, the value of $occ(k, F)$ is increased by the accumulated weight of k for that occurrence.

The value of $tfidf(k, F)$ is normalized as follows.

$$w(k, F) := \frac{tfidf(k, F)}{\sqrt{\sum_{k' \in F} tfidf(k', F)^2}}$$

By definition, $w(k, F)$ is 0 if k does not appear in F. We denote by K the set of all the keywords appearing in the corpus. Each fragment F in the corpus is associated with a vector V_F of size $|K|$. For each keyword k of K, the vector V_F has an entry $V_F[k]$ that holds $w(k, F)$.

For each topic T, we define V_T to be the following vector.

$$V_T[k] = \begin{cases} 1 & \text{if } k \in T_+ \cup T_o \\ -1 & \text{if } k \in T_- \\ 0 & \text{otherwise} \end{cases}$$

The score given to the fragment F by the ranker is the cosine between V_T and V_F. The value of this cosine is proportional to the following sum:

$$\sum_{k \in K} V_F[k] \times V_T[k] = \sum_{k \in T} V_F[k] \times V_T[k]$$

Note that the above equality holds because $V_T[k] = 0$ if $k \notin T$.

6.4 Proximity Ranker

Lexical Affinities for Text Retrieval

The idea behind the proximity ranker is to use *lexical affinities* (abbr. LA) of words. The ranker takes advantage of the correlation between words that appear in a single phrase in a certain proximity.

The notion of lexical affinities for text retrieval was first introduced by Saussure [13]. Later, it was developed by Maarek and Smadja [10], in the context of information retrieval.

Essentially, our ranker works as follows. Given a topic T containing the terms $t_1, \ldots, t_n$, the ranker creates a list that contains all possible pairs of distinct words (t_i, t_j), such that $t_i < t_j$ (words are compared lexicographically). For each fragment F, whenever the ranker finds in F an occurrence of a pair (t_i, t_j) in a single sentence, the score given to F is increased. Different increasing policies can be used.

Lexical Affinities for XML Retrieval

The following explains how LA retrieval is adapted to XML, in general, and to our system, in particular.

Two words that appear very far from each other should not be considered as a LA. A maximal distance must be defined, such that when exceeded, the two words are not considered to be correlated. Martin [11] showed that 98% of LA's relate words that are separated by at most five words within a single sentence. Maarek and Smadja [10] used this result by searching for co-occurrences in a sliding window (within a single sentence) of size 5. We have adapted this result to the context of XML as explained below.

In XML, structure and content are combined. Due to this lack of separation between structure and content, an XML file can have a logical unit of text in which the text does not appear in a sentence delimited by full stops, but rather delimited by tags. For example, consider the following XML fragment.

```
<author>John Washington</author>
<address>New Jersey State</address>
```

The absence of a full stop between Washington and New Jersey State could be mistakenly interpreted as a case where Washington State is a LA. In order to avoid such mistakes, we consider a closing tag followed by an opening tag as a delimiter of a logical unit.

When looking for lexical affinities in a topic (i.e., query), special attention must be paid to the structure of the topic in order to avoid an attempt to pair words that do not appear under the same tag. For words that are not under the same tag, a LA should not be created. For example, consider the following topic title.

```
//article//fm[
 (about(.//tig, '+software +architecture')
  or about(.//abs, '+software +architecture'))
  and about(., '-distributed -Web')]
```

In this topic, the pairs "software architecture" and "distributed Web" should be considered as LA's. The pairs "distributed architecture" and "software Web" should not be considered as LA's.

For words that appear under the same tag, but some of them in quotation marks, the LA's in quotation marks are given a larger weight. For example, consider the following topic.

```
/article[about(./fm/abs,
'"information retrieval" "digital libraries"')]
```

The pairs "information retrieval," "digital libraries," "information digital," "information libraries," "retrieval digital" and "digital libraries" are all considered as LA's. However, the occurrences of "information retrieval" or "digital libraries" in a fragment get a larger weight than the occurrences of "retrieval digital" or "digital libraries."

6.5 Similarity Ranker

The idea behind the similarity ranker is that if two words appears very frequently in proximity in the corpus, then they should be considered as related concepts. For example, if we find that "SQL" and "databases" are two words that frequently appear together, then we may conclude that the two words are closely related. Therefore, when looking for documents about databases, we may as well search for documents about SQL.

Let F be a fragment of a document D. F_T denotes the terms appearing either in F, in the title of D or in the abstract of D. As usual, T denotes the terms in the title of a given topic. The similarity ranker computes the score of F w.r.t. the given topic T according to the formula

$$\prod_{k \in T} \sum_{w \in F_T} (tw(tag) * D(k, w))$$

where tag is the tag with the largest weight among those containing w. The similarity ranker uses the keyword-distance index in order to get the value of the distance $D(k, w)$. The tag index is used in order to get the value of $tw(tag)$.

This ranker can be seen as an automatic query refinement. It differs from the work of Jing and Croft [8], since we do not use a probabilistic approach. It also differs from the work of Carmel et al. [5], since our refinement uses a global analysis of the *whole* corpus and assigns weights to all the co-occurrences in the fragment, rather than just to a limited number of LA's.

6.6 Merging the Results of the Rankers

Each fragment is given a score by each ranker. The overall score of a result according to a ranker is the sum of the scores given by the ranker to the different fragments composing the result.

A crucial issue is to determine the relative weight of each ranker in the final phase of merging the results of the various ranker. Tackling this issue requires extensive experimentation with the system. So far, only a rudimentary merger has been implemented and it is based on the simple idea of merging the results by lexicographically sorting the scores of the five rankers. The relative positions of the five rankers in the lexicographic sort is given in a configuration file and can be easily modified by the user through a browser.

We have experimented with different orders of the rankers; in all of them, the word-number ranker was first and idf ranker was second. Results were produced for the following three orders of the rankers:

- Word Number, Idf, Proximity, Similarity, Tf-Idf.
- Word Number, Idf, Similarity, Proximity, Tf-Idf.
- Word Number, Idf, Tf-Idf, Proximity, Similarity.

We always chose word number and idf to be the first and second rankers, since early experiments with the system indicated that it gave the best results. The proximity ranker, the similarity ranker and the tf-idf ranker were essentially used to tune the ranking of the first two rankers.

The following two restrictions were applied to the creation of the XML file that contains the final ranking of the fragments. First, the final result is limited to 1500 fragments. Secondly, at most 5 fragments from any single document could appear in the final result. These limitations could be easily modified by the user.

7. CONCLUSION AND FUTURE WORK

The main contribution of our work is a design of an extensible system that is capable of combining different types of rankers in a manner that takes into account both the structure and the content of the documents. Traditional as well as new information-retrieval techniques can be incorporated into our system, and the ranking score of each technique can be easily modified to include the weights assigned to tags. Our system is also extensible in the sense that it can be easily adapted to changes in the formal syntax of titles, due to the implementation of the topic processor by means of XSL.

Two major issues remain for future work. One is improving the efficiency of the system. The second is improving the quality (i.e., recall and precision) of the results. This requires extensive experimentation with the current rankers as well as with new ones. In particular, we plan to modify the merger so that it will use a single formula to aggregate the scores of the various rankers, rather than sorting the scores lexicographically. Towards this end, further experimentation is needed in order to find the optimal weight of each ranker relative to the other rankers.

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Retrieving the most relevant XML Components

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ABSTRACT

XML enables to encode semantics in full text documents through XML tags. While query results on corpora of full text documents is typically a sorted list of ranked documents, this granularity can be refined to return sub components when searching over XML documents. In this paper we describe an approach for finding the most relevant XML components for a given query.

Keywords

XML Search, Information Retrieval, Vector Space Model

1. INTRODUCTION

XML documents represent a family of semi-structured documents in which data has some structure but is not fully structured as in databases. It is thus not surprising that approaches for searching in collections of XML documents are either extension of Information Retrieval (IR) techniques or of database query languages. The main difference between the two approaches is that while the results of Information Retrieval techniques is a list of documents sorted by their relevance to the query, the results of a database query are strict matches with no relevance values. In this paper we focus on Information Retrieval approaches and explore a technique whereby we rank individual XML components rather than full documents.

The Initiative for the evaluation of XML Retrieval (INEX) [7] coined two types of queries over XML documents: In **Content Only (CO)** queries the user has no knowledge of the document structure and the search engine is supposed to return the best components that match the query concepts. In **Content and Structure (CAS)** queries the user has some knowledge of the document structure and can use it to constrain content to a specific structure and also to specify the XML components to be returned.

It should be noted that techniques that are suited for returning a specific XML component that matches a CAS query may be orthogonal to the task at hand, which requires that the best matching component be retrieved. Indeed the version of JuruXML[11] that we used in INEX'02[7] could retrieve XML components as specified by CAS topics yet it could score only full documents. Consequently, all relevant components in a retrieved document where assigned identical scores – the score of their enclosing document, and individual component ranking was not supported.

In modern Information Retrieval engines document ranking is done based on the vector space model[13]. The idea is to treat both the documents and the query as a vector of terms (typically words). Each term is given a weight proportional to its Term Frequency (TF) in a document/query and inversely proportional to its Document Frequency (DF), which is the number of documents in which the term appears. The similarity between a document and a query is defined as the distance between the two vectors usually measured as the cosine between the two.

In order to rank components rather than entire documents, this classic model must be expanded to take into account component level statistics. The problem is that components in XML documents are nested and this hierarchy needs to be taken into account when counting term occurrences. More specifically, a specific term should not be counted more than once. For example consider a term inside a paragraph, which is itself nested in a section. What is the component frequency of this term? If it is counted as belonging to two components, it may distort ranking since the term actually appears only once in the document. On the other hand, if it is counted only once, with which component should this count be associated?

In this paper we describe an extension to the classic vector space model that can correctly handle retrieval at the component level. We demonstrate the use of this method on the INEX topics. This method can be implemented as an extension of any vector space based text search engine with no need to modify its basic structures and algorithms, making it highly applicable for any search engine wishing to rank components.

The remainder of the paper is organized as follows: In section 2 we outline some related work. In section 3 we describe our novel approach for selecting the most relevant XML component and how it was used for the INEX CO topics. In section 4 we show how this method was extended to handle the CAS topics. Our method for result clustering and for filtering redundant components is described in Section 5. We conclude with summary and future work.

2. RELATED WORK

The idea of ranking document subcomponents has been explored in the context of *passage retrieval* [10],[14]. The goal there is to identify the sentences that best match the user's query and assemble them into passages that are then returned to the user. The returned unit can be any combination of sentences even if they are inconsecutive. This technique is not suitable for XML components retrieval where the returned unit must be a fixed XML component.

The work described in [12] tries to identify subject boundaries in a text document based on the assumption that words that are related to a certain subject will be repeated whenever that subject is mentioned. Again this work assumes a flat text document with freedom to pick a portion of the text as an answer. This is not suitable for XML retrieval where the retrieval unit must be a predefined XML component.

The idea of scoring XML components separately has been suggested in the context of XML retrieval [5] [6]. In both cases, the term and document frequency is accumulated at the basic component level. An augmentation factor is used to propagate statistics from child to parent components. The problem with this technique is that the augmentation factors are either set manually by the user or set empirically and thus cannot be proven to give the best results.

3. APPROACH FOR CO TOPICS

We start by describing our approach for Content Only (CO) tasks and then we show how this approach was extended to handle Context and Structure (CAS) topics as well.

As a reminder, in a CO task the query is specified in full text (with additions of +/- and phrases) and the search engine is expected to return the most relevant XML components that match the query concepts.

Based on a training set composed of the INEX'02 topics and assessments, we found that the majority of the highly ranked components for CO topics (1296 out of 1394) were taken from the set: {article, bdy, abs, sec, ss1, ss2, p and ip1}. This is quite intuitive since {sec, ss1, and ss2} stand for sections and sub sections and {p, ip1} represent meaningful paragraphs, all good reasonable results for a query. The entire article or its abstract {abs} are also good candidates for component retrieval. The only exception is the {bdy} component that constitutes the main part of the article so whenever a bdy is relevant so is its containing article and vice versa. In that case we rather return the article and not the body.

Realizing that we have a clear list of candidate components for retrieval, our goal was to modify JuruXML[11] so that it could rank each of these candidate components separately. The ranking method used in JuruXML is based on the Extended Vector Space Model[3] where both documents and queries are represented as vectors in a space where each dimension represents a distinct term. It is typically computed using a score of the *tf x idf* family that takes into account the following document and collection statistics -

- **N** - Total Number of documents in the collection
- **Term Frequency** $TF_D(t)$ – number of occurrences of a term *t* in a document *D*
- **Document Frequency** DF(t) – total number of documents containing a term *t*

The relevance of the document D to the query Q, denoted below as $\rho(Q,D)$, is then evaluated by using a measure of similarity between vectors such as the cosine measure (see Formula 1).

$$\rho(Q,D) = \frac{\sum_{ti \in Q \cap D} w_Q(t_i) * w_D(t_i)}{\|Q\| * \|D\|}$$

Formula 1

Where

$$w_{X \in \{Q,D\}}(t) = \log(TF_X(t)) * \log(\frac{N}{DF(t)})$$

Formula 2

It follows that the weight WD(t) is proportional to the number of occurrences of t in D ($TF_D(t)$) and inversely proportional to the number of documents in which t appears (DF(t)). The motivation is that a term t that appears in a few documents in the corpus, should contribute a relatively high weight to the score of a document in which it appears compared to terms that are frequent in many documents. The contribution to the document score is additionally proportional to the number of its occurrences in the document.

In order to rank components instead of entire documents, these statistics should be tallied at the component level. That is, it is necessary to keep track of the following component and collection statistics:

- **N** - Total Number of components in the collection
- **Term Frequency** $TF_C(t)$ – number of occurrences of a term *t* in a component *C*
- **Component Frequency** CF(t) - total number of components containing a term *t*

The problem is that XML components are nested. For example consider a collection consisting of a single document (see Figure 1).

```
<article>
        t1
        <sec>
            <p>t2</p>
        </sec>
</article>
```

Figure 1

The document contains three components {C_1=article, C_2=sec, C_3=p} and two terms {t_1, t_2}. Term t_1 appears only in the article while t_2 appears in all 3 components. Therefore we get

- N = 3
- $CF(t_1) = 1$, $CF(t_2) = 3$
- $TF_{C1}(t_1) = 1$, $TF_{C1}(t_2) = 1$
- $TF_{C2}(t_1) = 0$, $TF_{C2}(t_2) = 1$
- $TF_{C3}(t_1) = 0$, $TF_{C3}(t_2) = 1$

By Formula 2 applied to component level statistics, we would get that $W_{c1}(t_1) > W_{c1}(t_2)$ which is not necessarily true since both t_1 and t_2 appear an equal number of times in the document.

One can try to fix this by only counting the Term Frequency $TF_C(t)$ at the component level and still computing N & DF(t) at the document level. However, this imposes another problem that is illustrated in the following example (see Figure 2).

```
<article>
    <sec>t1</sec>
    <sec>t1</sec>
    <sec>t2</sec>
</article>
```

Figure 2

As before, the collection consists of a single document and we have

- $N = 1$
- $DF(t_1) = 1$, $DF(t_2) = 1$

If we mark the 3 sections by C_1, C_2, C_3 we get

- $TF_{C1}(t_1) = 1$
- $TF_{C2}(t_1) = 1$
- $TF_{C3}(t_2) = 1$

By Formula 2 it follows that $W_{c1}(t_1) = W_{c2}(t_1) = W_{c3}(t_2)$. However if we regard each section as a standalone component then since t_2 appears only in one section while t_1 appears in 2 sections we expect to get $W_{c1}(t_1) < W_{c3}(t_2)$ (which is what would have happened if the sections were in different documents, since we would then have then $DF(t_1) = 2$). With this approach to counting statistics it is thus impossible to differentiate between the rankings of the three sections.

In view of the above problems, we selected a strategy whereby we create a different index for each component type. Statistics can thus be tallied at the precise level of granularity for each component. In particular, we created six indices corresponding to the following tags: {article, abs, sec, ss1, ss2, p, and ip1[1]}. The *article* index contains the full data of all documents. The *sec* index contains each sec from each article as a separate document and so on for each of the six tags above. For example the document in Figure 2 above will result in 3 separate documents in the *sec* level index.
For each index, the entities are determined according to the topmost XML tag of the corresponding type. That is, nested components of the same type do not yield a new partition of the document. For example consider a document as in Figure 3

```
<Article>
    <sec>
        <p>some text
            <p>some internal text</p>
        </p>
    </sec>
    <p>some higher level text</p>
</article>
```

Figure 3

This document will add two "documents" to the paragraph level index (See Figure 4 & Figure 5)

```
<p>some text
    <p>some internal text</p>
</p>
```

Figure 4

[1] P and IP_1 were indexed into one Index

And

```
<p>some higher level text</p>
```

Figure 5

The search engine's regular ranking formula can now be used to accurately score and rank individual components among themselves. In other words, given a query, the system can return the best matching articles, sections, sub-sections, etc. Our goal however is to return one ranked list of the best matching components regardless of granularity and thus need to compare scores from the individual indices. To achieve this, the query is submitted in parallel to each index, resulting in six sorted lists of components – one from each index.

The scores in each index are normalized into the range (0,1) using a formula that ensures that this normalization yields absolute numbers and is index independent. This is achieved by each index computing *P(Q,Q)* (see Formula 1) which is the score of the query itself as if it was a document in the collection. Since the score measures the cosine between vectors, then the max value is achieved between two identical vectors. Each index therefore normalizes all its scores to its computed *P(Q,Q)*. The normalized results are then merged into a one ranked list consisting of components of all granularities.

It should be noted that this approach can be implemented on top of almost any full text ranking engine resulting in a system than is able to rank XML components without modifying the core search engine code. It simply requires an XML parser that can parse documents and feed the components into separate indexes. At run time, queries are submitted in parallel to each index and the results are merged as described above.

3.1 The CO runs

We now describe the implementation of this method on the INEX collection. The size of the collection is ~500Mb. Six indices were created as described above, resulting in the following index sizes:

- Article – 290Mb
- Sec – 270Mb
- Ss1 – 158Mb
- Ss2 – 38Mb
- P, ip1 – 280Mb
- Abs – 14Mb

Overall we get an index size that is about twice as large as the original collection. While this can be an inhibiting factor, our goal was to prove the viability of this method from a quality standpoint. We believe there is room for optimisation in terms of index sizes.

We submitted three CO runs. Recall that a CO topic consists of full text with additions of +/- and Phrases. According to the topic development guide [8] the +/- "should be interpreted with a fuzzy flavour and not simply as must contain and must not contain conditions". We applied this vagueness to "+" terms but still we believe that if the user specify a "-" term then this term should not be returned. Therefore we treated the "-" strictly (namely results that contain such terms were never returned). The runs we submitted were -

- In the first run we considered all query parts: Title, Description and Keywords (CO-TDK)

- In the second run we applied post clustering on the first run (see section 5 below) (CO-TDK-with-clustering)
- In the third run we considered only the Title. In this run we ignored phrases and treated the phrase terms as regular words. We applied the clustering algorithm on this run as well (see Section 5 below) (CO-T-with-clustering)

The recall precision results achieved for the above runs based on assessments version 2.4 and using the "Strict with Overlap" metric are summarized in Table 1 below. Strict means that only highly assessed elements are considered and overlapping means that the metric removes overlapping results and penalizes submissions that return redundant fragments.

	CO-TDK	CO-TDK-with-clustering	CO-T-with-clustering
P@5	0.42	0.41	0.42
P@10	0.38	0.36	0.30
P@20	0.35	0.29	0.26
P@100	0.24	0.21	0.15
P@1500	0.162	0.142	0.129

Table 1

The table shows results at several precisions. It is quite clear that the first two runs which included all topic parts (title, keywords and description) were superior to the third run which used only the topic's title. Between the two TDK runs the one without the clustering performed better. This result is discussed in Section 5 below.

4. APPROACH FOR CAS TOPICS

The Content and Structure (CAS) topics differ in two aspects from the CO topics. First the query content can be limited to a given XML tag and second there is less freedom in selecting the component to be returned. The topic format is XPath[15] augmented with an 'about' predicate[8]. The last component in the path specifies the component that should be returned.

For example topic 66 (Figure 6) defines a constraint on the year <yr> and on section <sec>. <sec> is also the element to be returned.

```
/article[./fm//yr < '2000']
            //sec[about(.,'"search engines"')]
```

Figure 6

To enable fuzziness in the query constraints we introduce a *Synonyms* mechanism. We divide the XML tags into synonym groups such that all tags in the same group are regarded equivalent. Whenever there is a tag in the query that belongs to some synonym group, we substitute it by all tags in its group.
For example if we set {sec, ss1} to be in the same synonym group then in the query in Figure 6 above we substitute *sec* by {sec, ss1} and we get[2] the query in Figure 7. The synonyms mechanism is used at different granularity levels for the SCAS and VCAS runs (see below).

```
/article[./fm//yr < '2000']
            //{sec,ss1}[about(.,'"search engines"')]
```

Figure 7

In order to find documents in which all of the query constraints are met, we need to execute the modified query on the full documents. This will indeed return relevant components that match the query constraints, but as described above the components cannot be scored individually using only this one index.
Therefore we execute each query in two steps – in the first step we use the *article* index to locate candidates that fulfill the query constraints. In the second step, relevant parts of the query are extracted for each index (see example below) and the relevant query is submitted in parallel to the other five indexes of {abs, sec, ss1, ss2, p+ip1}. A relevance value is computed only for elements that were marked valid in the first step and a ranked list of results is returned. The separate lists are then merged similarly to what described for the CO case, resulting in one ranked list of results.
Note that although our indices do not cover all of the possible tags in the corpus, we can still resolve queries that request a tag that does not have a dedicated index. For example, topic 67 defines <fm> as the last component in the XPath expression, thus requesting a component for which we do not have a special index. In this case, we simply stop after the first step and use the article's score as the score of the component.

Example

In the following example we define one synonym group that consists of {sec, ss1, ss2} tags and we use it to run the query in Figure 6 above. We run the query first against the *article* level index and then we run the relevant query part on each of the synonyms ∈ {sec, ss1, ss2} so we run

//sec[about(.,'"search engines"')]

against the *sec* level index,

//ss1[about(.,'"search engines"')]

against the *ss1* level index and

//ss2[about(.,'"search engines"')]

against the *ss2* level index. We then merge the results based on their normalized scores as described above.

4.1 SCAS and VCAS

This year there were 2 CAS variants - Strict CAS (SCAS) and Vague CAS (VCAS). The SCAS defines that "structural constraints of a query must be strictly matched" while the VCAS defines that "structural constraints of a query can be treated as vague conditions". The vague means that XML elements that are "structurally similar" to those specified in the query can be returned. We used our synonym groups in different configurations to support both SCAS and VCAS.

For the SCAS runs we used the equivalent tags that were defined in the INEX topic development guide[8]. The synonyms we used were:

- {sec, ss1, ss2} for sections.

[2] This is not the syntax we use, the actual substitution is done in the internal implementation.

- {p, ip1} for paragraphs

The other two tags {article} and {abs} were not synonyms to any other tags so in topics that requested article or abs as results, only those tags were returned.

For the VCAS topics we defined one large synonym group that included all the tags {sec, ss1, ss2, p, ip1, abs}, except for the {article} tag. Again in topics that requested the article tag as a result we returned only articles.

4.2 The CAS runs

We submitted 3 SCAS and 3 VCAS runs. In all runs we treated the "-" strictly and the "+" with a fuzzy flavour. In all runs we treated query constraints in a strict manner up to the synonym tags. So for example results for the query in Figure 6 will be only sections and all their synonym tags that discuss "search engines" but only from articles that were published before year 2000.

We ran the following 3 runs for both SCAS and VCAS

- In first run, we considered all query parts: Title, Description and Keywords.
- In the second run, we applied a post-clustering algorithm on the first run (see Section 5 below).
- In the third run, we considered only the Title and Keywords and applied a post-clustering algorithm (see Section 5 below).

At the time this report is written full CAS results are not yet available so we don't report these results here.

5. RESULT CLUSTERING

The approaches described above may result in redundant components that are returned to the user. For example consider a section with four paragraph children. We can identify two extreme scenarios -

In the first scenario assume all four paragraphs are highly relevant to the topic. In this case all four paragraphs as well as their parent section will be ranked in high positions.

In the second scenario assume that only the first paragraph is very relevant to the topic and therefore it is assigned a high score. As a result it may also contribute to its parent's section score even if it is the only relevant paragraph in that section. Again that paragraph and its parent section may be ranked in a high position when merging the results.

One expectation of a good search engine is that it should not return redundant results; therefore in the first scenario it should return the section and not the paragraphs, while in the second scenario it should return the first paragraph only.

To filter such redundancies we developed a clustering algorithm that maps related components to one of the scenarios above. The algorithm gets the result set of the original run and constructs a tree consistent with the parent-child relationship of the components in the XML document. Each node in the tree corresponds to a result component and has the following data -

- Its score as a number between 0 and 1
- Total number of descendant children in the original document. This number is extracted while parsing the document.

The algorithm processes the tree bottom up and at each level compare the score of a node to that of its children. When it manages to identify one of the two scenarios above it remove the redundant components from the result set.

Recall that a score is a number between 0 and 1 so we need some means to say when two scores are close to each other. Let a node's score be *s1* and a child's score be *s2*. We say that the two scores are *close* if $\frac{|s1 - s2|}{s1} < ScoreThresh$ for some configured *ScoreThresh* value. Otherwise we say that s1 is *higher* than s2 (if s1>s2) or *lower* (if s1<s2).

The algorithm clusters each node into the following cases –

- **HighParent** - If the node's score is *higher* than all its direct children, then we remove the children from the tree.
- **HighChild** - If some child's score is *higher* than the current node's score, then we remove the node from the tree.
- **ManyDescendants** – Let N_e be the number of *close* descendants and N_t the number of all descendants of our node. If $\frac{N_e}{N_t} > ManyDescendantsThresh$ for some configured *ManyDescendantThresh* then we say that there are many good children and we remove the direct children from the tree (corresponding to the first scenario above)
- **SingleChild** – For each direct child C_i let N_i be the number of *close* descendants of C_i and N the total number of *close* descendants of the current node. If there is a child C_i with $\frac{Ni}{N} > SingleChildThresh$ for some configured *SingleChildThresh* value then we say that most good results are concentrated in that child so we remove the parent from the tree (corresponding to the second scenario)

For all other cases no filtering takes place, and all components are returned

5.1 Clustering runs

We used the following values for the clustering runs:

- *ScoreThresh*=0.45
- *ManyDescendantThresh* = 0.2
- *SingleChildThresh*=0.42.

According to the INEX evaluations received thus far, it seems that the runs that applied clustering received a lower overall score than runs that did not apply clustering. It thus seems that there was no penalty for runs returning redundant results. This topic should be discussed in order to devise metrics that evaluate a good overall result set, rather than individual results.

6. CONCLUSIONS AND FUTURE WORK

We presented a novel approach and implementation for scoring and ranking individual components of XML documents. At the time this report is written, Recall Precision graphs for the CO topics were published and one of our runs was ranked first indicating that this approach indeed computes more accurate component scores. The approach presented here can be implemented on top of almost any full text search engine without modifying its code to return ranked components for Content Only queries. Similarly the approach can be used by XML search engines to compute more accurate scores for target components specified in CAS topics. One limitation of our approach is that the set of potential components to be returned must be known in advance. We believe however, that this is a reasonable requirement for any given collection. Additionally, some space as well as runtime overhead is incurred by multi-indexing. Improving the efficiency is left for future research.

7. ACKNOLEDGMENT

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XXL @ INEX 2003

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ABSTRACT

Information retrieval on XML combines retrieval on content data (element and attribute values) with retrieval on structural data (element and attribute names). Standard query languages for XML such as XPath or XQuery support Boolean retrieval: a query result is a (possibly restructured) subset of XML elements or entire documents that satisfy the search conditions of the query. Such search conditions consist of regular path expressions including wildcards for paths of arbitrary length and boolean content conditions.

We developed a flexible XML search language called XXL for probabilistic ranked retrieval on XML data. XXL offers a special operator '$\sim$' for specifying semantic similarity search conditions on element names as well as element values. Ontological knowledge and appropriate index structures are necessary for semantic similarity search on XML data extracted from the Web, intranets or other document collections. The XXL Search Engine is a Java–based prototype implementation that support probabilistic ranked retrieval on a large corpus of XML data.

This paper outlines the architecture of the XXL system and discusses its performance in the INEX benchmark.

1. INTRODUCTION

The main goal of the initiative for the evaluation of XML retrieval (INEX) is to promote the evaluation of content–based and structure–based XML retrieval by providing a hugh test collection of scientific XML documents, uniform scoring procedures, and a forum for organisations to compare their results. For that purpose, the INEX committee provides about 12.000 IEEE journal articles with a rich XML structure. In cooperation with the participanting groups a set of content–only queries (CO) and a set of content–and–structure queries (CAS) was created. Each group evaluated these queries on the given data with their XML retrieval system and submitted a set of query results.

In this paper we describe the main aspects of our XXL search engine. First of all, we present our flexible XML search language *XXL*. In addition, we describe our ontology model which we use for semantic similarity search on structural data and content data of the XML data graph. Then we give a short overview how XXL queries are evaluated in the XXL Search Engine and which index structures used to support an efficient evaluation. Finally, we present the our results in the INEX 2003 benchmark.

2. XML DATA MODEL

In our model, a collection of XML documents is represented as a directed graph where the nodes represent elements, attributes and their values. For identification, each node is assigned a unique ID, the `oid`. There is an directed edge from a node x to a node y if

- y is a subelement of x,
- y is an attribute of x,
- y contains the value of element x or
- y contains the value of attribute x.

Additionally, we model an XLink [7] from one element to another by adding a special, directed edge between the corresponding nodes. We call the resulting graph the *XML data graph* for the collection.

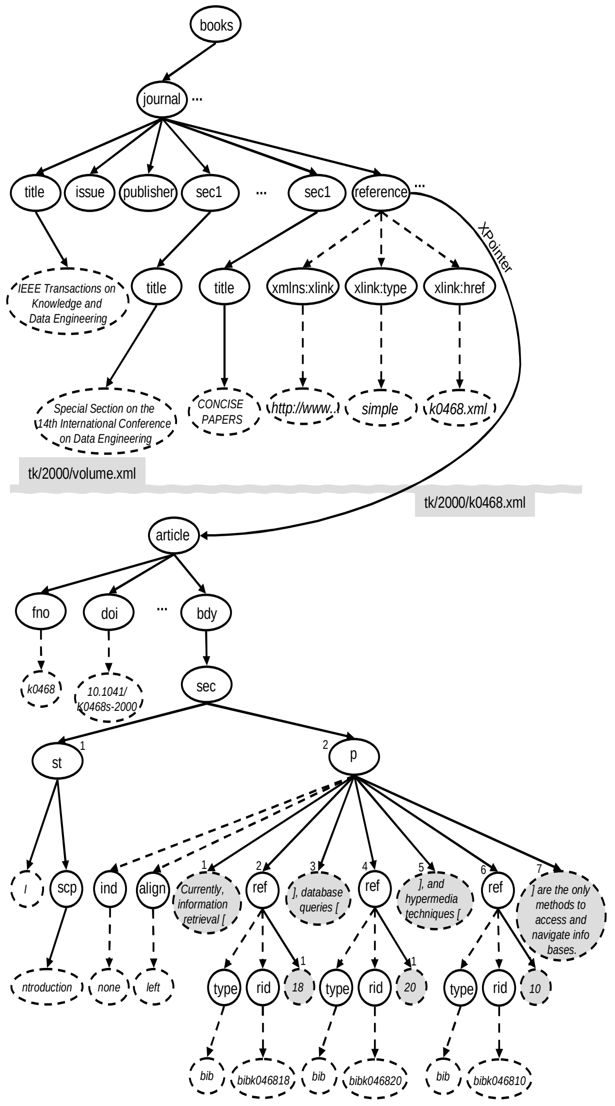


Figure 1: XML data graph

Figure 1 shows the XML data graph for a collection of two XML documents from the INEX collection (adapted as shown in Section 6): a journal document with an XLink pointing to an article document. Each node that contains an element or attribute name is called *n–node* (shown as normal nodes in Figure 1), and each node that contains an element or attribute value is called *c–node* (dashed nodes in Figure 1). To represent mixed content, we need a local order of the child nodes of a given element. In Figure 1 you can see a sentence which is partitioned into several shaded c–nodes.

3. THE FLEXIBLE XML QUERY LANGUAGE XXL

The Flexible XML Search Language XXL has been designed to allow SQL-style queries on XML data. We have adopted several concepts from XML-QL [8], XQuery[3] and similar languages as the core, with certain simplifications and resulting restrictions, and have added capabilities for ranked retrieval and ontological similarity. As an example for an XXL query, consider the following query that searches for publications about astronomy:

```
SELECT $T               // output of the XXL query
FROM   INDEX            // search space
WHERE  ~article AS $A   // search condition
  AND  $A/~title AS $T
  AND  $A/#/~section ~ "star | planet"
```

The SELECT clause of an XXL query specifies the output of the query: all bindings of a set of element variables. The FROM clause defines the search space, which can be a set of URLs or the index structure that is maintained by the XXL engine. The WHERE clause specifies the search condition; it consists of the logical conjunction of *path expressions*, where a path expression is a regular expression over *elementary conditions* and an elementary condition refers to the name or content of a single element or attribute. Regular expressions are formed using standard operators like '/' for concatenation, '|' for union, and '*' for the Kleene star. The operator '#' stands for an arbitrary path of elements. Each path expression can be followed by the keyword AS and a variable name that binds the end node of a qualifying path (i.e., the last element on the path and its attributes) to the variable, that can be used later on within path expressions, with the meaning that its bound value is substituted in the expression.

In contrast to other XML query languages we introduce a new operator '$\sim$' to express semantic similarity search conditions on XML element (or attribute) names as well as on XML element (or attribute) contents.

The result of an XXL query is a subgraph of the XML data graph, where the nodes are annotated with local relevance probabilities called similarity scores for the elementary search conditions given by the query. These similarity scores are combined into a global similarity score for expressing the relevance of the entire result graph. Full details of the semantics of XXL and especially the probabilistic computation of similarity scores can be found in [17, 18].

4. ONTOLOGY–BASED SIMILARITY

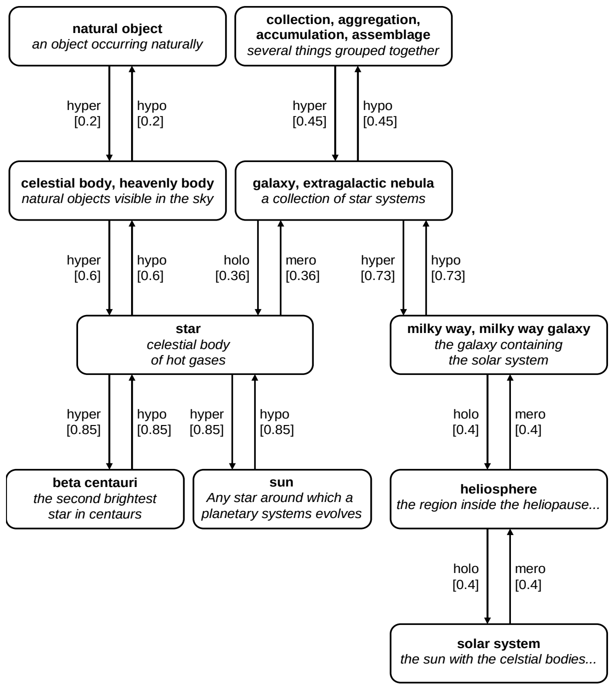
Ontologies have been used as a means for storing and retrieving knowledge about the words used in natural language and relations between them.

In our approach we consider a term t as a pair $t = (w, s)$ where w is a word over an alphabet Σ and s is the word sense (short: sense) of w, e.g.

```
t1 = (star, a celestial body of hot gases)
t2 = (heavenly body, a celestial body of hot gases)
t3 = (star, a plane figure with 5 or more points)
```

In order to determine which terms are related, we introduce semantic relationships between terms that are derived from common sense. We say that a term t is a *hypernym* (*hyponym*) of a term t' if the sense of t is more general (more specific) than the sense of t'. We also consider holonyms and meronyms, i.e., t is a *holonym* (*meronym*) of t' if t' means something that is a part of something meant by t (vice versa for meronyms). Finally, two terms are called *synonyms* if there senses are identical, i.e., their meaning is the same.

Based on these definitions we now define the ontology graph $O = (V_O, E_O)$ which is a data structure to represent concepts and relationships between them. This graph has concepts as nodes and an edge between two concepts whenever there is a semantic relationship between them. In addition, we label each edge with a weight and the type of the underlying relationship. The weight expresses the semantic similarity of two connected concepts. Figure 2 shows an excerpt of an example ontology graph around the first sense for the word "star".



natural object
an object occurring naturally
collection, aggregation, accumulation, assemblage
several things grouped together
hyper [0.2]
hypo [0.2]
hyper [0.45]
hypo [0.45]
celestial body, heavenly body
natural objects visible in the sky
galaxy, extragalactic nebula
a collection of star systems
hyper [0.6]
hypo [0.6]
holo [0.36]
mero [0.36]
hyper [0.73]
hypo [0.73]
star
celestial body of hot gases
milky way, milky way galaxy
the galaxy containing the solar system
hyper [0.85]
hypo [0.85]
hyper [0.85]
hypo [0.85]
holo [0.4]
mero [0.4]
beta centauri
the second brightest star in centaurs
sun
Any star around which a planetary systems evolves
heliosphere
the region inside the heliopause...
holo [0.4]
mero [0.4]
solar system
the sun with the celstial bodies...

Figure 2: Excerpt of an ontology graph O with labeled edges

To fill our ontology with concepts and releationship we use the voluminous electronical thesaurus WordNet as backbone. WordNet organzies words in synsets and presents relationships between synsets without any quantification.

For quantification of relationships we consider frequency–based correlations of concepts using large web crawls. In our approach, we compute the similarity of two concepts using correlation coefficients from statistics, e.g. the Dice or Overlap coefficient [14].

For two arbitrary nodes u and v that are connected by a path $p = \langle u = n_0 \ldots n_k = v \rangle$, we define the similarity $sim_p(u, v)$ of the start node u and the end node v along this path to be the product of the weights of the edges on the path:

$$sim_p(u,v) = \prod_{i=1}^{length(p)-1} weight(\langle n_i, n_{i+1} \rangle)$$

where $weight(\langle n_i, n_{i+1} \rangle)$ denotes the weight of the edge $e = (n_i, n_{i+1})$. The rationale for this formula is that the length of a path has direct influence on the similarity score. The similarity $sim(u,v)$ of two nodes u and v is then defined as the maximal similarity along any path between u and v:

$$sim(u,v) = \max\{sim_p(u,v) \mid p \text{ } path \text{ } from \text{ } u \text{ } to \text{ } v\}$$

However, the shortest path (the path with the smallest number of edges) need not always be the path with the highest similarity, as the triangular inequation does not necessarily hold. Thus, we need an algorithm that takes into account all possible paths between two given concepts, calculates the similarity scores for all paths, and chooses the maximum of the scores for the similarity of these concepts. This is a variant of the single–source shortest path problem in a directed, weighted graph. A good algorithm to find the similar concepts to a given concept and their similarity scores is a variant of Dijkstra's algorihm [6] that takes into account that we multiply the edge weights on the path and search for the path with the maximal weight instead of minimal weight.

Furthermore, as words may have more than one sense, it is a priori not clear in which sense a word is used in a query or in a document. To find semantically similar words, it is fundamental to disambiguate the word, i.e., to find out its current sense. In our work we compute the correlation of a context of a given word and the context of a potential appropriate concept from the ontology using correlation coefficients as described above. Here, the context of a word are other words in the proximity of the words in the query or document, and the context of a concept is built from the words of the neighbor nodes of the concept. See [15] for more techical details on the disambiguation process.

5. THE XXL SEARCH ENGINE

5.1 Architecture of the XXL Search Engine

The XXL Search Engine is a client-server system with a Java-based GUI. Its architecture is depicted in Figure 3.

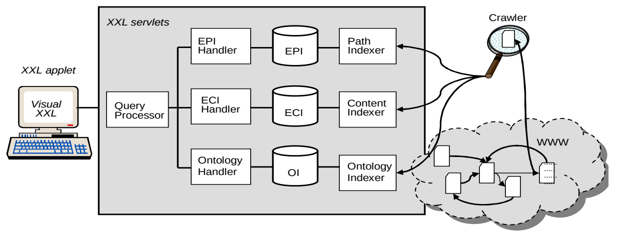


Figure 3: Architecture of the XXL search engine

The server consists of the following core components:

- *service components*: the crawler and the query processor, both Java servlets
- *algorithmic components*: parsing and indexing documents, parsing and checking XXL queries
- *data components*: data structures and their methods for storing various kinds of information like the element path index (EPI), the element content index (ECI), and the ontology index (OI).

The EPI contains the relevant information for evaluating simple path expressions that consist of the concatenation of one or more element names and path wildcards #. The ECI contains all terms that occur in the content of elements and attributes, together with their occurrences in documents; it corresponds to a standard text index with the units of indexing being elements rather than complete documents. The OI implements the ontology graph presented in Section 4.

5.2 Query Processing in the XXL Search Engine

The evaluation of the search conditions in the Where clause consists of the following two main steps:

- The XXL query is decomposed into subqueries. A global evaluation order for evaluating the various subqueries and a local evaluation order in which the components of each subquery are evaluated are chosen.
- For each subquery, subgraphs of the data graph that match the query graph are computed, exploiting the various indexes to the best possible extent. The subresults are then combined into the result for the original query.

5.2.1 *Query Decomposition*

As an example for an XXL query, consider the following XXL query where we are interested in scientific articles about information retrieval and databases:

```
SELECT $T
FROM   INDEX
WHERE ~article AS $A
  AND  $A/~title AS $T
  AND  $A/#/~section ~ "IR & database"
```

The Where clause of an XXL query consists of a conjunction `"W1 And ...  And Wn"` of subqueries `Wi`, where each subquery has one of the following types:

- `Pi`
- `Pi AS $A`
- `Pi` ∼`|LIKE|=|<>|<|> condition`

where each `Pi` is a regular path expression over elementary conditions, `$A` denotes a element variable to which the end node of a matching path is bound, and `condition` gives a content–based search condition using a binary operator. From the definitions of variables we derive the *variable dependency graph* that has an edge from `$V` to `$W` if the path bound to `$W` contains `$V`. We require the variable dependency graph of a valid XXL query to be acyclic.

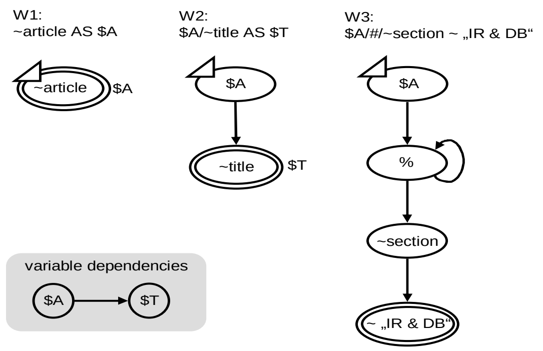


Figure 4: XXL search graphs for each subquery of the given XXL query

Each subquery corresponds to a regular expression over elementary conditions which can be described by an equivalent non-deterministic finite state automaton (NFSA). Figure 4 shows the search graphs of the example query together with the variable dependency graph.

5.2.2 *Query Evaluation*

To evaluate an XXL query, we first choose an order in which its subqueries are evaluated. This order must respect the variable dependency graph, i.e., before a subquery that defines a variable is evaluated, all subqueries that define variables used in this subquery must be evaluated. As this may still leaves us some choices how to order subqueries, we estimate the selectivity of each subquery using simple statistics about the frequency of element names and search terms that appear as constants in the subquery. Then we choose to evaluate subqueries and bind the corresponding variables in ascending order of selectivity (i.e., estimated size of the intermediate result).

Each subquery is mapped to its corresponding NFSA. A result for a single subquery, i.e. a *relevant path*, is a path of the XML data graph that matches a state sequence in the NFSA from an intial state to a final state. For such a result, the relevance score is computed by multiplying the local relevance scores of all nodes of the path. In addition, all variables that occur in the subquery are assigned to one node of the relevant path.

A result for the query is then constructed from a consistent union of the variable assignments and a set of relevant paths (one from each subquery) that satisfies the variable assignments. The global relevance for such a result is computed by multiplying the local relevances of the subresults.

The local evaluation order for a subquery specifies the order in which states of the subquery's NFSA are matched with elements in the XML data graph. The XXL prototype supports two alternative strategies: in top-down order the matching begins with the start state of the NFSA and then proceeds towards the final state(s); in bottom-up order the matching begins with the final state(s) and then proceeds towards the start state.

As an example, we show how the NFSA shown in Figure 5 is evaluated in top-down order on the data shown in that figure.

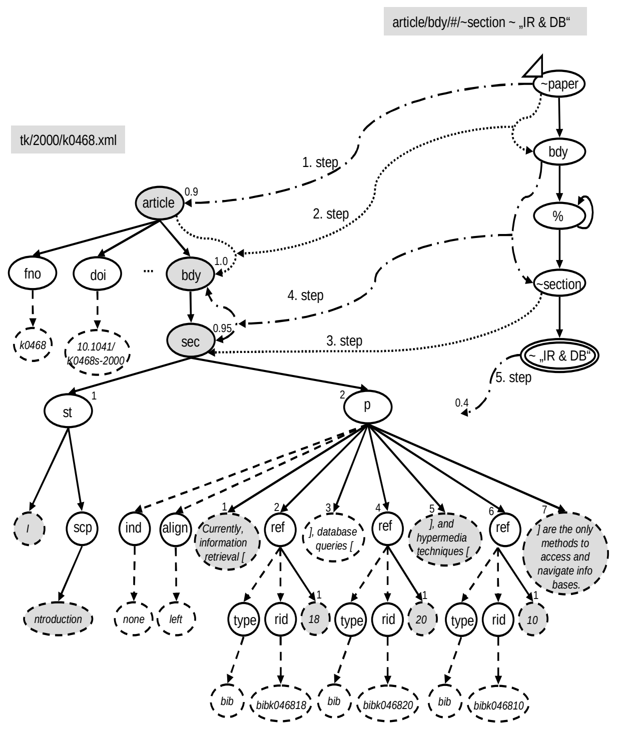


Figure 5: Evaluation of a XXL search graph in top–down manner

Step 1: The first elementary search condition contains a semantic similarity search condition on an element name. Thus, we consult the ontology index to get words which are similar to `paper`, yielding the word `article` with *sim(article, paper) = 0.9*. The first part of our result graph is therefore a n–node of the data graph named `article`, and it is assigned a local relevance score of 0.9.

Step 2: To be relevant for the query, a node from the result set of Step 1 must also have a child node with name `bdy`. As a result of Step 2, we consider result graphs formed by such nodes and their respective child.

Step 3: The next state in the NFSA corresponds to a wildcard for an arbitrary path in the data graph. Explicitly evaluating this condition at this stage would require an enumeration of the (possibly numerous) descendants of candidate results found so far, out of which only a few may satisfy the following conditions. We therefore proceed with the next condition in the NFSA and postpone evaluating the path wildcard to the next step. The following condition is again a semantic similarity condition, so we consult the ontology index to get words which are similar to `section`. Assume that the ontology index returns the word `sec` with a similarity score of 0.95. There are no n-nodes in the data that are named `section`, but we can add n–nodes named `sec` to our preliminary result with a local relevance score of 0.95.

Step 4: In this step we combine the results from steps 2 and 3 by combining n-nodes that are connected through an arbitrary path.

Step 5: The final state of the NFSA contains a content-based semantic similarity search condition which must be satisfied by the content of a `sec`-element in the result set of Step 4. We first decompose the search condition that may consist of a conjunction of search terms into the atomic formulas (i.e., single terms). For each atomic formula we consult the ontology index for similar words and combine them in a disjunctive manner. We then use a text search engine to evaluate the relevance of each element's content which is expressed through an tf/idf-based relevance score. This score is combined with the ontology-based similarity score to the relevance score of the atomic formula. Finally, we multiply the relevance scores for each formula to get the relevance score for the similarity condition.

In our example, the shaded nodes in Figure 5 form a relevant path for the given NFSA.

5.2.3 *Index Structures*

The XXL Search Engine provides appropriate index structures, namely the element path index (EPI), the element content index (ECI), and the ontology index (OI), that support the evaluation process described in the previous subsection.

The OI supports finding words that are semantically related to a given word, using the techniques presented in Section 4.

The ECI supports the evaluation of complex logical search conditions using an inverted file and a B+–tree over element names. Given an atomic formula, the ECI returns elements whose content is relevant with respect to that atomic formula and the tf/idf–based relevance score.

The EPI provides efficient methods to find children, parents, descendants and ascendants of a given node, and to test if two arbitrary nodes are connected. When the XML data graph forms a tree, we use the well-known pre- and postorder scheme by Grust et al. [10, 11] for this purpose. However, if the XML documents contain links, this scheme can no longer be applied. For such settings that occur frequently with documents from the Web, the XXL Search Engine provides the *HOPI* index [16] that utilizes the concept of a 2–hop cover of a graph. This is a compact representation of connections in the graph developed by Cohen et al. [4]. It maintains, for each node v of the graph, two sets $L_{in}(v)$ and $L_{out}(v)$ which contain appropriately choosen subsets of the transitive predecessors and successors of v. For each connection (u, v) in the XML data graph G, we choose a node w on a path from u to v as a *center node* and add w to $L_{out}(u)$ and to $L_{in}(v)$. We can efficiently test if two nodes u and v are connected by checking $L_{out}(u)$ and $L_{in}(v)$: there is a path from u to v iff $L_{out}(u) \cap L_{in}(v) \neq \emptyset$. The path from u to v can be separated into a first hop from u to some $w \in L_{out}(u) \cap L_{in}(v)$ and a second hop from w to v, hence the name of the method.

More technical details how we improved the theoretical concept of a 2–hop–cover can be found in [16] which covers both the efficient creation of the index using a divide-and-conquer algorithm and the incremental maintenance of the index.

5.3 Implementation Issues

In our prototype implementation we store XML data in an Oracle 9i database with the following relational database schema:

– URLS (urlid, url, lastmodified),
– NAMES(nid, name),
– NODES(oid, urlid, nid, pre, post),
– EDGES(oid1, oid2),
– LINKS(oid1, oid2),
– CONTENTS(oid, urlid, nid, content),

– LIN (oid1, oid2) and
– LOUT(oid1, oid2).

Here, NODES, EDGES and CONTENTS store the actual XML data, URLS contains the urls of all XML documents known to the system, and LINKS holds the links between XML documents. LIN and LOUT store the L_{in} and L_{out} sets used by the HOPI index. The ECI makes use of Oracle's text search engine.

The OI is represented by the following three tables:

– CONCEPTS (cid, concept, description, freq),
– WORDS (cid, word) and
– RELATIONSHIPS(cid1, cid2, type, freq, weight).

The entries in the ontology index are extracted from the well–known electronic thesaurus WordNet [9]. Frequencies and weights are computed as shown in Section 4.

Both the crawler used to parse and index XML documents from the Web and from local directories and the query processor of the XXL search engine used to evaluate XXL queries are implemented using Java.

6. XXL AND THE INEX BENCHMARK

6.1 The INEX Data

The INEX document collection consists of eighteen IEEE Computer Society journal publications with all volumes since 1995. Each journal is stored in its own directory. For each journal, the volumes are organized in subdirectories per year. Each volume consists of a main XML file `volume.xml` that includes the XML files for the articles in this volume using XML entities. Thus, importing all volumes using a standard XML parser yields 125 single documents.

This organization of the data appears somewhat artificial and is unsuitable for answering INEX queries, as these queries typically ask for URLs of articles, not volumes. Having only volumes available as separate XML files, the path to the originating article for a hit has to be reconstructed from metadata in the XML files (the `fno` entries) which unfortunately is not always correct.

To overcome this problem, we adapted the INEX data in the following way. We replaced each entity in the volume files by an XLink pointing to the root element of the corresponding article. This modification keeps the original semantics of the data, but allows us to return the correct URLs of results in all cases. Additionally, such an organization is much closer to what one would expect from data available on the Web or in digital libraries. After this modification, importing all documents yielded 125 journal volumes and 12,117 journal articles.

The following table shows the number of records of each table after crawling and indexing the slightly modified INEX document collection.

table	number of records
URLS	12.232
NAMES	215
NODES	12.061.220
EDGES	12.048.987
LINKS	407.960
CONTENTS	11.779.730
LIN	28.776.664
LOUT	4.924.420

In addition to this structural problem, the INEX collection has some other properties that makes retrieval based on semantic similarities difficult, if not infeasible:

- Most element and attribute names are, even though they are derived from natural language, no existing words. As an example, the element name `sbt` stands for "'subtitle"'. However, the ontology used by XXL does not contain such abbrevations, so it had to be manually adapted if it was to be used for the INEX queries.
- Some element names are used only for formatting and do not carry any semantics at all. As an example, elements with name `scp` contain textual content that should be typeset small caps font.
- Each journal article has a rich structure with possibly long paths (which XXL supports with its highly efficient path index structures). However, as all articles are conforming to the same DTD, they share the same structure, which renders structural similarity search obsolete.
- The queries mostly contain keywords that are not well represented in WordNet, yielding ontology lookups useless in most cases. For some keywords, we manually enhanced the ontology, but this was far less complete than the information usually available with WordNet.

As a preliminary conclusion, the INEX collection is inappropriate for exploiting and stress–testing similarity search features as provided by our query language XXL and also other approaches along these lines [1, 5, 12].

6.2 The INEX Topics

The INEX benchmark consists of a set of content–only queries (CO) and content–and–structure queries (CAS) given in a predefined XML format. Each *topic* (INEX query) consists of a short description and a longer description of the topic of request and a set of keywords, and CAS queries also contain an XPath expression. For example, consider the CO–topic

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<!DOCTYPE inex_topic SYSTEM "topic.dtd">
<inex_topic topic_id="98" query_type="CO" ct_no="26">
  <title>
    "Information Exchange", +"XML", "Information
     Integration"
  </title>
  <description>
    How to use XML to solve the information exchange
    (information integration) problem, especially in
    heterogeneous data sources?
  </description>
  <narrative>
    Relevant documents/components must talk about
    techniques of using XML to solve information
    exchange (information integration) among
    heterogeneous data sources where the structures
    of participating data sources are different
    although they might use the same ontologies
    about the same content.
  </narrative>
  <keywords>
    information exchange, XML, information integration,
    heterogeneous data sources
  </keywords>
</inex_topic>
```

To automatically transform a CO–topic into an XXL query we consider the keywords within the XML element `<title>` given for the query. As there is no way to automatically decice how to combine these keywords (conjunctively, disjunctively or mixed) in an optimal manner, we chose to combine them conjunctively. To get also results that are semantically similar to the keywords, we also add our similarity operator $\sim$. For the CO–topic 98 this process yields the following XXL query:

```
SELECT *
FROM INDEX
WHERE article/# ~  "(information exchange)
                    & XML
                    & (information integration)"
```

For CAS queries, we map the given XPath expression in a straightforward way to a corresponding XXL expression, adding semantic similarity conditions to all element names and keywords that appear in the XPath expression. However, as there are sometimes differences between the XPath expression and the natural language–based description of a query, this automatic transformation does not always yield optimal results. For the CAS–topic 63 this process yields the following XXL query:

```
SELECT $A
FROM INDEX
WHERE article AS $A
  AND $A ~ "digital library"
  AND $A/#/p ~ "authorization & (access control) &
               security"
```

6.3 The INEX Result Evaluation

For each topic the results of all participants are collected into a result pool for this topic. Then the potentially relevant components from each pool are assessed by a human who assigns an *exhaustivity* value and a *specificity* value. Exhaustivity describes the extent to which the component discusses the topic of request, specificity describes the extent to which the component focusses on the topic of request. Each parameter can accept four values:

0	not exhaustive/specific
1	marginally exhaustive/specific
2	fairly exhaustive/specific
3	highly exhaustive/specific

To assess the quality of a set of search results a metric based on the traditional recall/precision metrics is applied. In order to apply this metric, the assessors' judgements have to be quantised onto a single relevance value. Two different quantisation functions have been used:

1. *Strict* quantisation is used to evaluate whether a given retrieval approach is capable of retrieving highly exhaustive and highly specific document components.

$$f_{strict}(ex, spec) = \begin{cases} 1 & \textit{ex=3, spec=3 (short: 3/3)} \\ 0 & \textit{otherwise} \end{cases}$$

2. In order to credit document components according to their degree of relevance (generalised recall/precision), a *generalized* quantisation has been used.

$$f_{generalized}(ex, spec) = \begin{cases} 1 & 3/3 \\ 0.75 & 2/3, 3/2, 3/1 \\ 0.5 & 1/3, 2/2, 2/1 \\ 0.25 & 1/1, 1/2 \\ 0 & 0/0 \end{cases}$$

Given the type of quantisation described above, each document component in a result set is assigned a single relevance value using the human–based relevance assessment.

Now, the precision and recall for a submitted result can be calculated using strict quantisation or generalized quantisation.

6.4 The XXL Experiments

We submitted runs with and without enabling lookups in the ontology index. With the OI enabled, each keyword in the query is replaced by the disjunction of itself and all its related terms.

6.4.1 CO–Topics

For the first experiment we evaluate CO–topics with and without ontology support. This scenario is used to compare the precision and recall of the following two runs:

1. *CO:Init* . . . for this run we do not use the ontology index for query evaluation.
2. *CO:Onto* . . . for this run we use the ontology index for query expansion.

For example consider the CO–topic 98 with the keywords:

```
"Information Exchange" +"XML" "Information Integration"
```

The corresponding XXL query for the first run *CO:Init* without enabling lookups in the ontology index has the following where clause:

```
"information exchange" & "XML" & "information integration"
```

The corresponding XXL query for the second run *CO:Onto* using ontology–based query expansion has the following where clause:

```
("information exchange" | "data exchange" |
 "heterogeneous data") &
("XML" | "semistructured data") &
("information integration" | "information sharing")
```

For the first XXL query we obtain 7 results with an average precision of 0.0002 for the strict quantisation and with an average precision of 0.0043 for the generalized quantisation. For the second XXL query we obtain 28 results with an average precision of 0.0002 for the strict quantisation and with an average precision of 0.0065 for the generalized quantisation.

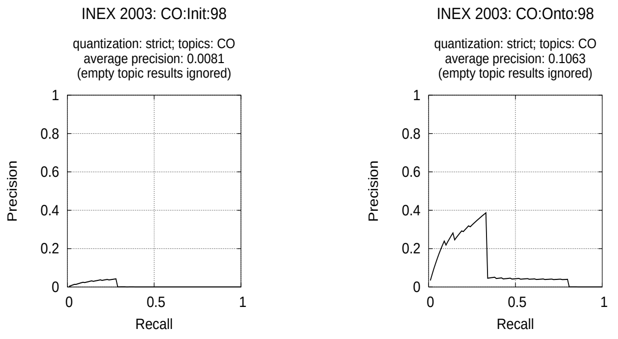
However, if we carefully look at the given topic, it turns out that a reformulation like the following could return better results. Thus, for the first XXL query we take:

```
("information exchange" | "information integration") &
"XML"
```

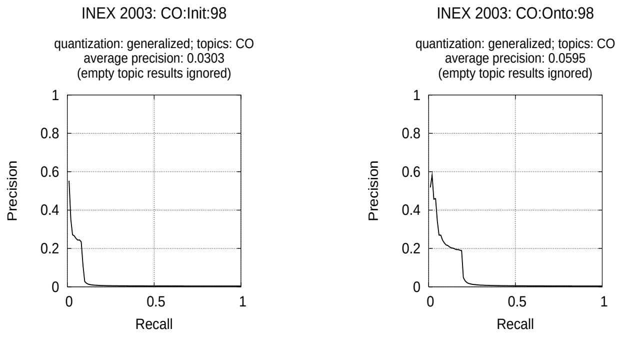
The second expanded XXL query has following structure:

```
(("information exchange" | "data exchange" |
  "heterogeneous data") |
 ("information integration" | "information sharing")) &
("XML" | "semistructured data") &
```

The following figure shows the average precision of the strict evaluation approach for the CO–topic 98 from the first run *CO:Init* (left) and from the second run *CO:Onto* (right).



The next diagrams show the average precision of the generalized evaluation approach for the CO–topic 98 from the first run *CO:Init* (left) and from the second run *CO:Onto* (right).



As the INEX runs had to use automatically generated queries such an optimization could not be applied. It turns out that this reformulation in fact yields even better results, even though the ontology–enabled results include some non–relevant results.

For the complete run of all 36 CO–topics submitted after official INEX deadline we obtain following results. The next two figures show the average precision with strict quantisation.

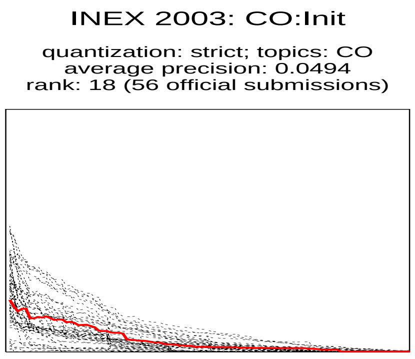


Figure 6: 36 CO–topics: XXL without OI (strict)

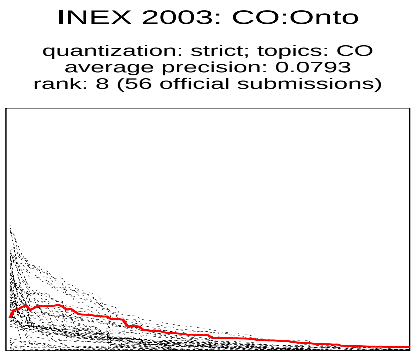


Figure 7: 36 CO–topics: XXL with OI (strict)

In the following two figures we see the average precision with generalized quantisation for the complete CO run.

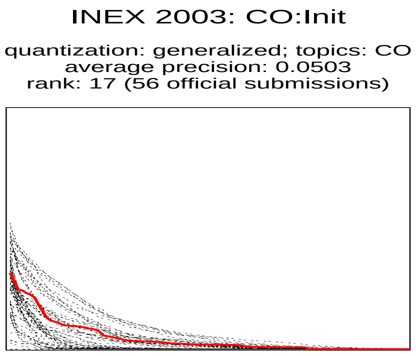


Figure 8: 36 CO–topics: XXL without OI (generalized)

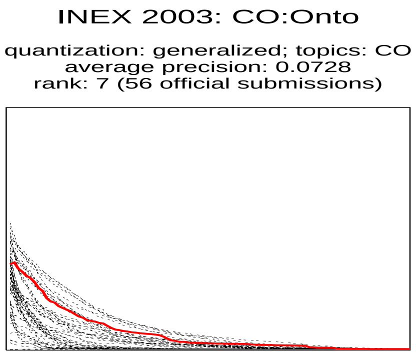


Figure 9: 36 CO–topics: XXL with OI (generalized)

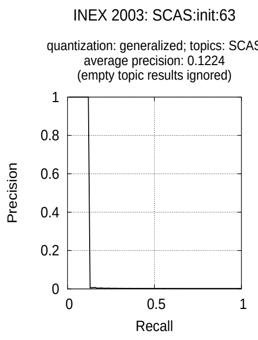
This experiment shows that ontology–based query expansion for keyword–based XML retrieval provides much better average precesion and better recall for each CO–topic.

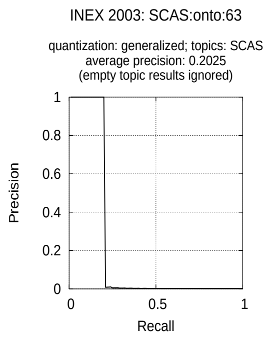
6.4.2 CAS–Topics

For the second experiment we evaluate CAS–topics with and without ontology support. This scenario is used to compare the precision and recall of the following two runs:

1. *SCAS:Init* ... for this run we evaluate the structural conditions exactly, but we do not use the ontology index for query evaluation.
2. *SCAS:Onto* ... for this run we evaluate the structural conditions exactly and we use the ontology index for query expansion.

Because of some technical problems, we did not run all 30 CAS–topics. As an example for the ontology–based query evaluation on CAS–topics we present the generalized results for the CAS–topic 63. The strict evaluation of the first and the second run provides an average precision of 1.0.





This experiments shows that the XXL search engine is able to evaluate conditons on XML structure as well as conditions on XML contents. In addition, the ontology–based query expansion for the content condition provides much better average precision and better recall.

7. CONCLUSIONS

The results obtained for our XXL Search Engine in the INEX benchmark clearly indicate that exploiting semantic similarity generally increases the quality of search results. Given the regular structure of the INEX data, we could not make use of the features for structural similarity provided by XXL.

To further extend the result quality, we plan to add a relevance feedback step to incrementally increase the quality. Additionally, we will integrate information from other, existing ontologies into our ontology and extend the ontology to capture more kinds of relationships (e.g., instance-of relationships).

For future INEX benchmarks we would appreciate to have data that has a more heterogenous structure. The INEX data that is currently available is well suited for exact structural search with long paths, but not for search engines that exploit structural diversity.

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Using value-added document representations in INEX

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ABSTRACT

Viewing Information Retrieval from the cognitive viewpoint we generated different functional and cognitive representations of the INEX corpus using both the XML structure and external sources. This included the use of a citation index and intellectually assigned descriptors, and an expansion of the document representation through a domain thesaurus. The aim was to investigate the possible benefits from applying the principle of polyrepresentation [3]. Results showed that neither the descriptors nor the expanded document representation through the thesaurus could improve results with the natural language queries used. The citation index achieved a similar performance to that obtained using various kinds of titles extracted from the XML structure.

1 INTRODUCTION

Highly structured XML documents offer unique opportunities for extracting many different representations of documents for Information Retrieval (IR) purposes. In this paper we describe our efforts to work with combinations of different representations generated from the corpus of the INEX collection as well as from external sources. The purpose of the experiments was to initiate tests of the principle of polyrepresentation [3] with different cognitive and functional representations of the document corpus.

The paper is structured as follows: The principle of polyrepresentation and the cognitive theory of IR interaction from which it is derived are briefly discussed as a theoretical framework for the experiments in section 2. Section 3 describes the experimental setup, and section 4 analyses the results. Section 5 gives tentative conclusions.

2 POLYREPRESENTATION

The cognitive theory of IR interaction and the principle of polyrepresentation derived from it [3] provides a theoretical background for working with different representations from several sources. In summary, it is hypothesised that overlaps between different cognitive and functional representations of both users' information needs as well as documents can be exploited for reducing the uncertainties inherent in Information Retrieval (IR), and thereby improve the performance of IR systems. Two or more different cognitive representations pointing at the same documents is regarded as multi-evidence of those documents being relevant, and suggests to apply a principle of 'intentional redundancy' [2] with the purpose of reducing the uncertainties by placing emphasis on overlaps between representations. Better results are expected when cognitively unlike representations are used, e.g., the document title (made by the author) vs. intellectually assigned descriptors from indexers.

Although cognitive theory of IR interaction and the principle of polyrepresentation is holistic in nature and amalgamates user-oriented approaches with both Boolean and best match principles it is, however, inherently *Boolean* in much of its reasoning. This is apparent in the pronounced focus on cognitive retrieval overlaps, i.e., *sets* of documents retrieved based on different cognitive representations, see, e.g., the appendix example in [3]. A little discussed, but inherent point is that the structure ensures the *quality* of the sets that are matched. But this structure does not necessarily have to be of a Boolean nature – other kinds of structure may be implemented. Such may include the probabilistic query operators in the InQuery IR system for instance as utilised by [4] to achieve various degrees of structure in queries.

Inspired by the work of Madsen and Pedersen [12] Larsen [9] proposes the idea of a polyrepresentation continuum (See Figure 1 below) as a model for discussing how structured a given implementation of polyrepresentation is.

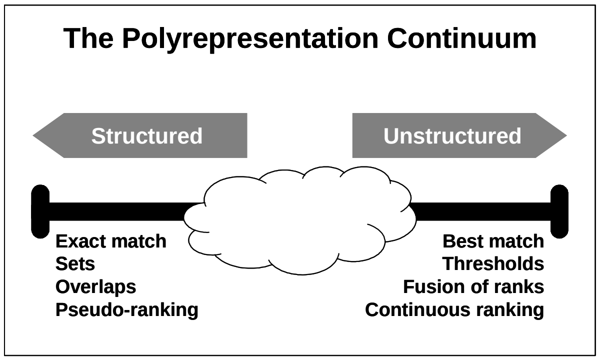

Figure 1. The polyrepresentation continuum [From 9, p. 36]

At the *structured* pole of the continuum the implementations are based on exact match principles, leading to sets of retrieved documents for each representation from which overlaps can be formed and a pseudo-ranking be constructed. At the *unstructured* pole of the continuum the implementations are based on best match principles leading to a rank of the documents that are retrieved as input for polyrepresentation. Rather than straight generation of overlaps between sets, the implementations at the unstructured pole of the polyrepresentation continuum will consist of fusing ranks to produce a final ranked output, perhaps aided by thresholds to provide the necessary quality by restricting the ranks to be fused to the top ranked documents only.

Few empirical investigations that explicitly tests the principle of polyrepresentation have been carried out so far. Larsen [8] reports a small online Boolean experiment at the structured end of the continuum. The MSc thesis of Madsen and Pedersen [12] combines a highly structured Boolean approach with probabilistic query operators in a best match system, and is as such placed closer to the middle of the continuum.

3 METHODS

The main focus of the runs submitted to INEX2003 was on obtaining functionally and cognitively different representations of the documents. Only simple fusion strategies for combining the representations were used because of lacking time to experiment with more advanced ones (See section 3.2). The runs submitted to INEX2003 were therefore close to the unstructured pole of the polyrepresentation continuum. The investigation of more advanced strategies for how to combine these in a suitable structured manner according to the principle of polyrepresentation is the subject of future work. Note that the purpose of the experiments reported in the present paper was to retrieve *whole* documents, and not document components as in most approaches in INEX.

Functionally different representations are defined as representations originating from the same cognitive agent, e.g., the article title or figure captions made by the author [3]. In relation to IR, representations are regarded as cognitively different if they originate from other cognitive agents than the author, e.g., descriptors from a thesaurus assigned intellectually to the documents, or later citations or links to the document by other authors. The corpus of the INEX test collections offers excellent opportunities for the generation of functionally different representations originating from the author because of the elaborate XML structure of the documents. In addition, a range of cognitively different representations of the documents are available because the journals in the corpus are indexed in the INSPEC database. A further opportunity offered by the INEX corpus is to exploit the references in the bibliographies to generate citation-based representations.

The InQuery IR system was used for all runs because it offers the possibility to store different representations of the documents in fields and to combine these using both Boolean and softer query operators.

3.1 Indexes and fields[1]

Two indexes were constructed, each containing three fields: one with author generated representations, one with intellectually assigned descriptors from a domain thesaurus, and one with a citation index generated from the corpus (See Figure 2 and Figure 3).

The first field consists of different types of *titles* from the documents: the article title, the section headings at all levels, and the cited titles from the bibliographies. These are either generated or selected by the author. The inclusion of section headings is inspired by the Subject Access Project (SAP) [1; 19] where section headings, figure and table captions were extracted as representations in addition to the article titles. The use of cited titles has been proposed by Kwok [6; 7], and tested by Salton and Zhang [17]. The latter experiment did not show any general gains from including cited titles. However, only those articles that were also source documents in the test collections used were included in the experiment, i.e., only a limited selection of cited titles was used in their experiments. The INEX corpus has *all* cited titles and may thus provide better results with the cited titles. The path used for extracting the cited titles was //bb/atl. This includes the titles of cited journal articles and conference papers, but not the

[1] After submission we discovered a number of errors in the indexing process. Attempts have been made to correct these, and the methods and results reported here are for the corrected runs.

titles of cited books or reports. More than 7,000 documents contained such cited titles with an average of 9.9 cited titles per document.

Titles (FLD001) (Article title, section titles, and cited titles)	//fm/tig/atl //st //bb/atl
Descriptors (FLD002)	Intellectually assigned descriptors
Citation index (FLD003) (Boomerang effect)	Best possible tuning with INEX2002 test collection

Figure 2. Index A (without expansion on descriptors)

The second field consists of intellectually assigned descriptors from the INSPEC thesaurus. These were available for 7,711 of the 12,107 documents in the INEX corpus. Because only relatively few descriptors are assigned to each document by the INSPEC indexers this representation contained relatively few index keys. In an effort to enlarge this representation we expanded the descriptors by adding all the synonyms (the used for (UF) relation) as well as the narrower terms (NT) from the INSPEC thesaurus. Index A contained the un-expanded descriptors (Figure 2), and Index B contained the expanded descriptors (Figure 3).

Titles (FLD001) (Article title, section titles, and cited titles)	/fm/tig/atl //st //bb/atl
Descriptors (FLD002) (expanded document representation)	Intellectually assigned descriptors, expanded from the INSPEC thesaurus (NT, UF)
Citation index (FLD003) (Boomerang effect)	Best possible tuning with INEX2002 test collection

Figure 3. Index B (with descriptors expanded from the thesaurus)

The third field in both indexes contained data for constructing a citation index, i.e., data to identify the references in each document. When indexed in the database documents can be retrieved that refer to (cite) a particular *seed document*. Such search strategies have shown promising results [See, e.g., 13; 14; 16], but have rarely been exploited in IR research[2]. This is probably partly due to a lack of citation data in the test collections developed in the last decade, and partly due to the lack of seed documents to represent the information need. A particular approach to identify such seeds automatically was used to construct queries for the citation index (See section 3.2). The index was constructed based on the cited titles discussed above in combination with the cited year. Because there were numerous typos etc. in the cited titles an implementation of the edit distance algorithm was used to identify variants to the same cited document[3]. 7,111 documents contained references with both cited titles and cited years. In these documents there were 70,634 unique citations after merging of variants, and these were mentioned a total of 192,881 times in the documents. The citations were represented by id-numbers to ease processing.

3.2 Queries

Only content only (CO) topics were used because only whole documents were retrieved with the tested approach.

The same queries were used for both the title field and the field containing descriptors (FLD001 and FLD002). These were constructed manually from the title elements of the CO topics translating the INEX operators into InQuery's probabilistic query operators (See Figure 4).

In order to be able to match the content of the citation index with the topics, the latter had to be translated into citations. This was done with a best match version of the so-called boomerang effect proposed in [8; 10]. In short, the boomerang effect extracted the citations from sets of documents retrieved by natural language queries from a range of functional and cognitive representations. These citations were used as seeds in a citation search that can retrieve later documents that cite the seeds. The occurrence of the citations between representations and their frequency was used to weight and select which citations to use as seeds as well as to weight the seeds in the query (See [10] for details). The boomerang effect used was the best possible tuning based on the INEX2002 test collection: citations were extracted from 8 documents resulting in 252 seed documents in average per query.

InQuery's #sum operator was used to combine the fields (See Figure 4). Only a simple strategy was used to fuse the fields because the main focus was on obtaining functionally and cognitively different representations of the documents. Therefore the runs can be characterised as being at the unstructured end of the polyrepresentation continuum. The same queries were used for index A and index B.

[2] Increasingly, web search engines exploit link data. However, there are indications that although similar in conception links and citations may be quite different in practice, see e.g., [18]. CiteSeer is an exception because it uses citations extracted from scientific papers [11].

[3] We greatly acknowledge the Department of Information Studies, University of Tampere, Finland for making the source code for this implementation available to us.

```
#sum (

#field (FLD001 #and(#1(natural language processing)
(#1(human language))) #not(#1(programming
language)) #not(#1(modeling language)))

#field (FLD002 #and(#1(natural language processing)
(#1(human language))) #not(#1(programming
language)) #not(#1(modeling language)))

#field (FLD003 #WSUM(1 3797.98 CIT_ID46361
2404.53 CIT_ID28456 1898.99 CIT_ID43757 1898.99
CIT_ID43816 1898.99 CIT_ID57141 ... )) )
```

Figure 4. Sample query (CO topic 111). Note that the citation query in FLD003 has been shortened.

3.3 Runs

The two main runs were the runs on index A and index B to study the effect of the expanded descriptors. We also did runs on the individual fields to assess their contribution to the overall result. Six runs are reported here: IndexA_run, IndexB_run, Titles_run, Descriptor_run, Descriptor_expanded_run, and Citation_index_run.

4 RESULTS

Table 1 shows the results for the strict and generalized quantification functions in inex_eval. Overall, the results display a low performance compared to the best runs in INEX2003: For instance, the highest strict AvgP value was 0.04292 for the Titles_run. The top 10 in INEX2003 was in the 0.1214-0.0664 range.

Run name	AvgP (strict)	AvgP (generalized)
IndexA_run	0.03818	0.01508
IndexB_run	0.03811	0.01510
Titles_run	0.04292	0.01550
Citation_index_run	0.03359	0.01198
Descriptor_run	0.00996	0.00724
Descriptor_expanded_run	0.00829	0.00699

Table 1. Overall results. Strict and generalized quantification functions.

Figures 5 to 7 show P-R curves for the runs. It is obvious from Figure 6 and Figure 8 as well as Table 1 that the expansion of the descriptor document representation did not improve performance; it rather decreased it slightly. The difference between the original and the expanded descriptors are not great though, and consequently the difference between the IndexA and IndexB runs are minimal (Figure 5 and Figure 7).

Figure 6 shows the performance each individual field. The un-expanded descriptors in themselves perform quite poorly (AvgP_strict = 0.00996), and the idea of expanding this representation is supported. The Titles_run have the best performance of all 6 runs (AvgP_strict = 0.04292), followed by the Citation_index_run (AvgP = 0.03359). The same patterns can be found when the results are measured with the generalized quantification function; the general level of performance is lower though.

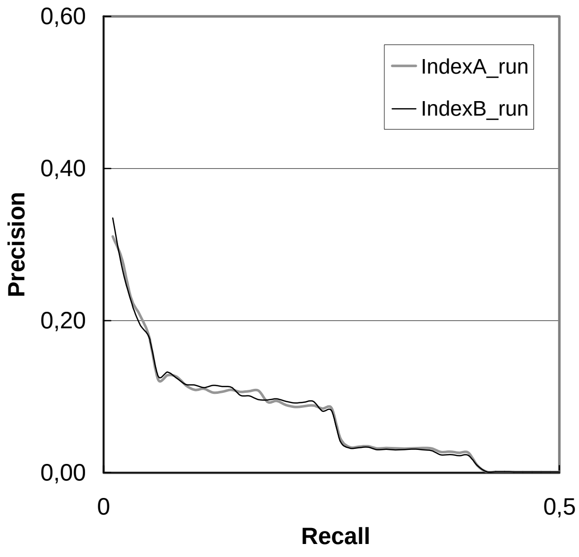

Figure 5. P-R curves for IndexA and IndexB run using the strict quantification function in inex_eval.

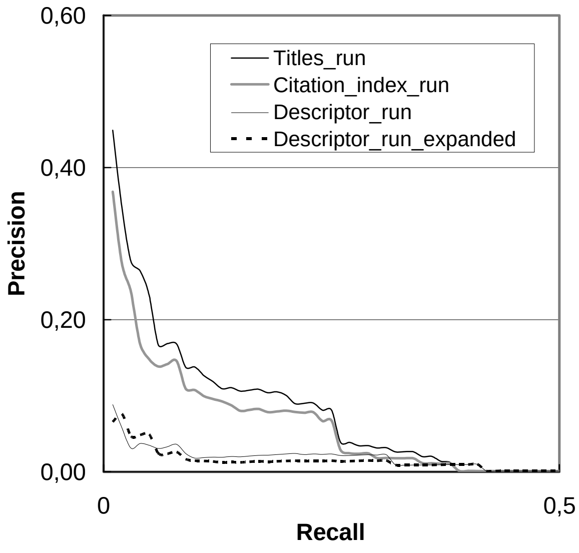

Figure 6. P-R curves for the individual fields using the strict quantification function in inex_eval.

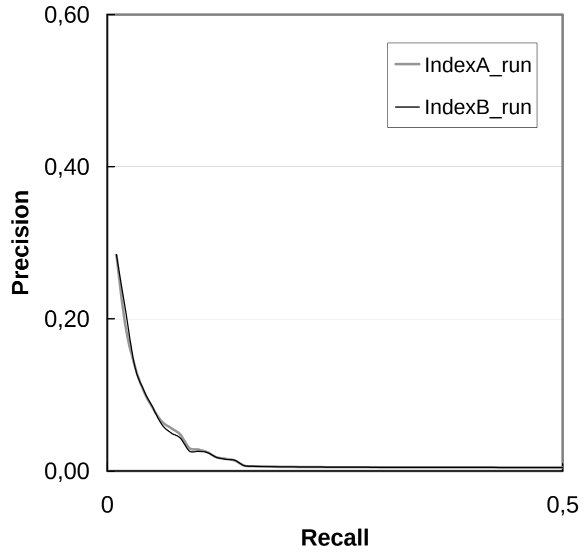

Figure 7. P-R curves for IndexA and IndexB run using the generalized quantification function in inex_eval.

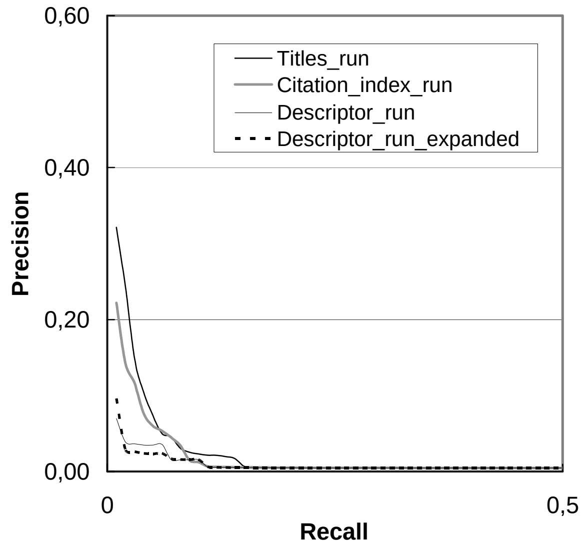

Figure 8. P-R curves for the individual fields using the generalized quantification function in inex_eval.

5 CONCLUSIONS

The overall aim of our runs submitted to INEX2003 was to work on obtaining functionally and cognitively different representations of the documents. Two of these were successful: The titles representation consisting of the article title, headings and cited titles, and the citation index, which performed fairly well. The intellectually assigned descriptors did not perform well, and it was attempted to expand these in the document representation by using the INSPEC thesaurus. This was not a success: the expansion resulted in slightly decreased performance.

Future work includes the investigation of other expansion techniques on the query side can also be implemented, e.g., similar to the ones tested in [5]. The approach tested in the runs was close to the un-structured pole of the polyrepresentation continuum. Future work also includes investigations of more advanced structured query strategies to improve the quality of the initial set used, and move the tests closer to the structured pole of the continuum.

6 ACKNOWLEDGMENTS

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Accurate Retrieval of XML Document Fragments using EXTIRP

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ABSTRACT

EXTIRP[1], a novel XML retrieval system, aims at finding elements with exact coverage by first dividing XML documents into a set of minimal XML fragments and then ranking and combining them into retrieved document fragments. With respect to a query, a similarity measure is computed for each fragment by combining the scores of a vector space model with term-based features and a text phrase model. The similarity measures are propagated bottom-up from the smallest units to article-sized ancestor elements. The system also includes query expansion, with which the score calculation can be iterated.

1. INTRODUCTION

In this paper, we focus on the problem of finding an answer with optimal coverage of the topic, given an unstructured query (CO topics in INEX). That is, we want to find a trade-off between responding to a query with a 15 page article and a fragment that is not sufficient when deprived of its context. The architecture of the interactive part of the system is presented in Figure 1. As input, the system takes a CO topic, and as output, it gives a ranked list of document fragments. In Figures 2 and 3, the non-interactive part of the system is described. This non-interactive part is run offline when the system is taken into use or when the document collection changes. Figure 2 shows how the document collection is transformed into inverted indices consisting of document fragments of different granularities. Figure 3 illustrates how an inverted text phrase index is created for each of the different granularities. MFS stands for Maximal Frequent Sequence (see Section 3.3.1 for definition).

Previously, every single element of the document collection has been indexed, e.g., see [6, 7], but modeling and computing a *Retrieval Status Value* (RSV) for each element causes a clear problem with efficiency. We limit the set of indexed elements to those that can be retrieved on their own, and define the minimal unit of retrieval, such that none of its parts is big enough to be of interest by itself. An RSV is computed for each minimal unit using words as features in the vector space model and multiword expressions. The

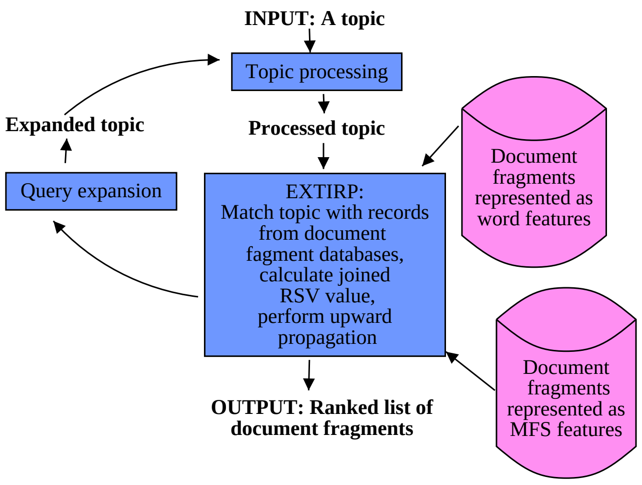
INPUT: A topic
Topic processing
Expanded topic
Processed topic
Query expansion
EXTIRP: Match topic with records from document fagment databases, calculate joined RSV value, perform upward propagation
Document fragments represented as word features
Document fragments represented as MFS features
OUTPUT: Ranked list of document fragments

Figure 1: The system architecture of the interactive part of EXTIRP.

RSVs of the minimal units are finally propagated upwards to their ancestors. One or more query expansion steps can be iterated to form more extensive topic descriptions.

Section 2 describes the XML-related processing of the document collection. Our document and query models are presented in Section 3, followed by the corresponding techniques to evaluate similarities within these models in Section 4. We explain our query expansion technique in Section 5. The system description ends in Section 6, where we present the method used to propagate RSVs upwards. We finally describe our runs in Section 7 and conclude.

2. PREPARATORY PROCEDURES

Finding the most relevant text documents for each given topic is the basic problem to be solved in traditional IR. But, as the document collection is in XML format, we can identify two additional challenges that must be overcome before any traditional IR methods can be applied. First, the document collection consists of 125 XML documents which alone are too big to be retrieved on their own. Therefore, the collection is divided into smaller XML units which we shall call *XML fragments*. Second, the XML fragments contain all the XML markup that is present in the original XML format.

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[1]EXacT coverage IR based on static Passage clusters

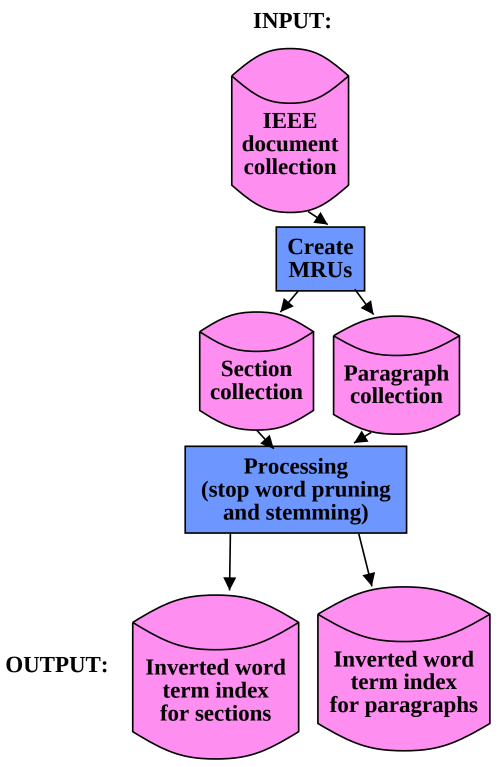
INPUT:
IEEE document collection
Create MRUs
Section collection
Paragraph collection
Processing (stop word pruning and stemming)
OUTPUT:
Inverted word term index for sections
Inverted word term index for paragraphs

Figure 2: This module transforms the IEEE document collection into word term indices.

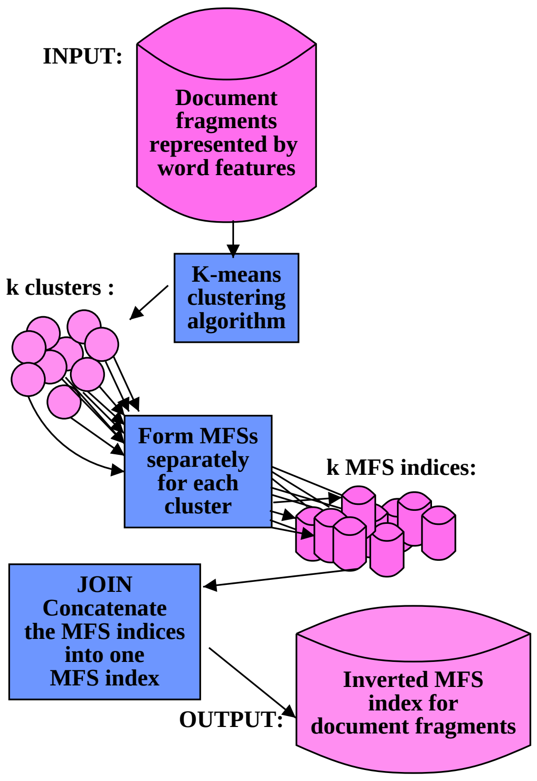
INPUT:
Document fragments represented by word features
K-means clustering algorithm
k clusters :
Form MFSs separately for each cluster
k MFS indices:
JOIN Concatenate the MFS indices into one MFS index
OUTPUT:
Inverted MFS index for document fragments

Figure 3: This module forms MFS indices. It is run separately for each of the different levels of granularitry.

Our goal is to convert the XML fragments into a text-only format where all XML markup has been removed without losing any of the information that is implicitly or explicitly coded in the XML structure of the original documents.

2.1 Division of the collection

The division of the collection was performed at two different levels of granularity called section-level and paragraph-level divisions. The levels for these two separate divisions were defined manually by looking into both the XML DTD and the XML documents. For example, the division into section-sized fragments concerned the following XML elements: `sec, fm, bm, dialog, vt`. In the document tree, all of these elements are close descendants of the `article` element, and none of them have text node children. In a similar fashion, the paragraph-sized elements taken into account in the paragraph-level division are `p, p1, p2, ip1, ip2, ip3, bq`. These elements have text node children, and also, most of the text content of the collection is covered by choosing these elements. A similar approach with a different set of element names was chosen by Ben-Aharon et al. [3].

By carefully defining the set of similar elements for each level, we intend to approximate an unsupervised division into fragments that is based on structural features only. Moreover, concentrating on structural similarity and discarding the information about element names will set us free from any particular document type or DTD. One might argue that contextual information is neglected by ignoring information specific to the document type. We believe, however, that identical content should be valued equally whether its parent element is called `sec` (section) or `bm` (back matter). Automating the division still remains part of our future work.

Intra-document links create connections between related XML elements. For example, footnotes are linked to the paragraphs that have a reference to the footnote element. Other examples include figure and table captions, biographical and bibliographical information, and other out-of-line content. Fragmentation of the collection separates linked elements unless both ends of the link belong to the same fragment. To avoid this, we have included some of the referred content that would increase the informational value of the fragment. Again, finding the intra-document links is possible without knowing the document type by a careful analysis of attribute values.

After the division, we have a collection of XML fragments. Each fragment is considered independent of the others, although information about the origin of the fragment is still included. The fragments can be combined later to make results with wider coverage, but dividing them further is hardly sensible as the size of a fragment is already supposed to be sufficiently small. In our system, these XML fragments constitute what are defined as *Minimal Retrieval Units* (MRU).

2.2 Structural conversion

The XML structure of an MRU is not ideal for linguistic processing. Although XML is a textual format and the tag names often are words, the semantics of the markup is different from that of the actual text content and thus should be treated differently. Our goal of a text-only format is achieved by simply removing all markup; however, this would lead to the loss of all the information carried by the structure. To avoid this unnecessary information loss, we suggest that the structure be analysed and utilised to the greatest extent possible before being removed.

Unlike Ben-Aharon et al., we set a goal that the structural analysis must not be specific to any document type. As a consequence, no particular element type has a special way of being processed, and also, elements of the same type are processed differently under different structural circumstances. Only the structural properties of an element should determine the way it is handled.

The starting point of the analysis is the highest level of text nodes in the tree representation of the XML fragment. Any text node at a lower level is seen to stand out, and it is usually formatted differently in a printable version of the document. For example, all the text with added emphasis is marked with inline-level tags which often imply changes in the current typeface. Although not all inline-level elements denote a change in the typeface, we have found heuristics with which we can automatically determine whether added emphasis or other inline-level content is in question. After detecting the emphasised content, we can remove the tags and preserve the emphasis by giving the content more weight in the index than the unemphasised content, e.g. by repetition.

3. DOCUMENT AND QUERY MODELS

In our approach, we represent the MRUs by word features of the vector space model, and by multiword expressions accounting for the sequential aspect of text. An RSV is computed for each of those two representations. These values are later combined to form a single RSV per MRU, that will later be propagated to parent nodes as described in Section 6.

3.1 Preprocessing

The first step of the modeling phase is to cleanse the data. We do this by skipping a set of words that are considered least informative, the *stopwords*. We also discarded all words of small size (less than three characters).

In addition, we reduced each word to its stem using the Porter algorithm [10]. For example, the words "models", "modelling" and "modeled" were all stemmed to "model". This technique for reducing words to their stems allows further reduction of the number of term features.

This feature selection phase brings more computational comfort for the next steps since it greatly reduces the size of the document collection representation in the vector space model (the *dimension* of the vector space).

3.2 Modeling document fragments

The set of the remaining word stems W is used to represent the MRUs of the document collection within the *vector space model*. Each minimal retrieval fragment is represented by a $\|W\|$-dimensional vector filled in with a weight standing for the importance of each word w.r.t. that fragment. To calculate this weight, we used a normalized *tfidf* variation following the "tfc" term-weighting components as detailed by Salton et al. [13], that is:

$$tfidf_w = \frac{tf_w \cdot \log \frac{N}{n_w}}{\sqrt{\sum_{w_i \in W} \left(tf_{w_i} \cdot \log \frac{N}{n_{w_i}} \right)^2}},$$

where tf_w is the term frequency of the word w. N is the total number of MRUs in the document collection and n the number of MRUs in which w occurs.

3.3 Extracting Maximal Frequent Sequences

3.3.1 Definition and technique

Maximal Frequent Sequences (MFS) are sequences of words that are frequent in the document collection and, moreover, that are not contained in any other longer frequent sequence. Given a frequency threshold σ, a sequence is considered to be frequent if it appears in at least σ documents.

Ahonen-Myka presents an algorithm combining bottom-up and greedy methods in [1], that permits to extract maximal sequences without considering all their frequent subsequences. This is a necessity, since maximal frequent sequences may be rather long.

Nevertheless, when we tried to extract the maximal frequent sequences from the collection of MRUs obtained as described in Section 2, their number and the total number of word features in the collection did pose a clear computational problem and did not actually permit to obtain any result.

To bypass this complexity problem, we partitioned the collection of MRUs into several disjoint subcollections, small enough so that we could efficiently extract the set of maximal frequent sequences of each subcollection. Joining all the MFS sets, we obtained an *approximate* of the maximal frequent sequence set for the full collection. This process is shown in Figure 3.

We conjecture that more consistent subcollections permit to obtain a better approximation. This is due to the fact that MFSs are formed from similar text fragments. Followingly, we formed the subcollection by clustering similar documents together using the common k-means algorithm (see for example [17, 5]).

3.3.2 Main Strengths of the MFSs

The method efficiently extracts all the maximal frequent word sequences from the collection. From the definitions above, a sequence is said to be maximal if and only if no other frequent sequence contains that sequence.

Furthermore, a *gap* between words is allowed: in a sentence, the words do not have to appear continuously. A parameter g tells how many other words two words in a sequence can have between them. This parameter g usually gets values between 1 and 3.

For instance, if g = 2, a phrase "president Bush" will be found in both of the following text fragments:

```
...President of the United States Bush...
...President George W. Bush...
```

Note: Articles and prepositions were pruned away.

This allowance of gaps between words of a sequence is probably the strongest specificity of the method, compared to the other existing methods for extracting text phrase descriptors. This greatly increases the quality of the phrases, since the variety of natural language is taken into account.

Another strength of the technique is the ability to extract maximal frequent sequences of any length. This permits to obtain a very compact description of documents. For example, by restricting the length of phrases to 8, a maximal frequent sequence of 25 words would have to be represented by thousands of phrases of size 8, even though they would represent the same knowledge !

3.4 Modeling queries

To build our queries, we only considered words found in the <title> and <keywords> elements. For consistency, we applied the same preprocessing to them as to MRUs.

Vector space model. A novelty in INEX 2003 was the possibility to precede keywords with various operators. A keyword preceded by "-" meant that this word was not desired, whereas a keyword preceded by "+" indicated that this word was especially important. We attached different weights to keywords preceded by such operators:

- no prefix operator: the normal case, weight 1
- +: especially important, weight 1.5
- -: especially not desired, negative weight -1

In practice, things were not that simple, since the same word could occur within two phrases with contradictory operators (e.g., "language" in topic 111 occurs in -"programming language" and in +"human language"). In such rare cases, we ignored the word (weight: 0).

Keyphrases. All the phrases occurring in the <title> and <keywords> elements are stored in the (possibly empty) set of keyphrases representing the topic. For example, topic 117 (see Figure 4) will be represented by the 4 phrases: "Patricia Tries", "text search", "string search algorithm", "string pattern matching".

4. EVALUATING DOCUMENTS

Once document fragments and queries are represented within our two models, a way to estimate the relevance of a fragment w.r.t. a query remains to be found. As mentioned earlier, we compute separate RSVs for the word features vector space model and the MFS model. In a second step, we aggregate these two RSVs into one single relevance score for each document fragment w.r.t. a query.

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<!DOCTYPE inex_topic SYSTEM "topic.dtd">
<inex_topic topic_id="117" query_type="CO"
  ct_no="98">
<title>Patricia Tries </title>
<description>Find documents/elements that describe
Patricia tries and their use.</description>
<narrative>To be relevant, a document/element
must deal with the use of Patricia Tries for text
search. Description of the standard algorithm,
optimisied implementation and use in Information
retrieval applications are all relevant.
</narrative>
<keywords>Patricia tries, tries, text search,
string search algorithm, string pattern matching
</keywords>
</inex_topic>
```

Figure 4: Topic 117.

4.1 Word features RSV

The vector space model offers a very convenient framework for computing similarities between MRUs and queries. Indeed, there exists a number of techniques to compare two vectors. Eucclidean distance, Jaccard and cosine similarity being the most frequently used in IR. We have used cosine similarity because of its computational efficiency. By normalizing the vectors, $cosine(\overrightarrow{d_1}, \overrightarrow{d_2})$ indeed simplifies to vector product $(d_1 \cdot d_2)$.

4.2 MFS RSV

To compute a RSV using MFSs, the first step is to create an MFS index for the MRU collection. Once a set of MFSs has been extracted and each document fragment has been attached to its corresponding phrases, as detailed in Section 3.3, it only remains to define the procedure to match a phrase describing a MRU to a keyphrase and compute a corresponding RSV for each MRU.

Note that from here onwards, *keyphrase* denotes a phrase found in a query, and *maximal sequence* denotes a phrase extracted from a document fragment.

To compare keyphrases and MFSs, our approach consists of decomposing keyphrases of a query into pairs. Each of these pairs is bound to a score representing its *quantity of relevance*. Informally speaking, the quantity of relevance of a word pair tells how much it makes a document relevant to include an occurrence of this pair. This value depends on the specificity of the pair (expressed in terms of inverted document frequency) and modifiers, among which an *adjacency coefficient*, reducing the quantity of relevance given to a pair formed by two words that are not adjacent.

4.2.1 Definitions:

Let D be a collection of N document fragments and $A_1 \ldots A_m$ a keyphrase of size m. Let A_i and A_j be 2 words of $A_1 \ldots A_m$ occurring in this order, and $n_{A_iA_j}$ be the number of MRUs of the collection in which A_iA_j was found. We define the quantity of relevance of the pair A_iA_j as:

$$Q_{rel}(A_iA_j) = idf(A_iA_j) \cdot adj(A_iA_j),$$

where $idf(A_iA_j, D)$ represents the specificity of A_iA_j in the collection D:

$$idf(A_iA_j) = \log\left(\frac{N}{n_{A_iA_j}}\right),$$

and when decomposing the keyphrase $A_1 \dots A_m$ into pairs, $adj(A_iA_j)$ is a score modifier to penalize word pairs A_iA_j formed from non adjacent words. d(A_i,A_j) indicates the number of words appearing between the two words A_i and A_j (d(A_i,A_j) = 0 means that A_i and A_j are adjacent):

$$adj(A_iA_j) = \begin{cases} 1, & & \text{if } d(A_i,A_j) = 0 \\ \alpha_1, & 0 \le \alpha_1 \le 1, & \text{if } d(A_i,A_j) = 1 \\ \alpha_2, & 0 \le \alpha_2 \le \alpha_1 & \text{if } d(A_i,A_j) = 2 \\ \dots & & \\ \alpha_{m-2}, & 0 \le \alpha_{m-2} \le \alpha_{m-3}, & \text{if } d(A_i,A_j) = m-2 \end{cases}$$

Followingly, the larger the distance between the two words, the lowest quantity of relevance is attributed to the corresponding pair. In our runs, we will actually ignore distances higher than 1 (i.e., $(k > 1) \Rightarrow (\alpha_k = 0)$).

4.2.2 Example:

For example, ignoring distances above 1, a keyphrase ABCD is decomposed into 5 tuples (pair, adjacency coefficient):

(AB, 1), (BC, 1), (CD, 1), (AC, α_1), (BD, α_1)

Let us compare this keyphrase to the documents d_1, d_2, d_3, d_4 and d_5, described respectively by the frequent sequences AB, AC, AFB, ABC and ACB. The corresponding quantities of relevance brought by the keyphrase ABCD are shown in table 1.

Assuming equal idf values, we observe that the quantities of relevance form a meaningful order. The longest matches rank first, and matches of equal size are untied by adjacency. Moreover, non adjacent matches (AC and ABC) are not ignored as in many other phrases representations [9].

4.3 Aggregated RSV

In practice, some queries do not contain any keyphrase, and some documents do not contain any MFS. However, there can of course be correct answers to these queries, and those documents can be relevant answers to some queries. Also, all document fragments containing the same matching phrases get the same MFS RSV. Therefore, it is necessary to find a way to separate them. The word-based cosine similarity measure is very appropriate for that.

Another possible response would have been to further decompose the pairs into single words and form fragment vectors accordingly. However, this would not be satisfying, because the least frequent words are missed by the algorithm for MFS extraction. An even more important category of missed words is that of frequent words that do not frequently cooccur with other words. The loss would be considerable.

This is the reason to compute another RSV using a basic word-features vector space model. To combine both RSVs to one single score, we must first make them comparable by mapping them onto a common interval. To do so, we used *Max Norm*, as presented in [14], which permits to bring all positives scores within the range [0,1]:

$$New\ Score = \frac{Old\ Score}{Max\ Score}$$

Following this normalization, we aggregate both RSVs using a linear interpolation factor λ representing the relative weight of scores obtained with each technique (similarly as in [8]).

$$Aggregated\,Score = \lambda \cdot RSV_{Word\ Features} + (1-\lambda) \cdot RSV_{MFS}$$

The evidence of experiments with the INEX 2002 collection showed good results when weighting the single word RSV with the number of distinct word terms in the query (let a be that number), and the MFS RSV with the number of distinct word terms found in keyphrases of the query (let b be that number). Thus:

$$\lambda = \frac{a}{a+b}$$

For example, in Figure 4 showing topic 117, there are 11 distinct word terms and 7 distinct word terms occurring in keyphrases. Thus, for this topic, we have $\lambda = \frac{11}{11+7}$.

5. QUERY EXPANSION

Query expansion (QE) was used in two of the three runs that we submitted to INEX 2003. Both of these runs performed better than the one with no expansion at all. However, as the two official runs using QE also contained some other parameters that differed from those used in the run without QE (See Section 7 for a detailed description of the parameters.), these runs cannot be used to assess the performance of QE. We did a separate experiment to assess the performance of QE alone, and it showed that the average precision was increased by 11,5 % (from 0.0357 to 0.0398) when using the strict measure and by 44 % (from 0.0207 to 0.0298) when using the generalized measure. In the rest of this chapter we will first describe some background concepts of QE. In Section 5.2, we will describe our QE method, and in 5.3, we will describe further work in developing the method.

5.1 Background

It is generally agreed that modern variants of query expansion improve the results of a query engine [2]. However, there are many different ways in which QE can be performed. Some methods are based on relevance feedback, which can be blind or which can involve feedback from the user. In both cases, the QE approach is local because it is based

Document	MFS	Corresponding pairs	Matches	Quantity of relevance
d_1	AB	AB	AB	idf(AB)
d_2	ACD	AC CD AD	AC CD	idf(CD) + α_1·idf(AC)
d_3	AFB	AF FB AB	AB	idf(AB)
d_4	ABC	AB BC AC	AB BC AC	idf(AB) + idf(BC) + α_1·idf(AC)
d_5	ACB	AC CB AB	AC AB	idf(AB) + α_1·idf(AC)

Table 1: Quantity of relevance stemming from various MFSs w.r.t. a keyphrase query ABCD

on the retrieved set of documents. A global QE approach uses the the information derived from the whole document collection. Modern global QE methods usually use an automatically constructed thesaurus [11, 4]. Other methods are based on manually crafted thesauri, such as WordNet, but experimental studies have shown that if the expansion terms from such theasuri are selected automatically, QE can even degrade the performance of the system [16].

5.2 The Process

Our QE process can be considered a form of blind relevance feedback that has been inspired by the standard Rocchio way [12] of calculating the modified query vectors. However, it is different from the traditional relevance feedback framework in that it takes into account only positive terms and no negative terms and in that it does not take into account all of the terms in the fragments, but only the best ones. This limits in practice the number of expansion terms per QE iteration between zero and ten. However, experimental studies have shown that even a few carefully selected QE terms can considerably improve the performance of a system [15].

Here is the outline of the process:

1. Run EXTIRP. The output from EXTIRP is a set of ranked lists of document fragments. There is one list per topic and the fragments are ranked according to their RSVs with regard to the topic.
2. Take the ten topmost items of each list.
3. Calculate the similarity threshold value.
4. For each topic do:
   (a) Take those fragments whose RSV is greater than the similarity threshold value. Make a list of words occurring in these fragments followed by their frequency count, and sort by frequency.
   (b) Take the ten topmost words and expand the topic with them.
   (c) Multiply the weights of the old terms by two and give the new terms a weight of 1.
5. Run EXTIRP with the expanded topics.

We will now describe each of the steps in the process in more detail. In steps 1 and 5 EXTIRP is run with the same parameters and the RSV is calculated according to these. This means that the only things that change from the first iteration to the second are the keywords in the topic and the threshold value for similarity.

In step 3, the similarity threshold for a given topic is determined in the following way: Read the topmost RSV of the matches for each topic and maintain a list of the six smallest values. The threshold value is the highest one among the six smallest values. This way of determining the similarity threshold value implies that there are always at least six topics that are not expanded. The topics vary a lot and it is thus necessary to treat them differently from each other. The number six was determined by training the QE method on the topics and assesments of the year 2002. This step of determining the similarity threshold value is crucial to the success of the QE step, because running EXTIRP with different parameters results in radically different RSVs.

In step 4 (a), a list of words occurring in the fragments is created. This list is pruned from stopwords, and the remaining words are stemmed with the Porter stemmer[2][10]. A standard list for English language as well as a collection-specific list is used as a stopword list. The collection-specific list is created simply by gathering the most frequent terms in the collection.

In step 4 (c), the weights of the old terms are multiplied by two and the new terms are given a weight of 1. The possible weights of the old terms are: -1, 1 and 1.5. This means that the term weights in the expanded topic vectors can have the following values: -2, 1, 2 and 3. The topic vectors are normalized so that their length is one when they are processed by EXTIRP.

5.3 Improvement and further work

The above QE method can be developed further in many ways. We plan to treat different topics in more individual ways, run the method through more iterations and perform QE on negative query terms as well. For example, EXTIRP can be run separately for each topic instead of running it for all topics at the same time. This would mean a loop in step 4. In this loop, EXTIRP would be run for each topic until the RSVs of the resulting fragments reach a stable level. In this way, the number of iterations performed per topic would vary. The topics that perform well in the beginning would receive less attention than those which do not perform well in the beginning but that have a potential for improvement.

Expansion of negative query terms can be performed in a similar way as expansion of positive query terms. In negative

[2]The program was obtained from http://www.tartarus.org/ martin/PorterStemmer/

```
1. Initialisation:
    • $\forall n \in N$, score($n$)=0
    • $\forall m \in M$, score($m$)=RSV($m$)
2. Iterate:
    • $\forall m \in M$: $\forall n_m \in N$ such that $n_m$ is an ancestor
      of $m$, $score(n_m) = score(n_m) + score(m)$
3. Final step:
    • $\forall n \in N$, score($n$)=$\frac{score(n)}{(size(n))^{UPF}}$
```

Figure 5: Greedy upward propagation algorithm.

expansion, we will run EXTIRP with the negative terms and expand the topics with those terms that are most common in the matches of this negative query.

6. UPWARD PROPAGATION OF MRU'S

The result of the previous steps is the assignment of an RSV to each MRU of the document collection. In this section, we propose a technique for assigning an RSV to each of their ancestors.

Its principle is to propagate upwards the relevance value of each MRU, weighting it upon the size of the corresponding element. We define the size of an element to be the sum of the sizes of all its MRU descendants. In turn, the size of an MRU is the number of characters it contains.

Let A be an XML document, N the set of elements of A, and M the set of MRUs of A. We compute the score of each element $n \in A$ as shown in Figure 5. UPF (*Upward Propagation Factor*) is a parameter that modulates the importance of the size of the elements. High UPF values give more penalty to big elements, and cause smaller ones to be promoted. On the other hand, if UPF=0, for any given article, the best score will always be given to the full article.

Because we assume that users go through answers in increasing rank order, we decided to avoid to propose them a document fragment they had already seen. Therefore, as a postprocessing, we decided to prune every element having an ancestor with a higher rank. This implies for instance, that if UPF=0, the set of answers will only contain full articles.

7. OUR RUNS

Our three official runs are described below. More details and the corresponding results are presented in Table 2.

- **UHel-Run1.**
  - Number of clusters: 200
  - MFS frequency threshold: $\sigma = 7$
- **UHel-Run2.**
  - Number of clusters: 100
  - MFS frequency threshold: $\sigma = 7$
- **UHel-Run3.**
  - Number of clusters: 100
  - MFS frequency threshold: $\sigma = 7$

The results of our first run are based on the paragraph-level division. Section-sized and bigger results are composites of the paragraph-sized fragments. Combining the paragraphs relies heavily on the upward propagation method described in Section 6. Due to their small size, paragraph-level fragments could benefit from Query Expansion more than bigger fragments, which partly explains the low evaluation scores of our first run. Also, small elements are more sensitive to changes in the fragment combination process.

The minimal result granularity of the second and the third run is a section. The section-level fragment count is substantially smaller than the corresponding paragraph count, which makes it slightly easier to find the best fragments for each query.

8. CONCLUSIONS

We came up with a new technique for exploiting the logical structure of XML documents so as to give more focused answers to information retrieval queries. We developed a system with the new ideas implemented, and the runs were submitted to INEX 2003. After preliminary observation, we notice that EXTIRP performs best at the very beginning of the top 1,500 answers where recall is relatively low. Considering the answers ranking between 1 and 50, our best runs are among the top of all submissions for CO topics.

There is a number of improvements to be achieved. First, we plan to reuse the clusterings formed prior to the extraction of maximal frequent sequences, aiming at query optimization. The idea is that by comparing queries to centroids of MRU clusters, we will be able to efficiently skip large quantities of MRUs, without having to compute similarity measures for each minimal unit individually.

Another concern is the fact that the current upward propagation formula is exponential in nature, meaning a small variation in the UPF factor can cause a switch from a set of answers with a large majority of minimal units to a set of answers with a large majority of full articles. Part of our future work is to explore the various ways to smooth this effect.

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Runs	MRU Granularity	UPF	QE	strict	generalized
UHel-Run1	paragraph	2	no	0.0061 (51st)	0.0105 (46th)
UHel-Run2	section	2	yes	0.0323 (31st)	0.0222 (39th)
UHel-Run3	section	5	yes	0.0449 (20th)	0.0235 (38th)

Table 2: Results and ranks of our official runs (out of 56).

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Keyword-based XML Fragment Retrieval: Experimental Evaluation based on INEX 2003 Relevance Assessments

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ABSTRACT

We have developed a keyword-based XML fragment retrieval system based on statistics of XML documents to improve both the efficiency and effectiveness of the system. Currently, relevance assessments for keyword-based XML fragment retrieval systems are provided only by the INEX project; thus we evaluate our system using them. However, our system performs poorly with respect to retrieval accuracy using the INEX 2003 relevance assessments. In this paper, we analyze all CO topics based on statistics of answer XML fragments and report our experimental results. After performing the experiments, we found that two types of CO topics is present in the INEX 2003 relevance assessments and has to be handled when in the experimental evaluations.

Categories and Subject Descriptors

H.3.4 [**Information Storage and Retrieval**]: Systems and Software—*Performance evaluation (efficiency and effectiveness)*

General Terms

Information retrieval, Performance evaluation

Keywords

Keyword-based XML fragment retrieval, Evaluation of both efficiency and effectiveness, Analysis of relevance assessments

1. INTRODUCTION

Extensible Markup Language (XML) [5] is becoming widely used as a standard document format in many application domains. In the near future, we believe that a great variety of documents will be produced in XML; therefore, in a similar way to developing Web search engines, XML information retrieval systems will become very important tools for users wishing to explore XML documents on the Internet or a company intranet.

XQuery [4], proposed by the World Wide Web Consortium (W3C), is known as a standard query language for retrieving fragments of XML documents. Using XQuery, users can issue a flexible query consisting of both some keywords and XPath notations[1]. If users already have knowledge of the structure of XML documents, users can issue XQuery-style queries. However, there are a lot of XML documents whose XML schemas are different to each other, and as a result, nobody can issue such a formulated query into information retrieval systems. Consequently, we believe that XML retrieval systems should employ a much simpler form of query such as keyword search services. Keyword search services enable users to retrieve needed information by providing them with a simple interface. It is, therefore, the most popular information retrieval method, since users need to know neither a query language nor the structure of XML.

Because of the aforementioned background on XML information retrieval, close attention has recently been paid to a keyword-based XML fragment retrieval system. Some keyword-based XML fragment retrieval systems have already been made available. They assume the existence of the document type declaration, which contains or points to markup declarations that provide a document-type definition (DTD) for a class of XML documents. As a result, they can deal with only one type of XML documents. It is true that the DTD facilitates the enhancement of retrieval accuracy and retrieval speed of keyword-based XML fragment retrieval systems. However, XML documents on the Internet or a company intranet do not always include DTDs; thus they cannot deal with multiple types of XML documents whose structures are different to each other. Because the XML documents feature many types of document structures, a next-generation Web search engine will have to treat XML documents whose structures are different.

To cope with the problems described above, we have developed a keyword-based XML fragment retrieval system using statistics of XML documents [12]. In XML fragment retrieval, we assume that users explicitly specify query keywords; thus, we believe that the size of retrieval results become small compared to document retrieval. On the other hand, we also believe that extremely small XML fragments have neither rhyme nor reason by themselves. To solve this

[1]Currently, the XML Query working group is just starting to develop full-text search functions [2, 6].

problem, we designed an XML fragment retrieval system that can return small (but not extremely small) and semantically useful XML fragments as retrieval results.

According to [14], the INEX 2002 relevance assessments tended to regard large-size XML fragments as correct retrieval results. This fact did not meet purpose of our XML fragment retrieval system. If the INEX 2003 relevance assessments are also similar to the previous one, our system might perform poorly in its retrieval accuracy. It is therefore necessary to analyze and evaluate CO topics of the INEX 2003 relevance assessments to determine whether they suit our purpose.

In this paper, we analyze the INEX 2003 relevance assessments based on their statistics, and evaluate our system using CO topics reflecting our analyses. We believe that analyzing the relevance assessments helps to both construct the next version of the relevance assessments and improve the efficiency and effectiveness of our system.

The remainder of this paper is organized as follows. First, we describe our keyword-based XML fragment retrieval system in Section 2. Then, we report analyses of the INEX 2003 relevance assessments in Section 3 and discuss controversial points of CO topics of the INEX 2003 relevance assessments in Section 4. Finally, we conclude this paper in Section 5.

2. OUR XML FRAGMENT RETRIEVAL SYSTEM

This section introduces proposed retrieval model and the purpose of our keyword-based XML fragment retrieval system. We also report preliminary experimental results obtained using our system, and explain our observations regarding XML fragment retrieval.

2.1 Data Model and Retrieval Model

For simplicity, our system's data model is similar to that of the XPath data model [7], because XML is modeled as a hierarchical tree. Actually, the only difference between the XPath data model and ours is that attribute node is regarded as a child of an element node[2].

In addition, for the sake of easy comprehension, our system's retrieval model bears a close resemblance to the proximal nodes model [17]. Basically, our logical model of an XML fragment is a sub-tree whose root node is an element node. Our system can identify XML fragments by their reference numbers derived from document order; therefore, our system can obtain similarities between user's query and XML fragments based on their document orders.

2.2 Purpose of Our Research

We distinguish two types of keyword-based XML fragment retrieval systems. This paper refers to these two types of systems as *XML data retrieval systems* and *XML information retrieval systems*, for the sake of convenience. The former is based on structured or semi-structured database systems with keyword proximity search functions that are modeled as labeled graphs, where the edges correspond to the relationship between an element and a sub-element and to `IDREF` pointers [1, 11, 13]. Dealing with XML documents as XML graphs facilitates the development of keyword-based information retrieval systems, which are able to perform the retrieval processing efficiently. On the other hand, the latter has been developed in the research field of information retrieval [8, 9], and enables us to retrieve XML fragments without indicating element names of XML documents. The large difference between the XML retrieval systems and the XML information retrieval systems derives from data characteristics of their retrieval targets. In short, we consider that the former focuses mainly on *data-centric* XML documents, whereas the latter deals with *document-centric* ones[3]. In the meanwhile, almost all XML data retrieval systems and XML information retrieval systems currently assume the existence of DTD of XML documents. It is a fact that DTD facilitates enhancing retrieval accuracy and retrieval speed of their systems. However, there are some problems associated with searching XML fragments on the Internet or a campany intranet, as described in Section 1; thus other types of XML retrieval systems, which do not utilize DTD, are required. Consequently, XML retrieval systems in the future will have to deal with XML documents whose structures are different.

To meet the needs of the new architecture of XML retrieval systems, we have developed a keyword-based XML fragment retrieval system using statistics of XML documents [12]. Our system focuses on retrieval of document-centric XML documents rather than that of data-centric ones, and does not utilize any information in relation to element names of XML documents, whereas the systems introduced above take advantage of such information for querying and indexing of XML documents. Our approach dictates that XML documents must be divided into fragments in order to develop a keyword-based XML retrieval system. Because XML is a markup language, XML documents can be automatically divided into their fragments using their markup [15]; a problem surfaces, however, because this gives rise to an unmanageable profusion of XML fragments. In other words, it takes very long time to retrieve XML fragments related to a keyword-based query using our approach. For this reason, not inspecting extracted all XML fragments, but retrieving only XML fragments which are informative enough for XML information retrieval would be better.

2.3 Evaluating Our System based on INEX 2003 Relevance Assessments

In this section, we report the retrieval accuracy of our keyword-based XML fragment retrieval system based on INEX 2003 relevance assessments. The relevance assessments defined two metrics, strict and generalized; thus we performed experimental evaluations based on both metrics. The metrics have two criteria, "exhaustiveness" and "specificity," for quality metrics of IR applications. The method of how recall and precision are computed is described in a report [18][4]. Based on the metrics, we drew recall-precision curves

[2]If element node has some attribute nodes that have brotherhood ties, they are owned by the element node.

[3]There is a data-centric and a document-centric view of XML described in [3].

[4]Another way is also available, described in a technical report [10]; however, we did not apply it in this paper.

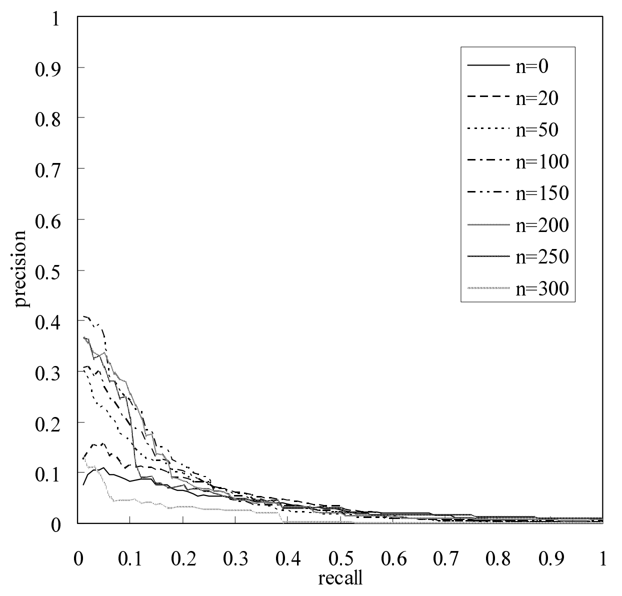

Figure 1: Evaluation of our system based on INEX 2003 relevance assessments (strict).

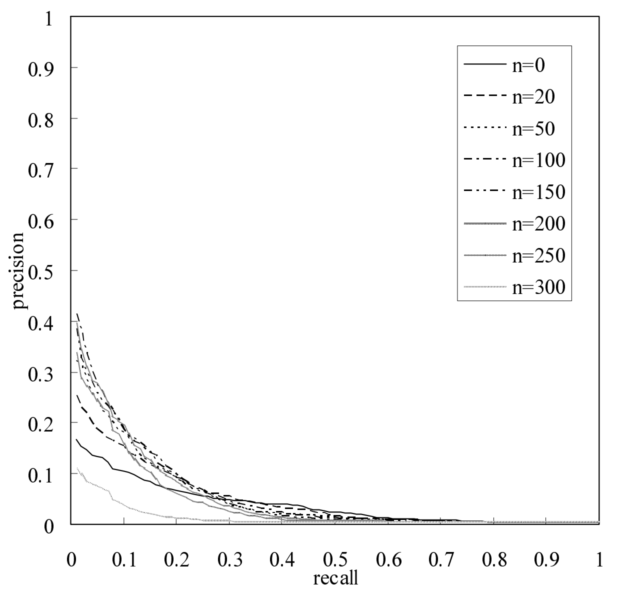

Figure 2: Evaluation of our system based on INEX 2003 relevance assessments (generalized).

to evaluate the XML fragment retrieval system. Figure 1 and 2 show recall-precision curves of our system based on INEX 2003 relevance assessments. In these figures, n means the minimum number of tokens, which is defined to eliminate extremely small XML fragments from retrieval targets[5]. In short, as n becomes larger, the retrieval accuracy of our system also increases, as does our system's retrieval speed.

As shown in these two figures, we think that our keyword-based XML fragment retrieval system may be performing poorly. Although we recognize the problems inherent in our system[6], it is thought that the problems may not only reside in our system, but also in the relevance assessments. If the INEX 2003 relevance assessments tend to regard large-size XML fragments as correct retrieval results in analogy with the INEX 2002 relevance assessments, our system will be a poorly-performing XML fragment retrieval system, because our system tends to retrieve small XML fragments, but not extremely small ones, as retrieval results described in Section 1. As a matter of fact, in the case where the threshold of the number of tokens is 150 (in strict relevance assessments) or 100 (in generalized ones), our system does work properly (see Table 1). From our perspective, we consider that this number of tokens is very large for XML fragment retrieval, because the number of tokens is comparable to XML fragments whose root node is `ss1`, `ss2`, or `ss3`, as shown in Table 2. We have designed our XML fragment retrieval to enable users to retrieve XML fragments corresponding to other XML fragments whose size is less than (sub)sections of the INEX document collection as retrieval results. Therefore, we can forecast that retrieval results by our system would give fewer XML fragments than answer XML fragments determined in the INEX 2003 relevance assessments[7].

Table 1: Average precision of our system.

n	strict	generalized
0	0.0356	0.0390
20	0.0436	0.0476
50	0.0502	0.0505
100	0.0568	<u>0.0568</u>
150	<u>0.0669</u>	0.0525
200	0.0630	0.0503
250	0.0572	0.0416
300	0.0163	0.0130

Based on the aforementioned points, we analyze answer XML fragments of the topics of INEX 2003 relevance assessments, choose the topics suitable for our system, and re-evaluate our system's retrieval accuracy in reference to a revised version of the relevance assessments.

3. ANALYSES OF INEX RELEVANCE ASSESSMENTS

3.1 Analyses of the Relevance Assessments

As we described in the previous section, we consider that the INEX 2003 relevance assessments may work against XML fragment retrieval systems, which tend to regard small-size XML fragments as correct retrieval results. Consequently, we analyze answer XML fragments defined in the relevance assessments. Our system can deal with only content-only

[5]The size of XML fragments is proportional to the number of tokens contained in the XML fragments.

[6]Our system cannot calculate similarities between a query and XML fragments using only contents of XML documents.

[7]Of course, this is our opinion. In [16], the authors claimed that 500 words is valid for answer XML fragments. The proper size of answer XML fragments depends on the retrieval purposes of each INEX participant.

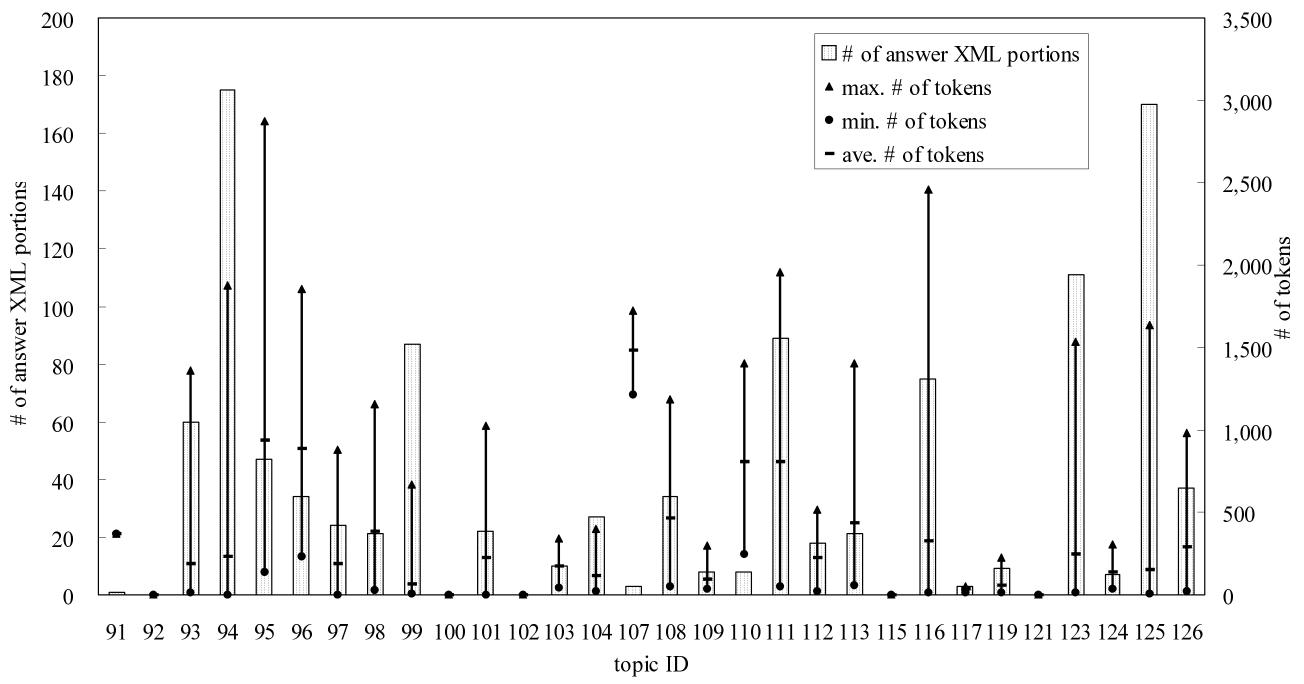

Figure 3: Analyses of the INEX 2003 relevance assessments.

(CO) topics of the relevance assessments; thus, only answer XML fragments of CO topics are analyzed here. In this section, we analyze the answer XML fragments whose exhaustiveness and specificity are 3.

Figure 3 shows analyses of CO topics of the INEX 2003 relevance assessments. Area bars represent the maximum, average, and minimum number of tokens of answer XML fragments, and line bars indicate the numbers of answer XML fragments. As shown in this figure, we first found that five CO topics of the relevance assessments (whose topic IDs are #92, #100, #102, #115, and #121) did not have answer XML fragments. It is doubtful that these topics were adopted as the CO topics of the relevance assessments, because we think that the CO topics with few answer XML fragments are not inappropriate for the relevance assessments. Moreover, we also found that the average number of tokens of almost all CO topics exceeded 100. In particular, the average number of tokens of CO topics whose IDs are #95, #96, #107, #110, and #111 was 500 and above; therefore, these CO topics distinctly work against our system. Furthermore, the number of answer XML fragments substantially differs with each CO topic.

From the aforementioned points, we select 14 CO topics (#93, #94, #97, #98, #99, #101, #104, #108, #112, #113, #116, #123, #125, #126) as the relevance assessments suitable for our system, and re-evaluate retrieval accuracy of our system based on them in the next section.

3.2 Reevaluation of Our System

Figures 4 and 5 show recall-precision curves of our system based on revised versions of INEX 2003 relevance assessments, while Table 3 shows average precision of each recall-precision curve. In comparison with previous evaluations described in Section 2.3, the retrieval accuracy of our system shows an improvement of 3.55% in this experiment. It is clear that our system performs better because of using selected CO topics. The thing which we want to assert is not improving retrieval accuracy of our system, but presence of two types of CO topics in XML fragment retrieval. In short, the CO topics for searching large-size XML fragments make our system worse retrieval accuracy of our system, which explains why our system could not return the XML fragments relevant to CO topics on the relevance assessments in the previous evaluations. Needless to say, we do not know whether our system's retrieval accuracy is better than that of other INEX participants' systems, though we could confirm controversial points of the relevance assessments for our system.

To reduce the scope of such arguments, we have to clarify what XML fragment retrieval is. It is difficult to define the granularity of XML documents for XML fragment retrieval; however, we think that it is important for INEX participants to determine topics of the relevance assessments suitable for their retrieval purposes and to automatically select the topics for evaluation by their respective retrieval systems. In the case of our keyword-based XML fragment retrieval system, small and semantically useful XML fragments are defined as correct retrieval results; thus, we consider that our only option is to use our relevance assessments explained in Section 3.1.

4. DISCUSSION

As we described in the previous section, retrieval accuracy of XML fragment retrieval systems depends on retrieval pur-

Table 2: Statistical analysis of XML fragments.

element	# of XML fragments	# of tokens		
		average	maximum	minimum
`book`	3,612,202	28,897	64,181	6,341
`journal`	6,314,623	7,342	14,903	3,982
`article`	11,801,575	974	4,727	29
`bdy`	9,271,423	765	3,943	11
`index`	72,993	623	1,593	230
`bm`	3,125,254	310	2,863	2
`dialog`	41,317	212	906	19
`sec`	14,078,415	201	2,613	1
`bib`	1,662,190	194	1,959	8
`bibl`	1,662,640	194	1,959	8
`app`	812,923	138	1,353	2
`ss1`	7,854,413	127	2,109	1
`ss2`	1,509,337	92	1,261	1
`ss3`	11,642	91	325	9
`fm`	797,123	65	289	9
`tgroup`	363,102	62	401	2
`proof`	229,144	60	801	5
`vt`	1,021,500	55	235	2
`dl`	18,670	52	745	5
`edintro`	28,923	50	272	4

Table 3: Average precision of our system based on revised INEX 2003 relevance assessments.

n	strict	generalized
0	0.0564	0.0630
20	0.0666	0.0697
50	0.0689	0.0667
100	0.0777	0.0774
150	0.0866	0.0731
200	0.0769	0.0695
250	0.0611	0.0645
300	0.0253	0.0217

pose of each topic in the relevance assessments. In short, an XML fragment retrieval system performs poorly in retrieval accuracy if the retrieval purpose of an XML fragment retrieval system does not correspond to answer XML fragments of the topics. In the case of our system, small (not extremely small) and semantically useful XML fragments are retrieved as retrieval results. However, some topics tend to retrieve large XML fragments, meaning that our system performed poorly in retrieval accuracy. Therefore, we consider that the XML fragment retrieval systems that tend to regard large XML fragments as retrieval results gain the upper hand in retrieval accuracy. In this section, we make specific mention of the controversial points about CO topics of the INEX 2003 relevance assessments.

4.1 Characteristics of CO Topics

As we described in Section 3.1, the size and the number of answer XML fragments of CO topics vary (see Figure 3), though we do notice there are two types of CO topics in the relevance assessments (see Section 3.2). One is for searching specific XML fragments (SCO) and the other is for searching aggregated XML fragments (ACO). Query keywords of SCO topics may consist of some proper nouns, such as "Charles Babbage," "XML," and "Markov." Consequently, SCO topics tend to retrieve small-size XML fragments. On the other hand, ACO topics tend to retrieve exhaustive XML fragments, resulting in large answer XML fragments.

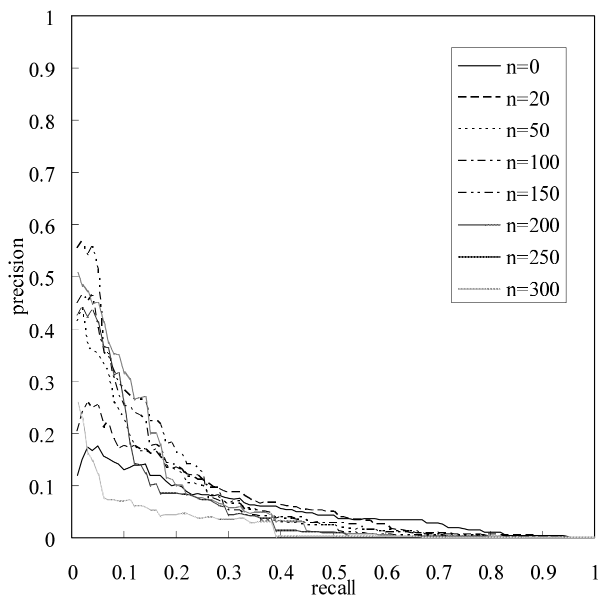

Figure 4: Evaluation of our system based on revised INEX 2003 relevance assessments (strict).

We think the existence of two types of CO topics are supported by the following statistical observations:

- Table 4 shows the topics of the INEX 2003 relevance assessments that have less than an average of 500 tokens in answer XML fragments whose ($exhaustiveness(E)$, $specificity(S)$) is equal to $(3, 3)$. We consider that the sizes of the answer XML fragments are smaller than those of XML fragments whose $(E, S) = (3, 2)$ or $(3, 1)$, which means the average number of tokens of answer XML fragments should also be smaller.

- Table 5 shows the topics of the INEX 2003 relevance assessments that have more than an average of 500 tokens in the answer XML fragments. A search of these topics is exhaustive because they do not contain any specific keywords. That is to say, the answer XML fragments should cover information on the contents of the topic. As a result, we expect that the XML fragments, which are assessed as $(E, S) = (3, 3)$, become aggregated XML fragments with comparatively large granularity.

Current relevance assessments do not consider these controversial points, but we believe that considering these points helps to construct a high-quality test collection for XML fragment retrieval. If indeed a high-quality test collection can be constructed, XML fragment retrieval systems only have to deal with two such types of CO topics.

Table 4: SCO topics of the INEX 2003 relevance assessments.

topic ID	title	# of tokens (average)		
		(E, S)		
		(3, 3)	(3,2), (3, 1)	(2, 3)
93	"Charles Babbage" -institute -inst	186	3,377	62
94	"hyperlink analysis" +"topic distillation"	232	83	333
97	Converting Fortran source code	186	753	27
98	"Information Exchange" +XML "Information Integration"	383	0	347
99	perl features	69	314	18
101	+"t test" +information	228	364	222
104	Toy Story	114	735	0
108	ontology ontologies overview "how to" practical example	466	872	367
112	+"Cascading Style Sheets" -"Content Scrambling System"	228	332	61
113	"Markov models" "user behavior"	438	1,010	90
116	"computer assisted art" "computer generated art"	330	702	207
123	multidimensional index "nearest neighbor search"	245	546	48
125	+wearable ubiquitous mobile computing devices	154	249	47
126	Open standards for digital video in distance learning	288	710	455

Table 5: ACO topics of the INEX 2003 relevance assessments.

topic ID	title	# of tokens (average)		
		(E, S)		
		(3, 3)	(3,2), (3, 1)	(2, 3)
95	+face recognition approach	940	593	486
96	+"software cost estimation"	885	1,174	537
107	"artificial intelligence" AI practical application industry "real world"	1,487	0	633
110	"stream delivery" "stream synchronization" audio video streaming applications	811	669	162
111	"natural language processing" -"programming language" -"modeling language" +"human language"	806	474	253

4.2 Consistent Criteria

As we described in Section 2.3, there are two criteria, exhaustiveness and specificity, in the INEX 2003 relevance assessments. Both exhaustiveness and specificity have four levels, though the definitions of each level are too vague for us to accurately evaluate which XML fragments are relevant to a given topic.

For example, Table 6 shows the XML fragments that were assessed as $(E, S) = (3, 3)$ in topic #125. We found in Table 6 that there are some nested relationships among the XML fragments, though at that time, we did not understand how to allocate marks to the XML fragments related to the topic. We think that XML fragments related to a topic depend on retrieval purpose of the topic; therefore there are a lot of possible interpretation to what constitutes a good XML retrieval unit. Such interpretations cause confusion, thus preventing strict evaluations of XML fragment retrieval systems. In the INEX 2002 relevance assessments, two criteria, "relevance" and "coverage," feature rules between a parent node and its children nodes in the XML fragments; thus, we think the above problems did not occur. Consequently, the INEX 2003 relevance assessments also require standards of judgment with regard to exhaustiveness and specificity. At minimum, we consider that a definition is needed for determining which XML fragment is the most relevant to topic #125 in Table 6. That is to say, we believe that we should clearly define what the answer XML fragments is in the relevance assessments and should obtain consensus about it among INEX participants.

5. CONCLUSION

In this paper, we analyzed the INEX 2003 relevance assessments based on statistics of their answer XML fragments on CO topics, and reported some controversial points of the relevance assessments.

We strongly recommend judging the validity of each topic; in particular a topic that has no answer XML fragments at all or has only a few answer XML fragments is inadequate for the topics in relevance assessments. We also found that there are two types of CO topics for analyzing the relevance assessments. Our system tends to regard small XML fragments as retrieval results, thus it performs poorly in retrieval accuracy using the topics for searching aggregated XML fragments. Retrieval purposes of XML fragment retrieval systems are different, making it difficult to construct relevance assessments that meet the requirements of all XML fragment retrieval systems. However, we will be able to evaluate XML fragment retrieval systems if each system can choose the topics that fulfill its retrieval purpose. It is, therefore, necessary in constructing the INEX 2004 relevance assessments to define SCO and ACO topics whose numbers are the same. Of course, XML fragment retrieval systems should automatically judge types of topics and choose one to suit retrieval purpose of the topics by themselvs.

Moreover, we think that it is important to refine the INEX test collection year by year, requiring that excellent topics be selected from the INEX 2002/2003 relevance assessments, and be reused in INEX 2004. In conclusion, we need to define the baseline of excellent topics, in addition to adopting

Table 6: XML fragments evaluated $(E, S) = (3, 3)$ of topic #125.

file	path	# of tokens
co/1999/r1057	/article[1]	1128
co/1999/r1057	/article[1]/bdy[1]	863
co/1999/r1057	/article[1]/bdy[1]/sec[3]	215
co/1999/r1057	/article[1]/bdy[1]/sec[3]/fig[1]	37
co/1999/r1057	/article[1]/bdy[1]/sec[3]/fig[1]/art[1]	11
co/1999/r1057	/article[1]/bdy[1]/sec[3]/fig[1]/fgc[1]	24
co/1999/r1057	/article[1]/bdy[1]/sec[3]/p[1]	63
co/1999/r1057	/article[1]/bdy[1]/sec[3]/p[2]	49
co/1999/r1057	/article[1]/bdy[1]/sec[3]/p[3]	32
co/1999/r1057	/article[1]/bdy[1]/sec[3]/p[4]	33
co/1999/r1057	/article[1]/bdy[1]/sec[3]/p[5]	82
co/1999/r1057	/article[1]/bdy[1]/sec[5]	343
co/1999/r1057	/article[1]/bdy[1]/sec[6]	308
co/1999/r1057	/article[1]/bm[1]/app[1]/p[1]	65
co/1999/r1057	/article[1]/bm[1]/app[1]/p[2]	68
co/1999/r1057	/article[1]/bm[1]/app[3]/p[1]	34
co/1999/r1057	/article[1]/bm[1]/app[3]/p[2]	54
co/1999/r1057	/article[1]/bm[1]/app[3]/p[3]	25

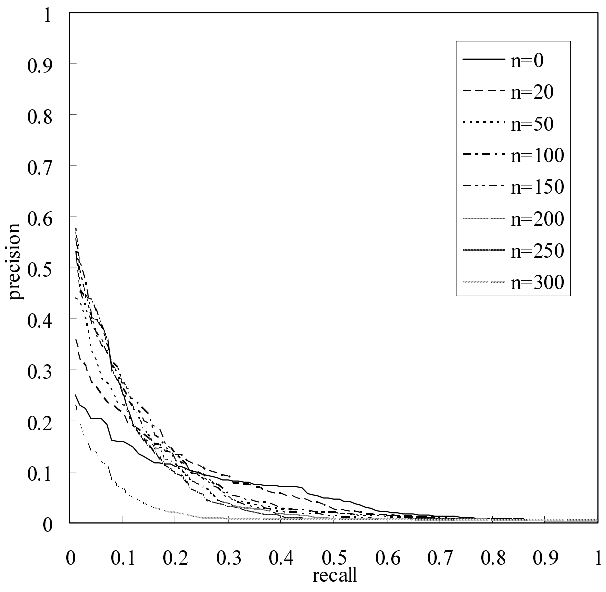

Figure 5: Evaluation of our system based on revised INEX 2003 relevance assessments (generalized).

the topics of INEX 2002/2003 relevance assessments that meet the baseline as topics of the INEX 2004 ones. Utilizing statistics of answer XML fragments is one solution.

6. ACKNOWLEDGMENTS

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An Approach to Structured Retrieval Based on the Extended Vector Model

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ABSTRACT

In this paper, we describe our approach to XML retrieval, which is based on the extended vector space model initially proposed by Fox [5]. The current implementation of our system and results to date are reported. The basic functions are performed using the Smart experimental retrieval system. Early results confirm the viability of the extended vector space model in this environment.

1. INTRODUCTION

When we began our work with INEX last year, our goal was to confirm the utility of Salton's vector space model [10] in its extended form for XML retrieval. Long familiarity with Smart [9] and its capabilities led us to believe that it could be used for this purpose. Our approach was described in the proceedings of last year's workshop [3]. Much initial effort was spent on the translation of documents and topics from XML to internal Smart format and the subsequent translation of results back into INEX format. When we reported our results in [3], our system was still in a very rudimentary stage.

In 2002, we had an idea and began implementation. During the past year, we have built upon and extended that work. We now have an operational system. For the sake of clarity, a brief overview follows.

1.1 Background

Everyone involved in information retrieval is familiar with the vector space model, wherein documents and queries are represented as weighted term vectors. The weight assigned to a term is indicative of the contribution of that term to the meaning of the document. Very commonly, *tf-idf* weights [11] or some variation thereof [12] are used. The similarity between vectors (e.g., document and query) is represented by the mathematical similarity of their corresponding term vectors.

In 1983, Fox [5] proposed an extension of the vector space model—the so-called *extended vector space model*—to allow for the incorporation of objective identifiers with content identifiers in the representation of a document. An extended vector can include different classes of information about a document, such as author name, publication date, etc., along with content terms. In this model, a document vector consists of a set of subvectors, where each subvector represents a different class of information (i.e., concept class or c-type). Our current representation of an XML document/topic consists of 18 c-types (i.e., *abs, ack, articl_au_fnm, article,au_snm, atl, au_aff, bibl_atl, bibl_au_fnm, bibl_au_snm, bibl_ti, ed_aff, ed_intro, kwd, rname, st, ti, pub_yr, bdy*) as defined in INEX guidelines. Subjective subvectors are those with a body of text associated with them (i.e., *abs*, *ack*, *atl*, *bibl_atl*, *bibl_ti*, *ed_intro*, *kwd*, *bdy*). Similarity between extended vectors is calculated as a linear combination of the similarities of the corresponding subvectors.

Use of the extended vector model for document retrieval normally raises at least two problems: the construction of the extended search request [4, 6] and the selection of the coefficients for combining subvector similarities. For XML retrieval, the CO query in particular can be roughly translated into extended vector form by distributing the keywords across the subjective subvectors. (CAS queries are more difficult; we are working on automating this process.) The second problem—the weighting of the subvectors themselves—remains open to investigation. Another issue of some interest here is the weighting of terms within the subvectors. (We have produced some useful results in relation to the term weighting issue; our work on the weighting of subvectors is promising but not well developed. In any case, subvector weighting is unlikely to have a measurable effect within the large INEX window.)

The extended vector capability of Smart appeared to us well suited for XML with respect to the retrieval of documents. But there is no facility for retrieving at the element level (or at various levels of granularity), which is a requirement of INEX tasks. We are interested in determining the feasibility of incorporating the functionality (i.e., flexibility and granularity) required for XML retrieval within the extended vector environment. We are currently investigating methods that have been suggested by others (e.g., Grabs and Schek [7, 8]). However, more work is necessary before conclusions can be drawn.

1.2 System Description

Our system handles the processing of XML text as follows:

(1) The documents are parsed using a simple XML parser available on the web. Each of our 18 c-types is now identifiable in terms of its XML path.

(2) The documents and queries are translated into Smart format and indexed by Smart as extended vectors. (The results reported in this paper are all based on an indexing which considers the body of the document as a single entity; i.e., paragraphs and sections, for example, are not recognized.)

(3) Retrieval takes place by running the queries against the indexed collection. The result is a list of articles ordered by decreasing similarity to the query. (A number of term weighting schemes are available through Smart.)

(4) For each query, the top 100 articles are converted back into INEX format and reported.

The retrieval itself is straight-forward. The only variation is the splitting of certain CAS queries into separate portions which are then run in parallel to ensure that the elements retrieved meet the specified criteria. See Section 2.2 for an example of this type.

2. EXPERIMENTS

In the following sections, we describe the experiments performed with respect to the processing of the CO and CAS topics, respectively. In all cases, we used only the topic title and keywords as search words in query construction. As indicated previously, this year's effort focused on producing a working system—by our definition, a system that returns competitive results with respect to at least some INEX task(s). To demonstrate that our system is functional, we first processed the INEX 2002 topics (under the original *inex_eval*) to compare our results to those already reported. We then processed the 2003 topics. The results are all reported here.

2.1 Using CO Topics

Our first task is to formulate the CO topic in extended vector form. Of the 18 c-types composing the extended vector, 8 contain subjective identifiers (i.e., *abs*, *ack*, *atl*, *bibl_atl*, *bibl_ti, ed_intro*, *kwd, bdy*). The extended vector topic is formed by associating the search words of the topic with each of these 8 c-types. The remaining c-types contain objective identifiers and are not used in formulating CO queries. Our more interesting experiments are discussed briefly below. (See [1] for details.) The subvectors are equally weighted in all these cases.

2.1.1 2002 Topics

Our term weighting experiments include:

Tuned *Lnu-ltu* Term Weighting: In this experiment, we tuned the collection as indicated by Singhal, *et. al*., in [13]. Results under generalized quantization were 0.065 whereas strict quantization produced 0.095.

Augmented *tf-idf* (*atc*) Term Weighting: 2002 topics under generalized quantization produced an average precision of 0.033.

Retrieval at the Element Level: In this experiment, we used indexings of the collection at the paragraph and section levels in addition to the article level. (Untuned or estimated *Lnu-ltu* weights were used in these early experiments.) For each query, the rank-ordered lists were sorted and the top 100 elements reported. Average precision was 0.042 under generalized quantization.

2.1.2 2003 Topics

Our 2003 CO submission was based on parameters that produced the best results for 2002 CO topics, i.e., *Lnu-ltu* term weighting with equal subvector weights. The recall-precision graphs for 2003 CO topics under the revised *inex_eval* are given below in Figures 1 and 2. The results under *inex_eval_ng* (overlap ignored) are shown in Figures 3 and 4. Corresponding results under *inex_eval_ng* (overlap considered) are shown in Figures 5 and 6.

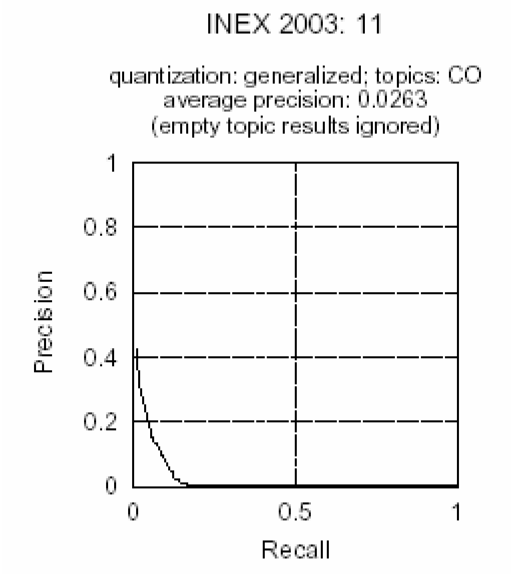

Figure 1. Recall-precision for CO, Gen

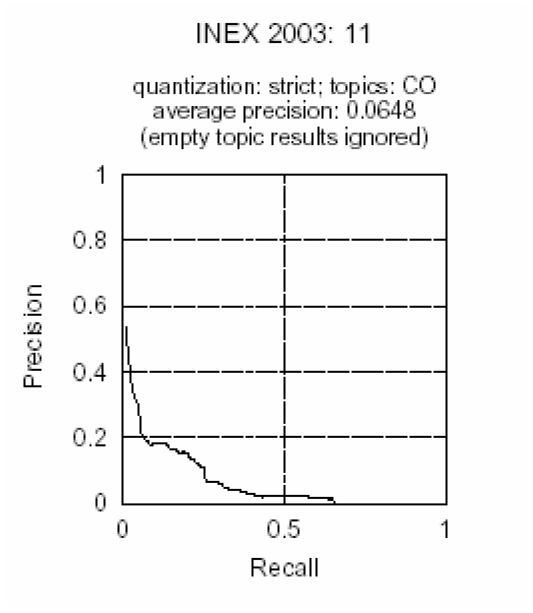

Figure 2. Recall-precision for CO, Strict

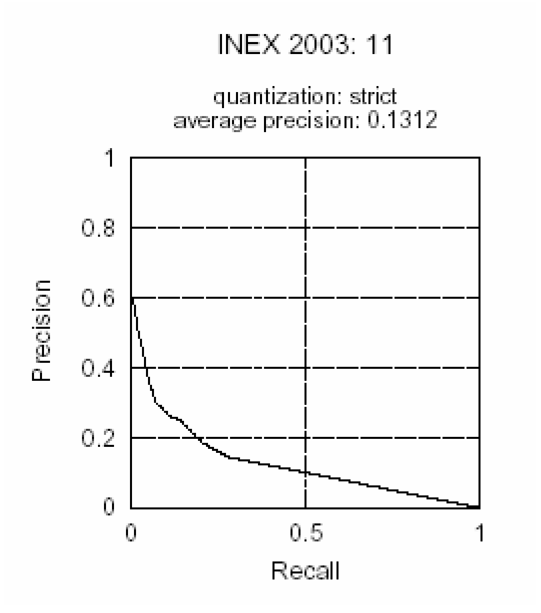

Figure 4: Recall-precision for CO, Strict under ng (overlap ignored)

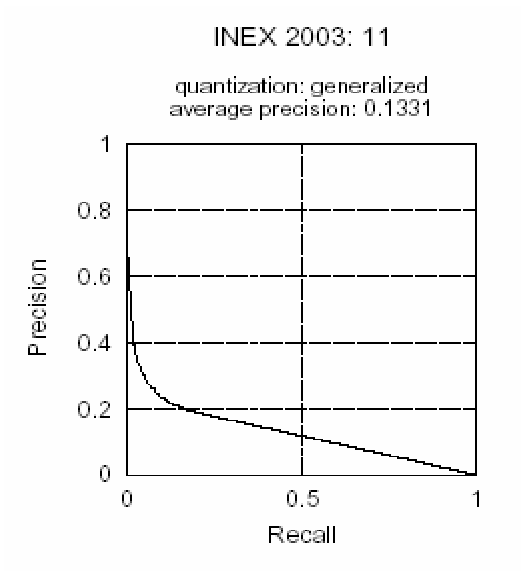

Figure 3: Recall-precision for CO, Gen under ng (overlap ignored)

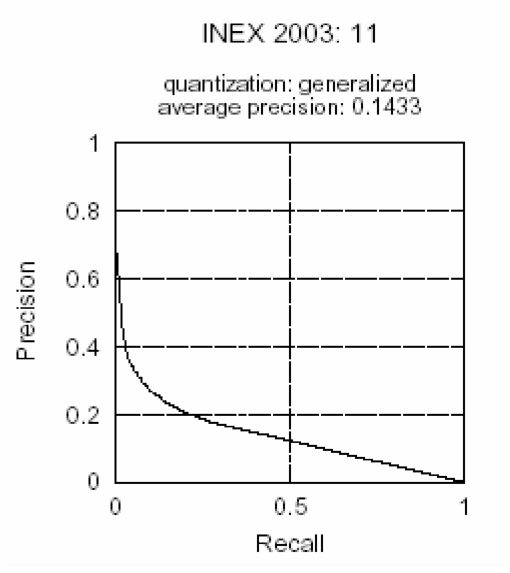

Figure 5: Recall-precision for CO, Gen under ng (overlap considered)

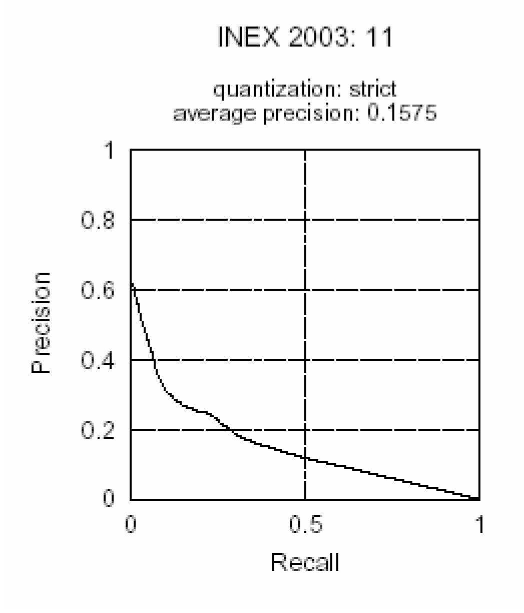

Figure 6: Recall-precision for CO, Strict under ng (overlap considered)

To recap: Our results for 2003 INEX CO topics are on the whole good, ranking in the top 10 of the 4 evaluations (Figures 3, 4, 5, and 6) under *inex_eval_ng.* Yet although we were able to produce decent results for the 2002 CO topics under the original *inex_eval*, our results for the 2003 CO topics under the revised *inex_eval* fall far from the top. We are still assessing the causes.

2.2 Using CAS Topics

We were able to formalize the extended vector CO topics fairly easily. The extended vector CAS topic formulations, on the other hand, present more of a challenge. Direct use of the extended vector model does not guarantee that each keyword will occur in the specified context. To effect this result, we currently split certain CAS queries into separate portions which are then run in parallel to ensure that the elements retrieved meet the specified criteria. Consider, for example, the title section of CAS query 8:

```
<title>
        <te>article</te>
        <cw>ibm</cw><ce>fm/aff</ce>
        <cw>certificates</cw><ce>bdy/sec</ce>
</title>
```

In this case, the query is to return a ranked list of articles as specified by the target element <te>. The narrative specifies that the body or sections of relevant documents should contain information about the use of certificates for authenticating users on the Internet. And since the context of the content word *ibm* is fm/aff, the author(s) of those documents must be affiliated with IBM. Thus the query should retrieve only those articles on the use of certificates whose author(s) are affiliated with IBM. To guarantee that the system returns *only* those articles, we split the query into two parallel queries as follows:

```
Q1: <cw>ibm></cw><ce>fm/aff</ce>
Q2: <cw>certificates</cw><ce><bdy/sec</ce>
```

Affiliation and section are two different c-types. So query 1 searches for documents containing the objective identifier *ibm* in the affiliation subvector. Query 2 seeks articles whose body or section(s) contain the term *certificate.* Smart returns a ranked list of documents for both queries. The intersection of these lists is the final, ranked list of documents returned. This approach—the splitting of a query into parts—is a first step in the process of using objective ctypes to filter results appropriately.

This year we experimented with different term weighting schemes for CAS topics. We performed these experiments first on the 2002 topics. Equal subvector weighting was applied in each case. Experiments performed during the past year using the INEX 2002 queries are described briefly below. (See [2] for details.) Evaluation for these topics was performed through the original *inex_eval.*

2.2.1 2002 Topics

Untuned *Lnu_ltu* Term Weighting: All subvectors are weighted in this fashion. Average precision was 0.179 under generalized and 0.222 under strict quantization.

Lnu_ltu (for subjective subvectors) and *nnn* (for objective subvectors) Term Weighting: Here we used simple term frequency weights (*nnn*) for the objective subvectors combined with *Lnu_ltu* weights for the subjective subvectors. Average precision was 0.187 under generalized and 0.235 under strict quantization.

Augmented tf-idf (*atc*) Term Weighting: All subvectors were weighted with *atc* weights. Average precision was 0.194 and 0.238 under generalized and strict quantization, respectively.

Augmented tf-idf (*atc*—for subjective subvectors) and *nnn* (for objective subvectors) Term Weighting: These weights returned an average precision of 0.192 under generalized and 0.243 under strict quantization.

All of these results rank in the top 10 when compared to the best case results reported for INEX 2002 topics.

2.2.2 2003 Topics

Our 2003 submission used *atc* term weighting for all subvectors with equal subvector weights. Due to the exigencies of the academic schedule, we were able to submit only under VCAS. Results await availability of the corresponding INEX evaluation package, but we do not expect them to be useful at this point. We need to modify our methods so that the appropriate filters are applied before results are returned.

During the past year, we produced a working system. An overview of our results may be seen in Table 1. The column labeled UMD (for University of Minnesota Duluth) presents our results, which may be compared with the best result reported for that task (in the INEX column).

3. CONCLUSIONS

In 2003, our efforts were directed at producing a working system for structured retrieval based on the extended vector model. In our view, this year's results have demonstrated the viability of such an approach. However, structured retrieval requires additional capabilities beyond the scope of normal vector-based systems, and thus the question remains. Is our model—the extended vector model—able to support the functionality required in this environment?

Our system is still in an early stage of development. The issue of term weighting has now become clearer; the weighting of the subvectors themselves is still an open question. The major challenge is to develop a method of returning results at the element level, i.e., to retrieve at the desired level of granularity. Our plans include further investigation of the methods of others along with the development of an approach that may be better suited to our own environment. Another major focus is the development of appropriate techniques for handling CAS topics effectively.

Table 1. Comparison of Best Case Avg Precision for CO Topics

	UMD		INEX	
	gen	strict	gen	strict
'02 Topics	0.0650	0.0950	0.0700	0.0880
'03 Topics: inex_eval	0.0263	0.0648	0.1036	0.1214
'03 Topics: inex_eval_ng*	0.1331	0.1312	0.1783	0.1857
'03 Topics: inex_eval_ng**	0.1433	0.1575	0.1542	0.1584

* overlap ignored; ** overlap considered

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Cooperative XML (CoXML) Query Answering at INEX 03

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ABSTRACT

The Extensible Markup Language (XML) is becoming the most popular format for information representation and data exchange. Much research has been done in providing flexible query facilities while aiming at efficient techniques to extract data from XML documents. However, most are focused on only the exact matching of query conditions. In this paper, we describe a cooperative XML query answering system, CoXML, which cooperates with the users by extending query relaxation techniques and provides approximate matching of query conditions. We also present our participation effort in the Initiative for the Evaluation of XML Retrieval (INEX) with CoXML.

1. INTRODUCTION

With the growing popularity of the Extensible Markup Language (XML) [13], much information is stored and exchanged in the XML format [1]. XML is essentially a textual representation of hierarchical (tree-like) data where a meaningful piece of data is bounded by matching starting and ending tags, such as <name> and </name>.

To cope with the tree-like structures in the XML model, several XML-specific query languages have been proposed (e.g., XPath [16], Quilt [3], XML-QL [14] and XQuery [17]) lately. All these XML query languages aim at only the exact matching of query conditions. Answers are found when those XML documents match the given query conditions *exactly*. However, this may not always be the case in the XML model. To remedy this condition, we are developing a query relaxation framework for searching answers that match the given query conditions *approximately*. *Query relaxation* enables systems to relax a query to a less restricted form to derive approximate answers. Such a technique has been successfully used in the relational databases (e.g., CoBase [5]) and has proven to be a valuable technique for deriving approximate answers.

In the XML domain, the need for query relaxation increases since the flexible nature of the XML model allows varied structure or values, and the non-rigid XML tag syntax enables users to embed a wealth of meta-information in XML documents. Query relaxation is more important for the XML model than for the relational model because:

1. The schema in the XML model [15] is substantially larger and more complex than the schema in the relational model. Therefore, it is often unrealistic for users to understand the full schema and compose very complex queries. Thus, it is critical to be able to relax a user's query when the original query yields null or insufficient answers.

2. As the number of data sources available on the web increases, it is becoming increasingly common to build systems that gather data from the heterogeneous data sources. The structures of these data sources are different although using the same ontology for similar contents. Therefore, the capability to query against differently-structured data sources is becoming increasingly important [8, 9]. Query relaxation allows a query to relax its structure and matches data sources with relaxed structures.

Query relaxation in the XML model, however, introduces new challenges. Query relaxation in the relational model is basically focused on the value aspect. For example, for a relational query "*find a person with a salary range 50K – 55K*", if there is no answer or not enough answers available, it can be relaxed to a query "*find person with a salary range 45K – 60K.*" In the XML model, in addition to the value relaxation, a new type of relaxation called *structure relaxation* is introduced. Structure relaxation relaxes the nodes and/or edges of a query tree.

Further, we shall develop a methodology to provide automatic structure relaxations and to evaluate the effectiveness of XML structure relaxations.

A knowledge-based relaxation index structure called XML Type Abstraction Hierarchy (X-TAH) is introduced to provide scalable XML query relaxations. X-TAH is a hierarchical tree-like knowledge structure that builds multi-level knowledge representation about the XML data tree. X-TAH can be used to guide the XML query relaxation process.

The paper is organized as follows: section 2 provides some background information including XML data model, query model and XML query relaxation types. Section 3 describes the system architecture used for INEX 03 retrieval task. Query execution and query relaxation processes are presented in Section 4. The experimental performance is discussed in Section 5. Finally we summarize our participation effort in INEX 03 and discuss future works in Section 6.

2. BACKGROUND

We first briefly describe the XML data and query model and then introduce query relaxation types in the XML model.

2.1 Data Model and Query Model

An XML document can typically be represented as an ordered, labeled tree where nodes correspond to elements and attributes, and edges represent element inclusion relationships. Each node has a label which is the tag name of its corresponding element or attribute. Elements' text content or attributes' values become the values of their corresponding nodes. Similarly, a query against an XML document can be represented as a tree with two types of edges: a parent-child edge denoted as "/", or an ancestor-descendant edge denoted as "//".

Note that in the paper, we treat an attribute as a sub-element of an element and a reference IDREF as a special type of value.

2.2 Query Relaxation Types

In the XML model, there are two types of query relaxations, value relaxations and structure relaxations:

2.2.1 Value Relaxation

In the XML context, value relaxation involves expanding the value scope of certain nodes to allow the matching of additional answers. A value can be relaxed to a range of numeric values or a set of non-numeric values. Figure 1 illustrates an example of numeric value relaxation and an example of non-numeric value relaxation. The query in Figure 1b is a relaxed query for that in Figure 1a by a numerical value relaxation, and the query in Figure 1d is a relaxed query for that in Figure 1c by a non-numeric value relaxation.

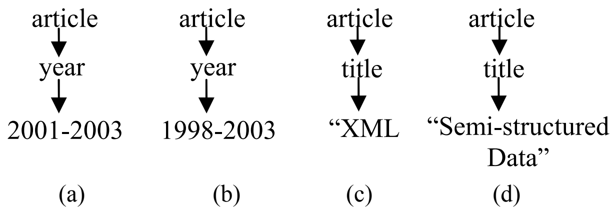


Figure 1: Two examples of value relaxation.

2.2.2 Structure Relaxation

In the XML context, structural relaxation is the process of relaxing the nodes and/or edges of a query tree. After the relaxation, a new query tree may have a different structure than the original query tree. There are three types of structural relaxations.

1) Node Re-label

In this relaxation type, certain nodes can be re-labeled to similar or equivalent tag names according to the domain knowledge. For example, in INEX 03, domain experts have identified sets of equivalent tags as shown in Figure 2. With this domain knowledge, the query */article/bdy//sec[about(., "XML")]* can be relaxed to */article/bdy//section[about(., "XML")]* by generalizing node *sec*'s label to *section*. Thus, subsections (i.e., */article/bdy//ss1*, */article/bdy//ss2* and */article/bdy//ss3*) about XML can also be returned as approximate answers.

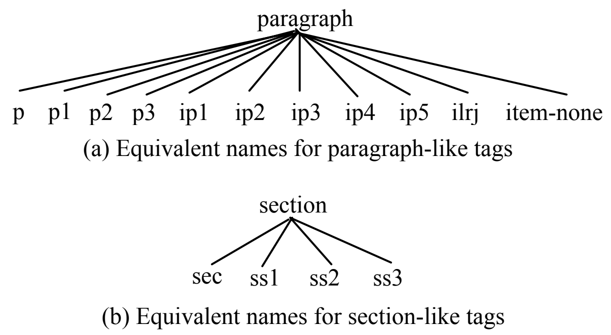

paragraph
p
p1
p2
p3
ip1
ip2
ip3
ip4
ip5
ilrj
item-none
(a) Equivalent names for paragraph-like tags
section
sec
ss1
ss2
ss3
(b) Equivalent names for section-like tags

Figure 2: Domain knowledge for equivalent tags in INEX.

2) Edge Relaxation

In an edge relaxation, a parent-child edge ('/') in a query tree can be relaxed to an ancestor-descendant edge ('//'). The semantics of an edge relaxation is that while the original query finds answers with only a parent-child relationship, the new query will be able to find answers with an ancestor-descendent relationship which is a superset of a parent-child relationship. For example, a query */article /bdy/sec[about(.,"IR")]* can be relaxed to */article/bdy //sec[about(.,"IR")]* by relaxing the structural relationship between *bdy* and *sec* from "/" to "//". */article/bdy// sec[about(., "IR")]* can be further relaxed to */article/bdy//section[about(., "IR")]*. As a result, any subsection within an article's body about IR is also returned as an approximate answer.

3) Node Deletion

In this relaxation type, certain nodes can be deleted while preserving the "superset" property. When a node *v* is a leaf node, it can simply be removed. When *v* is an internal node, the children of node *v* will be connected to the parent of *v* with ancestor-descendant edges ("//"). For example, a query */article/bdy/sec[about(., "IR")]* can be relaxed to */article//sec[about(.,"IR")]* by deleting internal node *bdy* so that a section in an article's appendix about IR can also be returned as an approximate answer.

3. THE CoXML FRAMEWORK

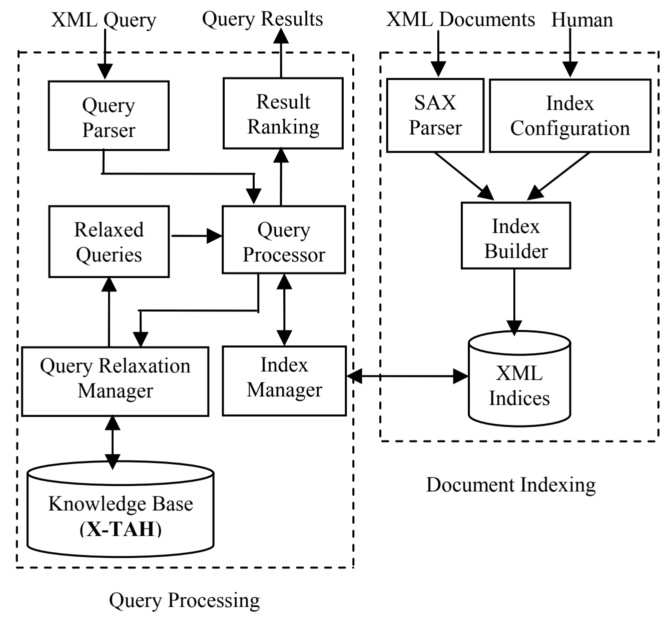


Figure 3: The CoXML System Architecture.

Figure 3 shows the architecture of the cooperative XML query answering system (CoXML), which performs two types of functions: document indexing and query processing.

Document Indexing

While a *SAX parser* [12] parses XML documents, the *Index Builder* builds indices on the data based on the index configurations provided by the *Index Configuration* module (Section 3.1). The *Index Builder* module builds several types of indices (Section 3.2) for query processing.

Query Processing

An XML query is first parsed by the *Query Parser* to check its correctness. If the query is invalid, it will be returned to the user with the error information. Otherwise, the *Query Processor* will consult the *Index Manager* to load the corresponding indices to process the query. If there are enough XML answers returned, the *Result Ranking* module will rank the results based on their relevancy to the query and return the ranked results to the user. If there are null or insufficient answers available, the X-TAH in the *Knowledge Base* will guide the *Query Relaxation Manager* to relax the query. Then the relaxed queries will be resubmitted to the *Query Processor* for answering. This process will be repeated until there are enough answers available or the query is no longer relaxable.

3.1 Index Configurations

XML documents in the INEX collection are document-centric. There are two types of tags in these documents: 1) semantic tags, and 2) presentation tags. Semantic tags describe the semantics of the elements, such as <*article*>, <*bdy*> and <*sec*> in Figure 4. Presentation tags, however, encode no semantics but the presentation styles of their embedding texts. For example, <*scp*> in Figure 4 is a presentation tag: it informs a browser to display the text bounded by <*scp*> and <*/scp*> in small caps.

```
1. <article>
2.  <bdy>….
3.    <sec>
4.       <st>K<scp>NOWLEDGE</scp> B<scp>ASED</scp>
5.            S<scp>EMANTIC</scp> T<scp>EMPORAL</scp>
6.             I<scp>MAGE</scp> M<scp>ODEL</scp>
7.      </st> …
8.    </sec> ….
10.  </bdy> ….
11. </article>
```

Figure 4 : An XML document fragment.

Presentation tags sometimes are undesirable in query processing. For example, suppose a user wants to find an article that has a section with a title containing a keyword "knowledge", which can be expressed in XPath as *//article [contains(//sec/st, "knowledge")]*. Intuitively, the XML document fragment in Figure 4 is an answer because the title of the article's section (Line 4-7) is "Knowledge Based…". However, if we do not ignore the markup <*scp*> and <*/scp*> (Line 4), it will not be returned as relevant since the presentation tag <*scp*> separates "K" from "NOWLEDGE".

To support keyword and phrase matching in document-centric XML documents, it is necessary to ignore such presentation tags [2]. The set of ignorable tags during indexing is listed in the *Index Configuration* module (Figure 3). For XML documents in the INEX collection, the list of ignorable tags for index configurations is shown in Table 1.

Category	Ignorable Tags
List-items	item-bold, item-both, item-bullet, item-diamond, item-letpara, item-mdash, item-numpara, item-roman, item-text
Lists	li, l1, l2, l3, l4, l5, l6, l7, l8, l9, la, lb, lc, ld, le, list, numeric-list, numeric-rbrace, bullet-list
Text font, style, size, emphasis etc	ss, tt, b, ub, it, rm, scp, u, sub, super, large, ariel, bi, bu, bui, cen, rom, h, h1, h1a, h2, h2a, h3, h4

Table 1: Index configurations used in INEX 03.

3.2 Indexing XML Documents

Each node in an XML data tree is represented by a triple (ID, size, level), where *ID* uniquely identifies the node in the XML document collections, *size* indicates the size of the sub-tree rooted at this node and *level* describes the node's height in the data tree. The advantage of this encoding scheme is that the hierarchical relationship (either parent-child or ancestor-descendant) between any pair of nodes can be checked in constant time.

Values of nodes are processed in the following three steps:

1) A stop word list is used to delete words with weak discriminative powers (such as articles, pronouns, conjunctions and auxiliary words). This step significantly reduces the index size.

2) The Lovins stemmer [7] is used to derive word stems. For example, the stem for "clustering", "clusters" and "clustered" is "cluster". Word stemming reduces the index size and also supports keyword matching.

3) Each stem is represented as a pair (ID, pos), where *ID* is the unique identifier of a node containing this stem and *pos* is its relative position in the node's value. We assign a node's ID to its corresponding value to avoid the expensive join operations between nodes and their values; and keep each stem's relative position in a node's value to support phrase matching. The use of relative position minimizes index size. More importantly, relative positions are easily adaptable to changes in XML documents. Deleting a stem from or inserting a new stem into a node *v* in an XML document only affects the relative positions of the stems in node *v*, but not any other stems in the XML document. Using a stem's global position in a document to represent a stem, however, is expensive to maintain in case of any change in XML documents. Deleting a stem from or inserting a new stem into an XML document affects the global positions of all the following stems in the XML document.

To support efficient and scalable query processing, the *Index Builder* builds several types of indices, as listed below:

- Tag Name Index (tag name → name identifier)

  Each tag name *s* is mapped to a unique name identifier (NID) to minimize index size and computation overhead by eliminating string comparisons.

- Node Index (name identifier → (ID, size, level))

  Each name identifier is mapped to a set of nodes (in the form of (ID, size, level)) whose labels are the same as the one represented by the name identifier.

- Inverted Stem Index (stem s → (ID, pos))

  Each stem *s* is mapped to a set of pairs (ID, pos), where *ID* is the unique identifier of the node that contains stem *s* and *pos* is its relative position in the node's value.

- Text Size Index (ID → text size)

  For each node that has a value, its ID is mapped to the number of words it contains. The text size index is useful for result ranking (Section 4.4).

The indices for the XML document in Figure 5 are shown in Table 2, which consist of four indices: a tag name index (Table 2.a); a node index (Table 2.b); an inverted stem index (Table 2.c) and a text size index (Table 2.d).

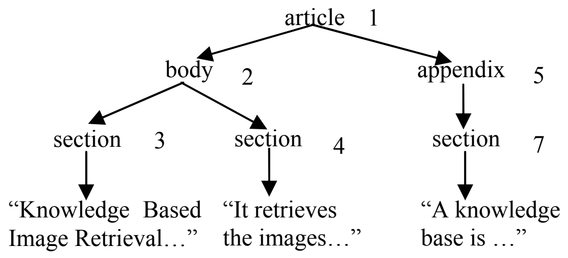


Figure 5 : A sample XML document tree.

Tag Name	NID
article	0
appendix	1
body	2
section	3

(a) A tag name index

NID	Nodes (ID, size, level)
0	(1, 5, 1)
1	(5, 1, 2)
2	(2, 2, 2)
3	(3, 0, 3) (4, 0, 3) (7, 0, 3)

(b) A node index

Stem	(ID, pos) pairs
bas	(3, 1) (7, 2)
imag	(3,2) (4, 3)
knowledg	(3, 0) (7, 1)
retrief	(3, 3) (4, 1)

(c) An inverted stem index

ID	Text Size
1	1000
2	600
…	…
7	100

(d) A text size index

Table 2: Indices for the XML document in Figure 5: a) maps a tag name to a unique name identifier; b) maps a name identifier to a set of nodes in the format of (ID, size, level); c) maps a stem to a set of (ID, pos) pairs; and d) maps a node ID to its text size.

3.3 Knowledge Base

Knowledge Base is an important part in the system architecture, which facilitates XML query relaxation and consists of the following two parts:

1) Domain Ontology

Domain ontology provides the semantic relationships among the tag names in an XML dataset, such as groups of equivalent or similar tag names, which can guide the node re-label. For example, Figure 2 lists two sets of equivalent or similar tag names for INEX 03, one for paragraph-like nodes (Figure 2a) and another for section-like nodes (Figure 2b).

2) Knowledge-based XML Relaxation Index (X-TAH)

Query relaxation enlarges the search scope of query conditions which can be accomplished by viewing a query object at a higher conceptual level. To support query relaxation in the XML model, we are generating two types of relaxation index structures, XML Type Abstract Hierarchy - X-TAH: value relaxation index and structure relaxation index for guiding value and structure relaxations respectively.

An X-TAH is a tree-like multi-level knowledge representation of the structure and value characteristics of an XML data tree. X-TAH can be automatically generated by first identifying a set of similar objects (i.e., similar values or similar structure fragments) based on XML relation types, then clustering these objects based on their inter-object distance, and finally assigning meaningful internal node representatives [6]. Objects in an XML value relaxation index are values of XML elements and attributes, while objects in an XML structure relaxation index are structure fragments of XML data trees. X-TAH has two types of nodes: internal nodes and leaf nodes. This differentiates it from a traditional cluster which has no internal nodes. An internal node in an X-TAH is a representative that summarizes the characteristics of all the objects in that cluster, while a leaf node is an object that is either a value (in the XML value relaxation index) or a structure fragment of an XML data tree (in the XML structure relaxation index). For example, Figure 6 is an X-TAH for the values of *//fig//no* in the INEX collection. Figure 7 is an X-TAH for structure relaxation for *//article/*//sec*.

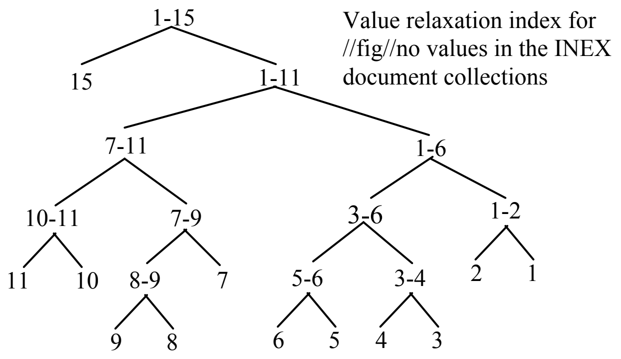
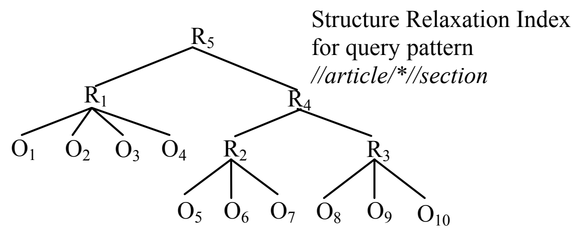

Value relaxation index for //fig//no values in the INEX document collections
1-15
15
1-11
7-11
1-6
10-11
7-9
3-6
1-2
11
10
8-9
7
5-6
3-4
2
1
9
8
6
5
4
3

Figure 6: An Example of value relaxation index.

4. QUERY PROCESSING&RELAXATION

The control flow for processing the INEX query topics is illustrated in Figure 8. First, each topic is translated into a tree representation that the *Query Processor* can follow


Structure Relaxation Index for query pattern *//article/*//section*
R_5
R_1
R_4
O_1 O_2 O_3 O_4
R_2
R_3
O_5 O_6 O_7 O_8 O_9 O_{10}

O_1: //article/bdy/sec	O_2: //article/bdy/sec/ss1
O_3: //article/bdy/sec/ss1/ss2	O_4: //article/bdy/sec/ss1/ss2/ss3
O_5: //article/bm/sec	O_6: //article/bm/sec/ss1
O_7: //article/bm/sec/ss1/ss2	O_8: //article/bm/app/sec
O_9: //article/bm/app/sec/ss1	O_{10} : //article/bm/app/sec/ss1/ss2
R_1 : //article/bdy//sec	R_2 & R_4: //article/bm//sec
R_3 : //article/bm/app//sec	R_5 : //article//sec

Figure 7: An example of structure relaxation index.

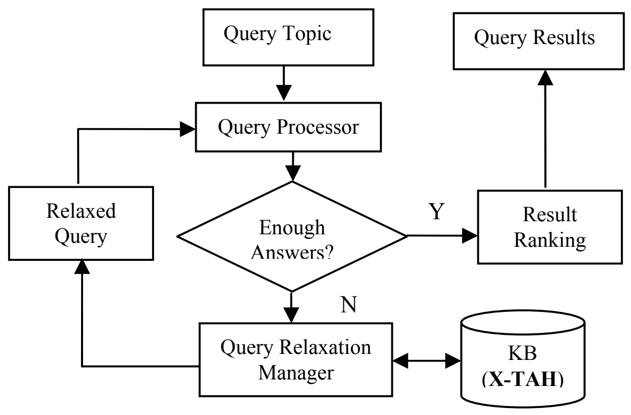


Figure 8: The control flow of CoXML query processing.

and process. Next, the query is executed to produce a set of results. If there are enough answers produced, the *Result Ranking* ranks each result based on its relevancy to the query. Otherwise, the *Query Relaxation Manager* relaxes the query based on an X-TAH (*Knowledge Base*). The relaxed queries are then submitted to the *Query Processor* for deriving approximate answers. This process will iterate until either there are enough answers or the query is no longer relaxable.

4.1 Transformation of INEX Query Topics

The topic transformation can be accomplished by the following three steps:

1) Translating each INEX query topic expressed in XPath [16] into a tree representation. This is a straightforward step as most XPath expressions use tree structures.

2) Categorizing each term and phrase in the <title></title> part of a query into one of the three categories as defined below:

- PREFER (P): any term or phrase prefixed by "+" belongs to this category.
- REJECT (R): any term or phrase prefixed with "-" or appearing after "!=" operator belongs to this category.
- NORMAL (N): any term or phrase not in the PREFER or REJECT category is classified in the NORMAL category.

3) Expanding a query's value predicates in the <title></title> part with terms and phrases in the <keyword></keyword> part that do not appear in the <title></title> part. Such terms and phrases are in the KEYWORD (K) category.

For example, the tree representation for the INEX 03 query topic 89 (Figure 9) with classified terms and phrases and expanded keyword value predicates is shown in Figure 10.

```
<inex_topic topic_id="89" query_type="CAS" ct_no="123">
<title>
//article[about(./bdy,'clustering "vector quantization" +fuzzy +k-means
+c-means -SOFM -SOM')]//bm//bb[about(.,'"vector quantization"
+fuzzy clustering +k-means +c-means') AND about(./pdt,'1999')
AND ./au/snm != 'kohonen']
 </title>
<description>
Find articles about vector quantization or clustering and return
bibliography details of cited publications about clustering and vector
quantization methods, from recent years, not authored by Kohonen.
</description>
<narrative>
Bibliography elements of publications, preferably from around 2000
(1996 to 2002 is fine, descending relevance thereafter). Preferred
documents have reference to k-means or c-means clustering. Not
interested in publications where the author is Kohonen, or in his work
on self organizing feature maps (SOM SOFM). The citing article and
the cited publication should be about clustering or vector quantization
methods.
</narrative>
<keywords>
cluster analysis,adaptive clustering,Generalized Lloyd, LBG, GLA
</keywords>
</inex_topic>
```

Figure 9: INEX 03 Query Topic 89.

4.2 Query Processing

After topic translation, a query tree is sent to the *Query Processor* for execution. Several query processing strategies have been proposed for XML tree pattern queries (e.g., [10, 11]). The basic idea of these query processing strategies is to decompose an XML tree pattern query into a set of basic structural relationships (i.e., parent-child and ancestor-descendant) between pairs of nodes. Query answers can be derived by first matching each of these basic structural relationships and then combining these basic matches. Matching each structural relationship is usually based on XML indices and structural join algorithms (e.g., [10, 4]). We leverage on these query processing strategies for deriving the exact matched query answers with additional care for processing value constraints in a query tree.

As illustrated in section 4.1, each term and phrase in the <title></title> and <keyword></keyword> part of a query topic is classified into one of the four categories. The semantics for terms and phrases in the PREFER, NORMAL and KEYWORD categories are quite clear. The semantics for terms and phrases in the REJECT category, however, is context sensitive. If a value predicate in a query contains only REJECT category terms and phrases, it is interpreted as "strictly MUST NOT". Otherwise it means "fuzzy MUST NOT". For example, for the query tree in Figure 10, the semantics for "R: SOFT, SOM" under node *bdy* is different from that for "R: Kohonen" under node *snm*. The semantics for the first one is that if an article's body (*bdy*) contains either term "SOFT" or "SOM", it is still an answer but with lower relevancy. However, the semantics for the second one is that if an author's surname (*snm)* contains the term "Kohonen", it will not be returned as an answer.

4.3 Query Relaxation

If there is no answer or not enough available answers, the *Query Processor* will call the *Query Relaxation Manager* to relax the query in the following three steps:

1) A set of relaxable conditions as well as their respective relaxation order are generated. For example, for INEX 03 query topic 85, *//article[.fm//yr >= 1998 and .//fig//no >9]//sec[about(.//p, 'VR, "virtual reality", "virtual environment", cyberspace "augmented reality"')]*, the set of relaxable conditions and their relaxation order may be assigned as: relaxing the value of figure numbers (*//article//figure/no > 9*) first and then relaxing the value of the article's year (*//article/fm/yr >= 1998*).

2) For each relaxable condition, a relaxation index (X-TAH) will be selected to guide the relaxation process. The *Query Relaxation Manager* will first examine the internal representatives to find the one that contains the exact or closest match to the relaxable condition and relax the query condition accordingly. There are two types of operations in an X-TAH: i) *Generalization* – moving up the hierarchy to enlarge the search scope; and ii) *Specification* – moving down the hierarchy to narrow the search scope. The query relaxation process may incur a sequence of *Generalization* and *Specification* operations.

3) The relaxed queries will be sent to the *Query Processor* to derive approximate answers. This relaxation process will continue until there are enough answers or the query is no longer relaxable.

For example, in the query topic 85, to relax the query condition, *//article//figure//no > 9*, the *Query Relaxation Manager* will select the value relaxation index in Figure 6

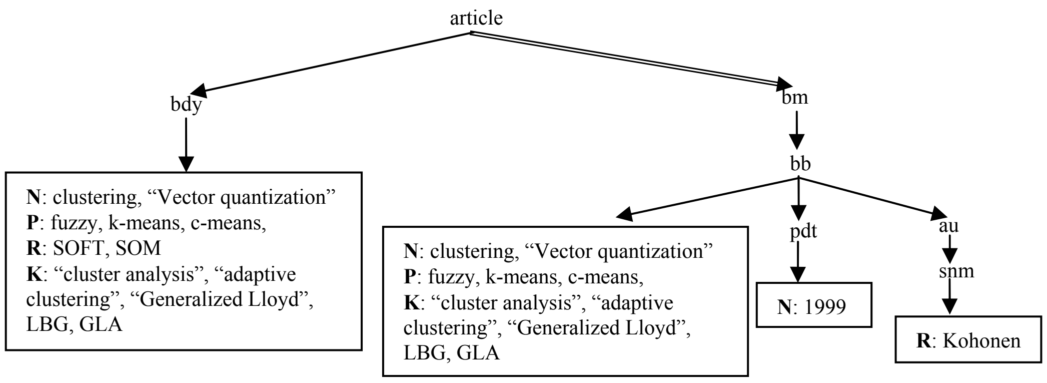

article
bdy
bm
bb
pdt
au
snm
N: clustering, "Vector quantization"
P: fuzzy, k-means, c-means,
R: SOFT, SOM
K: "cluster analysis", "adaptive clustering", "Generalized Lloyd", LBG, GLA
N: clustering, "Vector quantization"
P: fuzzy, k-means, c-means,
K: "cluster analysis", "adaptive clustering", "Generalized Lloyd", LBG, GLA
N: 1999
R: Kohonen

Figure10: The tree representation of query topic 89 in INEX 03.

to guide the relaxation process. The system first locates the closest matched internal representative, which is 8-9, and then relaxes the query condition to *//article//figure//no > 8* to derive approximate answers.

Similarly, to relax the structure constraint //article/bdy/sec in the query topic 69 (i.e., */article/bdy/sec[about(.//st, '"information retrieval"')]*), the *Query Relaxation Manager* will first locate the closest matched internal representative, which is *//article/bdy//sec*, and then relax the query topic to *//article/bdy//sec[about(.//st, '"information retrieval"')]* to derive approximate answers.

4.4 Result Ranking

The query results are ranked by the *Result Ranking* module before returning them to the user. Query results are ranked according to the following priorities: first query results from the original query and then approximate answers from the relaxed queries. The approximate answers are further ranked according to the relaxation order. For example, for the query topic 85, there are two relaxation conditions: 1) *//article//fig//no >* 9 and 2) *//article/fm//yr > 1998*. The relaxation order between them is to relax the first condition and then the second one. As a result, the approximate answers for the first relaxation condition are ranked before the approximate answers for the second relaxation condition.

For the query results in the same category, they are ranked according to the following formula:

$$rank_u = \sum_{i = P, N, K, R} \left(\frac{w_i}{|C_i|} \sum_{j=1}^{|C_i|} \frac{frequency\ of\ term_{ij}}{Text\ Size\ of\ node\ u} \right)$$

where w_i is the weight assigned to one of the four categories C_i (i = P, N, K R); $|C_i|$ is the total number of stems (a phrase is counted as a term) in the category; *frequency of term*$_{ij}$ is the number of occurrence of term$_j$ from category C_i in node *u*; and *Text Size of node u* refers to the total number of words in node *u*, which can be accessed from the text size index.

5. EXPERIMENTAL OBSERVATIONS

We implemented XML indexing and query processing algorithms in Java; and carried out INEX 03 experiments on a Linux machine with a 2.4GHz XEON III CPU and 1 GB main memory. We shall now discuss the experimental results based on two performance measurements: index size and query execution times.

The indices for all the INEX document collections occupy about 1.2GB, which is roughly about twice the size of the XML document collections. Four types of indices are built by the *Index Builder*: tag name index, node index, text size index, and inverted stem index. The first three are relatively small and the last one is quite large.

Query processing time depends on the following factors:

1) Number of stems and phrases in a query and their corresponding frequency in the XML data.

The query processing time depends on the number of stems and phrases a query contains and their corresponding frequencies in XML documents. More frequent stems and phrases require longer query processing time than less frequent ones.

2) Number of structure constraints in a query and their corresponding frequency in the XML data.

The required query processing time is sensitive to the number of structure constraints a query contains. It is also sensitive to their frequencies in XML documents. For example, a less frequent structure constraint, Q_1 *//article/fm//pdt*, can be processed much faster than a more frequent one Q_2 *//article/bdy//p*. (Q_1 returns the publication date (*pdt*) element of an article in its front matter part (*fm*) and Q_2 returns the paragraph (*p*) elements of an article in its body part (*bdy*)).

3) The level of query relaxation and the number of relaxable conditions existed in the query.

The more relaxable query conditions a query topic contains, the longer it takes to derive the approximate answers.

Depending on the complexity of its value and structure constraints, a content-and-structure (CAS) query takes from several seconds to over a minute to get exact matched answers. For a relaxable query, it might take several minutes to generate the relaxed queries and derive approximate answers.

Due to the unavailability of VCAS relevancy assessment, we did not report the precision/recall performance of our cooperative query answering system in this paper.

6. SUMMARY AND FUTURE WORKS

In this paper, we describe how we index XML documents and extend the query relaxation technique to the XML model to support cooperative XML query answering.

During our INEX 03 investigation, several problems were discovered, which needs future investigations:

1) Index Configurations

Our current index configuration only contains a list of ignorable tags. We plan to support other index configurations, such as ignorable annotations in which both elements and their value can be ignored.

2) Uniform Value Index Scheme

In our current system, we index the elements' text content and attributes' values in XML documents uniformly. Each non-stop word is stemmed without considering the value's characteristics. Such an index approach sometimes may return undesirable results. For example, for a content-only (CO) query "*web, internet*", the document fragment "*<author><snm>webb</snm></author>*" will be returned as an answer since "webb" and "web" share the same stem: "web". To avoid such undesirable results, we plan to work on a configurable value index framework which supports multiple value processing options and index types based on the value's characteristics.

3) Ranking Functions

Our current system only supports relative ranking. Ranking functions for query results needed to be investigated to provide more user and context sensitive ranking.

4) Query Relaxation Language

No explicit relaxation constructs is available in a query topic for specifying the relaxable query conditions as well as their relaxation order. We plan to develop a cooperative query language that enables users to specify relaxation constructs in the queries.

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The TIJAH XML-IR system at INEX 2003

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ABSTRACT

This paper discusses our participation in INEX (the Initiative for the Evaluation of XML Retrieval) using the TIJAH XML-IR system. TIJAH's system design follows a 'standard' layered database architecture, carefully separating the conceptual, logical and physical levels. At the conceptual level, we classify the INEX XPath-based query expressions into three different query patterns. For each pattern, we present its mapping into a query execution strategy. The logical layer exploits *probabilistic region algebra* as the basis for query processing. We discuss the region operators used to select and manipulate XML document components. The logical algebra expressions are mapped into efficient relational algebra expressions over a physical representation of the XML document collection using the 'pre-post numbering scheme'. The paper concludes with a preliminary analysis of the evaluation results of the submitted runs.

1. INTRODUCTION

This paper describes our research for INEX 2003 (the Initiative for the Evaluation of XML Retrieval). We participated with the TIJAH XML-IR retrieval system, a research prototype built on top of the MonetDB database kernel [1]. Key feature of the TIJAH system is its layered design, following the basic system architecture of relational database management systems.

Traditional information retrieval systems represent a document as a 'bag-of-words'. Inverted file structures provide the basis for implementing a retrieval system for such 'flat' documents. In the case of structured documents however, we think designing the retrieval system following 'the database approach' is best to keep the more complex data representation manageable.

The main characteristic of the database approach is a strong separation between conceptual, logical and physical levels, and the usage of different data models and query languages at each of those levels [20]. In relational database systems, a significant benefit of this *data abstraction* (through the separation between the levels in database design) is to enable query optimization. A SQL query (a 'calculus expression') at the conceptual level is first translated into relational algebra. The algebraic version used at the logical level is then rewritten by the query optimizer into an efficient physical query plan. The physical algebra exploits techniques like hashing and sorting to improve efficiency [8].

For XML-IR systems, following this separation in layers gives another, additional advantage: by choosing the appropriate level of abstraction for the logical level, the development of probabilistic techniques handling structural information is simplified, and kept orthogonal to the rest of the system design. Section 3 details our approach, based on a probabilistic extension of text region algebras.

The paper is organized along the layers of the TIJAH system design. The following Section describes the query language used at the conceptual level, identifies three patterns in the INEX topic set, and explains how the language modeling approach to information retrieval is used for the *about* operator. Section 3 presents a probabilistic region algebra for expressing the three query patterns. Section 4 explains how the algebraic expressions are mapped into efficient relational algebra expressions over a physical representation of the XML document collection using the 'pre-post numbering scheme'. We conclude with a discussion of the experiments performed with our approach for the three INEX search tasks.

2. CONCEPTUAL LEVEL

For the conceptual level, we used the INEX query language as proposed by the INEX Initiative in 2002. The INEX query language extends XPath with a special *about* function, ranking XML elements by their estimated relevance to a textual query. As such, the invocation of the *about* function can be regarded as the instantiation of a retrieval model.

The retrieval model used for the *about* function is essentially the same as that used at INEX 2002 [12, 14]. We calculate the probability of complete relevance of a document component, assuming independence between the probability of relevance on exhaustivity and the probability of relevance on specificity.

The probability of relevance on exhaustivity, $P(R_E)$, is estimated using the language modeling approach to information retrieval [11]. Instead of document frequency, we have used collection frequencies for the background model. The probability of relevance on specificity, $P(R_S)$, is assumed to be directly related to the component length (following a log-normal distribution). Its steep slope at the start discounts the likelihood that very short document components are relevant. Its long tail reflects that we do not expect long document components to be focused on the topic of request either.

The language model as used by our system disregards structure within a document component, i.e., the model treats a document component as a 'flat-text' document. This model property, and an informal inspection of the INEX 2003 topic list, led us to use only a subset of possible location step axes within an *about* function call; we only used the *descendant-or-self::qname* location step axis. Allowing other axes, like *sibling::qname* or *following::qname* requires correct probabilistic modeling for estimating probabilities in the language model, which our model did not offer at the time of evaluation.

Table 1: SCAS and VCAS pattern set. Note that *xp*, *xp2*, *axp*, *axp1* and *axp2* are location steps, and *'t/p'* denotes any set of terms or phrases to search for.

Pattern	Pattern definition
P1	xp[about(axp, 't/p')]
P2	xp[about(axp1, 't1/p1') AND about(axp2, 't2/p2')]
	xp[about(axp1, 't1/p1') OR about(axp2, 't2/p2')]
P3	xp[about(axp1, 't1/p1')]/xp2[about(axp2, 't2/p2')]
	xp[about(axp1, 't1/p1')]//xp2[about(axp2, 't2/p2')]

Since we did not have an automatic query processing facility, we processed the queries manually but in a mechanic fashion. Processing the INEX query patterns takes place in two steps:

- classify the query into (a sequence of) three basic *query patterns* (shown in Table 1);
- create a query plan to process the queries. The query patterns are visualized in Figure 1.

The basic pattern for all XPath based queries is the single *location step*, as defined in [7], augmented with an *about* function call (pattern *P1* in Table 1). When referring to, for example *xp*, we refer to the node-set representing the location step *xp*; in other words, a path leading to a certain location (or node) in the XML syntax tree. The first query pattern consists of one location step to identify the nodes to be retrieved, ranked by an *about* expression over a node-set reached by a second location step. The two other (more complex) patterns *P2* and *P3* are essentially multiple interrelated instances of the basic pattern *P1*. The XPath location steps may also apply (Boolean) predicate filters, e.g. selecting nodes with a particular value range for `yr`.

3. LOGICAL LEVEL

The logical level is based on a probabilistic region algebra. Region algebra was introduced by Burkowski [2], Clarke et al. [3], and Tova and Milo [4]. The aim of the earliest text region algebra approaches has been to enable structured text search. Later, it has been applied to related tasks as well, including search on nested text regions [13], processing of structured text [17], and ranked retrieval from structured text documents [15].

The basic idea behind region algebra approaches is the representation of text documents as a set of 'extents', where

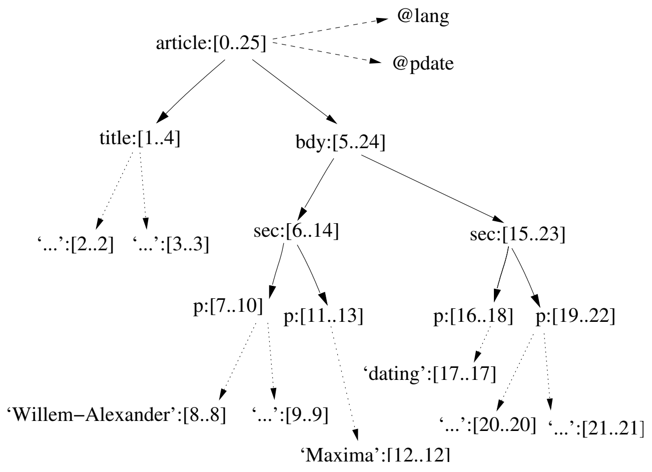

Figure 2: Example XML syntax tree with start and endpoint assignment.

each extent is defined by its starting and end position. The application of the idea of text extents to XML documents is straightforward. If we regard each XML document instance as a linearized string or a set of *tokens* (including the document text itself), each component can then be considered as a text region or a contiguous subset of the entire linearized string. Therefore, a text region a can be identified by its starting point s_a and ending point e_a within the entire linearized string. Figure 2 visualizes an example XML document (as a syntax tree) with the start point and end point numbering for the nodes or regions in the tree. As an example, the *bdy*-region corresponds to (closed) interval [5..24].

Let us introduce the basic set of region operators. We use capital letters (A, B, C) to denote the region sets, and their corresponding non-capitals to denote regions in these region sets (a, b, c). The operators take region sets as input and give a result which is again a region set. The definition of region operators is given in Table 2. Interval operator $I(t)$ returns the region set representing the occurrences of term t as a content word in the XML document; note that it gives a result set in which $s_a = e_a$ for every region, assuming t is a single term and not a phrase. Location operator $L(xp)$ denotes the sequential application of XPath location steps, i.e., axis- and node-tests (a definition of axis- and node-tests can be found in [16]). Optionally, location step operator L also processes predicate tests on node or attribute values specified in the XPath expression.

Table 2: Region Algebra Operators.

Operator	Operator definition
$I(t)$	$\{a \mid s_a, e_a$ are pre and post index of term t$\}$
$L(xp)$	$C = XPath(xp)$
$A \rhd B$	$\{a \mid a \in A \wedge b \in B \wedge s_a \leq s_b \wedge e_a \geq e_b\}$
$A \lhd B$	$\{a \mid a \in A \wedge b \in B \wedge s_a \geq s_b \wedge e_a \leq e_b\}$
$A \bigtriangleup B$	$\{c \mid c \in A \wedge c \in B\}$
$A \bigtriangledown B$	$\{c \mid c \in A \vee c \in B\}$

Table 3 expresses the patterns identified in the previous Section using region algebra operators (ignoring ranking for

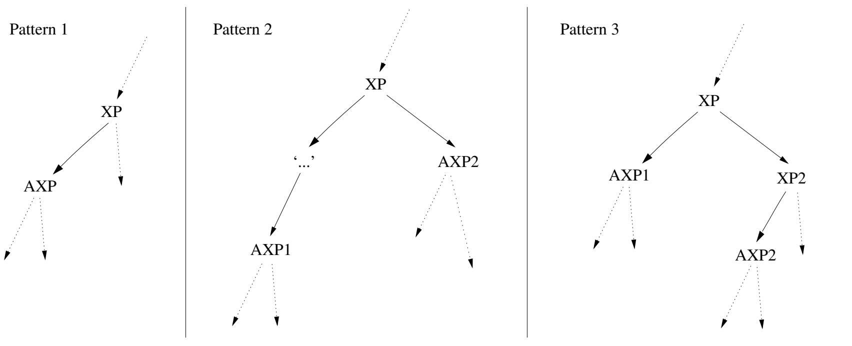

Figure 1: Example instances of the three defined patterns.

Table 3: Pattern definitions based on pure region algebra operators.

Pattern	Algebraic expression
$P_1(xp, axp)$	$L(xp) \triangleright (L(axp) \triangleright I(t))$ $L(xp) \triangleright ((L(axp) \triangleright I(t_1)) \bigtriangleup (L(axp) \triangleright I(t_2)) \bigtriangleup ... \bigtriangleup (L(axp) \triangleright I(t_n)))$
$P_2(xp, axp1, axp2)$	$P_1(xp, axp1) \bigtriangleup P_1(xp, axp2)$ $P_1(xp, axp1) \bigtriangledown P_1(xp, axp2)$
$P_3(xp1, xp2, axp1, axp2)$	$P_1(xp2, axp2) \lhd P_1(xp1, axp1)$

now). Pattern 1 distinguishes between term (t) and phrase expressions ($p = \{t_1, t_2, ..., t_n\}$). Patterns 2 and 3 are rewritten into several interrelated instances of pattern 1. Table 4 introduces a probabilistic extension of the pure region algebra operators. In order to introduce ranking, we extend the notion of region with its *relevance score*; i.e., every region a has an associated relevance score p_a. In cases where pure region algebra operators are used, the value of the introduced relevance score is equal to a predefined default value (e.g., $p_a = 1$) for each resulting region in a region set.

Table 5 gives the probabilistic region algebra expressions corresponding to the INEX query patterns identified before. The *tp1* is used to denote *'t1/p1'* or the combination of *'t1/p1'* and *'t2/p2'* (the choice between these options is made at the conceptual level). Similarly, *tp2* is either *'t2/p2'* or a combination of *'t2/p2'* and *'t1/p1'*.

Expressing query plans using the operators given in Table 4 preserves *data independence* between the logical and the physical level of a database. Similarly, these operators enable the separation between the structural query processing and the underlying probabilistic model used for ranked retrieval: a design property termed *content independence* in [6]. The instantiation of these probabilistic operators is implementation dependent and does not influence the global system architecture. This gives us the opportunity to change the probabilistic model used or to modify the existing model while keeping the system framework, creating the opportunity to compare different probabilistic models with minimal implementation effort.

4. PHYSICAL LEVEL

The physical level of the TIJAH system relies on the MonetDB binary relational database kernel [1]. This Section details implementation and execution strategy for each of the patterns.

The text extents used at the logical level are represented by XML text regions at the physical level, and encoded using a preorder/postorder tree encoding scheme, following [9, 10]. The XML text regions are stored as three-tuples $\{ s_i, e_i, t_i \}$, where:

- s_i and e_i represent the start and end positions of XML region i;
- t_i is the (XML) tag of each region.

The set of all XML region tuples is named the *node index* $\mathcal{N}$. Index terms present in the XML documents are stored in a separate relation called the *word index* $\mathcal{W}$. Index terms are considered text regions as well, but physically the term identifier is re-used as both start and end position to reduce memory usage. The physical layer has been extended with the text region operators shown in Table 6. Boolean predicate filters are always applied first. For further details on this indexing scheme, refer to [5, 14].

4.1 Pattern 1

Pattern 1 for VCAS Processing pattern 1 in Table 1 requires two basic steps: relating node-sets *xp* and *axp* to each other, and processing the *about* operator. Nodesets *xp* and *axp* must have a parent - descendant[1] structural relation-

[1]Parent - child relationships are considered a specific variant of parent - descendant relationships.

Table 6: Text region operators at the physical level.

Operator	Definition
$a \supset b$	$true \iff s_b > s_a \wedge e_b < e_a$
$a \subset b$	$true \iff s_a > s_b \wedge e_a < e_b$
$A \bowtie_{\supset} B$	$\{(s_a, s_b)\vert\ a \leftarrow A,\ b \leftarrow B,\ a \supset b\}$
$A \bowtie_{\subset} B$	$\{(s_a, s_b)\vert\ a \leftarrow A,\ b \leftarrow B,\ a \subset b\}$

Table 4: Probabilistic region algebra operators. Note that the "ranked containing" and "ranked and" operators are used to define the *about* function.

Operator	Operator description	Operator usage examples
$A \triangleright B$	ranked containing (based on LM)	$L(axp) \triangleright I(t)$
$A \trianglerighteq B$	average containing	$L(xp) \trianglerighteq (L(axp) \triangleright I(t))$
$A \Delta B$	ranked and (based on LM)	$L(xp) \trianglerighteq ((L(axp) \triangleright I(t_1)) \Delta (L(axp) \triangleright I(t_2)))$
$A \trianglelefteq B$	average contained	$(L(xp1) \trianglerighteq (L(axp1) \triangleright I(t_1))) \trianglelefteq (L(xp2) \trianglerighteq (L(axp2) \triangleright I(t_2)))$
$A \bigtriangleup B$	complex and	$(L(xp) \trianglerighteq (L(axp1) \triangleright I(t_1))) \bigtriangleup (L(xp) \trianglerighteq (L(axp2) \triangleright I(t_2)))$
$A \bigtriangledown B$	complex or	$(L(xp) \trianglerighteq (L(axp1) \triangleright I(t_1))) \bigtriangledown (L(xp) \trianglerighteq (L(axp2) \triangleright I(t_2)))$

Table 5: Pattern definitions based on probabilistic region algebra operators.

Pattern	Algebraic expression
$P_1(xp, axp, t)$	$L(xp) \trianglerighteq (L(axp) \triangleright I(t))$
$P_1(xp, axp, p)$	$L(xp) \trianglerighteq ((L(axp) \triangleright I(t_1)) \Delta (L(axp) \triangleright I(t_2)) \Delta ... \Delta (L(axp) \triangleright I(t_n)))$
$P_2(xp, axp1, axp2, tp1, tp2)$	$P_1(xp, axp1, tp1) \bigtriangleup P_1(xp, axp2, tp2)$
	$P_1(xp, axp1, tp1) \bigtriangledown P_1(xp, axp2, tp2)$
$P_3(xp1, xp2, axp1, axp2, tp1, tp2)$	$P_1(xp2, axp2, tp2) \trianglelefteq P_1(xp1, axp1, tp1)$

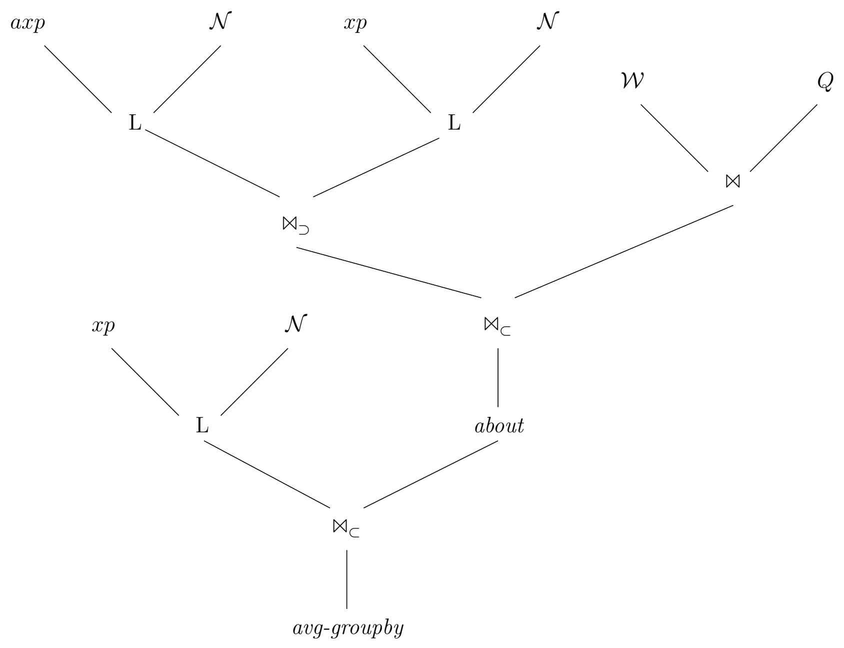

Figure 3: Physical query plan for pattern 1.

ship. So, the pattern is processed as follows (visualized in Figure 3):

- Determine the correct *axp* node-set for ranking. On the physical level, this is done by executing a containment join between the node-sets *xp* and *axp*: $axp \bowtie_{\subset} xp$. The result of this containment join is *cxp* or the set of those nodes of *axp* which are contained within nodes in *xp*;
- Perform the *about* operation on the nodes in *cxp* (the combination of $\triangleright$ and Δ operators on the logical level);
- Return the ranking for the *xp* node-set, based on the rankings of the nodes present in *cxp*. Note that it is possible that the ranking returns a ranking for multiple *axp* descendant nodes for a single *xp* node (for example, multiple sections within an article). In that case, we take the **average** as the final score for the *xp* node in question. This step is the physical equivalent of the logical $\triangleright$ (one descendant of the type of *axp*) or logical $\trianglerighteq$ (multiple descendants of the type of *axp*) operator.

Pattern 1 for SCAS The processing of pattern 1 for the SCAS run does not differ from the processing performed for the VCAS run. The containment join will automatically remove those *xp* nodes not containing one or more *axp* nodes. This ensures only the 'correct' *axp* nodes, those within a node from the *xp* node-set, will be ranked.

4.2 Pattern 2

Pattern 2 for VCAS For the processing of pattern 2 for the VCAS scenario, we assume that conjunctions and disjunctions specified in the query relate to the structure, and never to the query terms. In case node-sets *axp1* and *axp2* are equal, the pattern is rewritten to a pattern 1. If the node-sets *axp1* and *axp2* are not equal, it is possible these node-sets represent completely different parts of the (sub)tree below *xp*, as depicted in Figure 1. In path-based terms, if the (sub)tree starting at *xp* does not contain both paths *axp1* and *axp2*, that *xp* tree cannot be relevant for the strict scenario.

However, for a more vague query scenario, we argue that the absence of a descendant node does not render the requested (ancestor) target node irrelevant completely. Consider the following expression:

```
/article[
    about(./abstract, 'information retrieval')
            AND about(.//section, 'XML data')
    ]
```

If an article contains no abstract, but it does score on 'XML data' in one or more of the sections, the question is whether the article is completely irrelevant. For a vague retrieval scenario this might not be the case. Therefore, we decided to process these expression types as follows. We split up the expression into a series of pattern 1 expressions, and combine the results of the individual pattern 1 executions. The example above is split up into the following two pattern 1 expressions:

```
- /article[about(./abs, 'information retrieval XML data')]
- /article[about(.//sec, 'information retrieval XML data')]
```

Both subpatterns are processed as pattern 1. The two resulting node-sets need to be combined for a final ranking. An intuitive combination function for the $\triangle$ operator is taking the **minimum** of the (non-zero) descendant scores, and for the $\bigtriangledown$ operator the **maximum**. Note that, alternatively, a more formal probabilistic choice would be to use product and sum instead of minimum and maximum; whether this yields better results is an open question for further research.

Pattern 2 for SCAS For the SCAS scenario, all of the descendant nodes present in *axp1* and *axp2* need to be present in the context of an *xp* node. In path-based terms: if the path *xp* does not contain both a path *axp1* and a path *axp2*, the path *xp* cannot be relevant. We filter out those *xp* paths, not containing both the *axp1* and *axp2* paths. This additional filtering step and the choice of operator to implement the complex 'and' ($\triangle$) and 'or' ($\bigtriangledown$) operators define together the difference between strict and vague scenarios.

4.3 Pattern 3

Pattern 3 for VCAS Pattern 3 can be processed like pattern 2, except for the fact that the target element now lies deeper in the tree. We process this pattern by first splitting it up into multiple instances of pattern 1:

```
- xp[about(axp1, 't1/p1 t2/p2')]
- xp/xp2[about(axp2, 't1/p1 t2/p2')]
```

The pattern 1 execution already provides for aggregation of scores of a set of nodes of the same type, within a target element. The question remains however how to combine the scores of the nodes present in node-sets */xp/axp1* and */xp/xp2/axp2*. Like before, these node-sets can represent nodes in completely different parts of the (sub)tree.

Based on the observation that the user explicitly asks for the nodes present in the */xp/xp2* node-set, we decided to use the rankings of those nodes as the final rankings. The first *about* predicate reduces node-set *xp* to those nodes for which a path *axp1* exists. For the vague scenario however, we argue that absence or presence of *axp1* does not really influence target element relevance (similar to pattern 2 in subsection 4.2).

Summarizing, the first *about* predicate in the pattern mentioned at the start of this subsection is dropped, rewriting the resulting pattern to a pattern 1 instance:

```
/xp/xp2[about(axp2, 't1/p1 t2/p2')]
```

This results in the following execution strategy for pattern 3 under the VCAS scenario: remove all *about* predicates from all location steps, except for the *about* predicate on the target element.

Pattern 3 for SCAS The processing of pattern 3 for the SCAS scenario is stricter in the sense that we can not simply drop intermediate *about* predicates, as we did for the VCAS scenario. The general procedure consists of:

- splitting up the pattern into separate location steps;
- structural correlation of the resulting node-sets of each location step.

The target elements are ranked by their corresponding *about* predicate only; thus, ignoring the scores produced for the other *about* clauses in the query. Like in pattern 1, the target element can have multiple descendants; in that case, the descendants' scores are averaged to produce the target element scores.

As an example, consider the following expression:

```
    /article[about(./abstract, 't1/p1')]
            //section[about(./header, 't2/p2')]
            //p[about(., 't3/p3')]
```

We first split up the above expression into:

```
- /article[(about(./abstract, 't1/p1 t2/p2 t3/p3')]
- //section[about(./header, 't1/p1 t2/p2 t3/p3')]
- //p[about(., 't1/p1 t2/p2 t3/p3')]
```

All of the patterns above produce intermediate result node-sets that have to be structurally correlated to each other. We can choose to perform a top-down correlation sequence, or a bottom-up correlation sequence consisting of containment joins. The choice between a top-down or bottom-up sequence can be an optimization decision, made at runtime by the retrieval system. For example, if a collection contains many paragraph elements, not contained within article elements, the system might decide to limit the amount of unnecessary executed *about* predicates by choosing a top-down approach. In the current implementation, the patterns are always processed top-down.

5. EXPERIMENTS

For the content only (CO) topics, we designed three experimentation runs. The first run (R_{art}) represents the baseline run of 'flat-document' retrieval, i.e., retrieval of documents which possess no structure. After examination of the document collection, we decided to perform retrieval of article-components. The second run regarded all subtrees in the collection as separate documents (R_{comp}). For the third run we re-used the result sets of the second run and used a log-normal distribution to model the quantity dimension ($R_{comp-logn}$). To penalize the retrieval of extremely long document components, as well as extremely short document components, we set the mean at 2516. Experiments for INEX 2002 showed that 2516 words was the average document component length of relevant document components according to the strict evaluation function used in INEX 2002. Table 7 gives a summary of our experimentation runs.

Table 7: Original CO experimentation runs; note that we used a length of 2516 as preferred component length for the $R_{comp-logn}$ run. The experiments for INEX 2002 showed 2516 was the average document component length of relevant components, according to the strict evaluation function used in INEX 2002.

Run	Retr. Unit	Dimension(s)	MAP
R_{art}	$\{tr('article')\}$	*topicality*	0.0392
R_{comp}	$\{tr('*')\}$	*topicality*	0.0387
$R_{comp-logn}$	$\{tr('*')\}$	*top., quant.(2516)*	0.0374

For both the SCAS (strict content-and-structure) and VCAS (vague content-and-structure), we submitted one run each (not mentioned in Table 7); the topics executed according to the conceptual, logical and physical SCAS and VCAS pattern rule-sets as detailed in the previous Sections. The mean average precision (MAP) value of the SCAS run is 0.2595.

The originally submitted CO-runs all used the keywords present in the keyword-element of each topic. Before executing each topics, query stop words were removed using the SMART query stop word list, and all remaining keywords were stemmed with the Porter stemmer. Stop word removal (using the SMART stop word list) and stemming was also performed on the indexed collection terms, as well as the removal of those terms shorter than 2 characters and longer than 25 characters.

We performed several additional CO runs of which the mean average precision values are summarized in Table 8.[2] First, we extracted, for each topic, the terms occurring in the title *about* clauses (T) and in the description (D) and keyword (K) component text. We then made combinations of the T, D and K keyword sets, and used the combinations in additional runs (TD and TK). Second, we also created CO-runs where we replaced the log-normal element length prior (*logn* runs) with a standard element length prior (*logs* runs):

$$lp(E) = \log(P(E)) = \log(\sum_t tf(t, E))$$

Finally, after observing a big difference in system performance with the approach by Sigurbjörnsson, Kamps and de Rijke [19], which is based on the same language modeling technique, we decided to reproduce their approach of combining surrounding document evidence with element evidence (*aw* runs).

From the average precision values in Table 8, the following observations are clear:

- large elements should not be discounted (under the current metrics of evaluation; difference between *logn* and *logs* runs);
- combining element scores with their surrounding con-

[2]The differences between the R_{comp} and $R_{comp-logn}$ MAP scores in Tables 7 and 8 originate from the (different) ordering of elements with equal score.

Table 8: Mean average precision values for the additional CO runs. The last three columns denote the topic part used for the run: T for title, TD for title and description terms, and TK for title and keyword terms. For evaluation, the strict evaluation measure (for 2003) was used.

Run	Task	K	TD	TK
R_{comp}	CO	0.0341	0.0383	0.0447
$R_{comp-logn}$	CO	0.0351	0.0390	0.045
$R_{comp-logs}$	CO	0.0652	0.0766	0.0740
$R_{comp-logn-aw}$	CO	0.0697	0.0863	0.0905
$R_{comp-logs-aw}$	CO	0.1043	0.1224	0.1205

text scores appears to improve performance significantly (*aw* runs);

- in spite of the noise in the description text, using the description terms improves retrieval results (comparing columns *K* and *TD*).

We plan to further investigate the cause of the performance difference between the *logn* and *logs* runs. One explanation could be that the log-normal's mean value of 2516 words, as desired component size, is not the correct value given the relevance assessments. Another explanation for this discrepancy between evaluation results and our intuition, expressed in the log-normal length prior, could be sought in the current evaluation metrics that reward exhaustivity over specificity.

Besides measuring the effectiveness of our retrieval system, we also measured the efficiency of indexing and querying the collection. Table 9 shows the average topic execution times of all created runs. For a given run, we averaged the topic execution times of the topics in that given run (with CO runs having 36 topics and the SCAS and VCAS runs having 30 topics). All measurements are wallclock timings, measured in seconds. The hardware used for the executions of the runs is an AMD Opteron machine, running at 1.4GHz and having 2GB of main memory. The indexing time is divided into two separate parts:

- the time needed for insertion of data T_{insert}, measured at 176 seconds;
- the time needed for post-processing $T_{postprocess}$, measured at 191 seconds. Post-processing consists of determining collection frequencies, component text lengths (component lengths disregarding markup) and indexing of topics.

Memory use of our system varied between 250MB and 1GB, where 1GB was reached when materializing large components, or large component sets (large with regard to the number of components in the result set) for executing the language model. Moreover, memory use was increased by behavior of the database kernel used: the kernel loads tables completely into memory when they are needed, even if not all parts of the table are used. This redundant memory use as a result of loading irrelevant data can be avoided by, for example, horizontal fragmentation of the tables as in [18]. The extra time needed for the *logn* and *logs* runs (when compared to the *comp* run) can be explained by extra join-operations against parts of the index, needed for retrieving the component text lengths and calculation of the logarithm values. Also, the *aw* runs take more execution time as a result of the extra containment joins needed to resolve the specified structural constraints.

Table 9: Average topic execution times for all runs, in seconds (wallclock time). Note that the first row is the original article run, performed with keywords only (the K column). The execution times of our originally submitted three runs are displayed in the first three rows and the third column (boldfaced). The other timings are the timings for the additional unofficial runs, and the last two rows show the execution times for our original SCAS and VCAS runs.

Run	Task	K	TD	TK
R_{art}	CO	**6.75**	-	-
R_{comp}	CO	**44.08**	68.19	53.22
$R_{comp-logn}$	CO	**45.13**	69.58	54.47
$R_{comp-logs}$	CO	45.25	69.69	54.47
$R_{comp-logn-aw}$	CO	47.16	72.22	56.80
$R_{comp-logs-aw}$	CO	47.25	74.44	57
R_{scas}	SCAS	-	-	35.37
R_{vcas}	VCAS	-	-	35.24

The time needed for indexing can be reduced further. First, for the sake of simplicity, the system indexes the full XPath (in string format) for each component in the collection. This full XPath indexing is redundant and can be replaced by a facility to resolve the component XPaths when presenting results to the user, or by a more compact index structure. Second, we are looking into possibilities for encoding other parts of the index into more compact structures, e.g., bitvectors.

6. CONCLUSIONS AND FUTURE WORK

Our participation in INEX can be summed up as an exercise in applying current and state of the art information retrieval technology to a structured document collection. We described a relatively straightforward approach to simplify the implementation of retrieval models that combine structural and content properties. We hope to take advantage of this flexibility to a larger extend in our future research, as the current approach to retrieval has only used a small proportion of all the structural information present in XML documents. Other research includes more extensive experimentation in the area of relevance feedback, and develop a different normalization mechanism to remove the bias of the language model on short components. Lastly, we aim to improve the efficiency of the system, both memory and CPU wise, by applying horizontal fragmentation and encoding of data into more compact structures.

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XPath Inverted File for Information Retrieval

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ABSTRACT
In this paper we describe the implementation of a search engine for XML document collections. The system is keyword based and is built upon an XML inverted file system. We describe the approach that was adopted to meet the requirements of Strict Content and Structure queries (SCAS) and Vague Content and Structure queries (VCAS) in INEX 2003.

Keywords: Information Retrieval, Inverted File, XML, XPath, INEX, Assessment, Evaluation, Search Engine

1. Introduction
Recently, the widespread use of Extensible Markup Language (XML) has led to appropriate Information Retrieval methods for XML documents [4]. A key difference between XML documents and conventional text documents is the separation of structure and content [5]. A standard solution for efficient Information Retrieval is to use an inverted file index. Zobel [6] identifies two dominate methods for indexing of large text databases: inverted files and signature files. Zobel compared these two methods and concluded that inverted files are superior in almost every respect, including speed, space and functionality.

In an inverted file, for each term in the collection of documents, a list of occurrences is maintained. Information about each occurrence of a term includes the document-id and term position within the document. Maintaining a term position in the inverted lists allows for proximity searches, the identification of phrases, and other context-sensitive search operators. This simple structure, combined with basic operations such as set-union and set-intersect, support the implementation of rather powerful keyword based search engines.

XML documents contain rich information about document structure. The objective of the XML Information Retrieval System that we describe in this paper is to facilitate access to information that is based on both content and structural constraints. We extend the Inverted File scheme in a natural manner, to store XML context in the inverted lists.

2. XML File Inversion
In our scheme each term in an XML document is identified by 3 elements. File path, absolute XPath context, and term position within the XPath context.

The file path identifies documents in the collection; for instance:

C:/INEX/ex/2001/x0321.xml

The absolute XPath expression identifies a leaf XML element within the document, relative to the file's root element:

/article[1]/bdy[1]/sec[5]/p[3]

Finally, term position identifies the ordinal position of the term within the XPath context.

One additional modification that we adopted allowed us to support queries on XML tag attributes. This is not a strictly content search feature, but rather structure oriented search feature. For instance, it allows us to query on the 2nd named author of an article by imposing the additional query constraint of looking for that qualification in the attribute element of the XML author element. The representation of attribute values is similar to normal text with a minor modification to the XPath context representation – the attribute name is appended to the absolute XPath expression. For instance:

article[1]/bdy[1]/sec[6]/p[6]/ref[1]/@rid[1]

Here the character '@' is used to flag the fact that "rid" is not an XML tag, but rather an attribute of the preceding tag <ref>.

An inverted list for a given term, omitting the File path and the Term position, may look something like this:

Context
XPath
article[1]/bdy[1]/sec[6]/p[6]/ref[1]
article[1]/bdy[1]/sec[6]/p[6]/ref[1]/@rid[1]
article[1]/bdy[1]/sec[6]/p[6]/ref[1]/@type[1]
article[1]/bm[1]/bib[1]/bibl[1]/bb[13]/pp[1]

Context
XPath
article[1]/bm[1]/bib[1]/bibl[1]/bb[14]/pdt[1]/day[1]
article[1]/bm[1]/bib[1]/bibl[1]/bb[14]/pp[1]
article[1]/bm[1]/bib[1]/bibl[1]/bb[15]
article[1]/bm[1]/bib[1]/bibl[1]/bb[15]/@id[1]
article[1]/bm[1]/bib[1]/bibl[1]/bb[15]/ti[1]
article[1]/bm[1]/bib[1]/bibl[1]/bb[15]/obi[1]

In principle at least, a single table can hold the entire cross reference list (our inverted file). Suitable indexing of terms can support fast retrieval of term inverted lists. However, it is evident that there is extreme redundancy in the specification of partial absolute XPath expressions (substrings). There is also extreme redundancy in full absolute XPath expressions where multiple terms in the same document share the same leaf context (e.g. all terms in a paragraph). Furthermore, many XPath leaf contexts exist in almost every document (e.g. /article[1]/fm[1]/abs[1]).

We have chosen to work with certain imposed constraints. Specifically, we aimed at implementing the system on a PC and base it on the Microsoft Access database engine. This is a widely available off-the-shelf system and would allow the system to be used on virtually any PC running under any variant of the standard Microsoft Windows operating system. This choice implied a strict constraint on the size of the database – the total size of an Access database is limited to 2Gbyte. This constraint implied that a flat list structure was infeasible and we had to normalise the inverted list table to reduce redundancy.

3. Normalized Database Structure

The structure of the database used to store the inverted lists is depicted in Figure 1. It consists of 4 tables. The ***Terms*** table is the starting point of a query on a given term. Two columns in this table are indexed - The ***Term*** column and the ***Term_Stem*** column. The ***Term_Stem*** column holds the Porter stem of the original term. The ***List_Position*** is a foreign key from the ***Terms*** table into the ***List*** Table. It identifies the starting position in the inverted list for the corresponding term. The ***List_Length*** is the number of list entries corresponding to that term. The ***List*** table is (transparently) sorted by Term so that the inverted list for any given term is contiguous. As an aside, the maintenance of a sorted list in a dynamic database poses some problems, but these are not as serious as might seem at first, and although we have solved the problem it is outside the scope of this paper and is not discussed any further. A search proceeds as follows. Given a search term we obtain a starting position within the List table. We then retrieve the specified number of entries by reading sequentially.

The ***Document*** and ***Context*** tables contain the actual file path and absolute XPath of a given term, respeciively. The inverted list for a given term is thus obtained by a *Join* (SQL) of the selected List table entries (as described above) with the ***Document*** and ***Context*** tables to obtain the complete de-normalised inverted list for the term. The XPath context is then checked with a regular expression parser to ensure that it satisfies the topic's <Title> XPath constraints.

The retrieval by ***Term_Stem*** is similar. First we obtain the Porter stem of the search term.

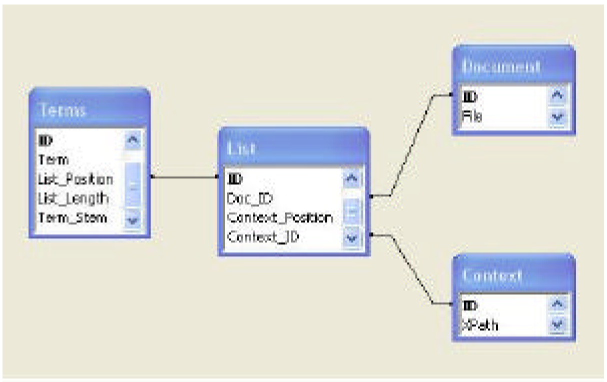

Figure 1: Database Schema for XML Inverted File.

Then we search the list by ***Term_Stem*** – usually getting duplicate matches. All the lists for the duplicate hits on the ***Terms*** table are then concatenated. The ***Context_Position*** is the ordinal position of the term within the leaf node of the article's XML tree. Phrases and other proximity constraints can be easily evaluated by using the ***Context_Position*** of individual terms in the ***List*** table.

We have not compressed XPath expressions to minimise the extreme redundancy of XPath substrings in the ***Context*** table. With this normalization the database size was reduced to 1.6GByte and within the Microsoft Access limits.

4. The CASQuery Engine

Before discussing the implementation details of the CASQuery engine it is necessary to introduce some terminology. We then describe the implementation of the search engine.

4.1 Terminology

- **XPath Query**: An XPath Query is a query that meets the criteria of the INEX query specification. It can be considered a subset of the W3C's XPath language.

- **Step**: A Step is a component of an XPath query that specifies some Axis (child, descendant, descendant-or-self etc.) a NodeTest (e.g. a NameText that tests the name of an element) and optionally some Predicate
- **Path**: A Path is a sequential list of Steps
- **Predicate**: A predicate contains a filter that specifies some condition that a node must meet in-order to satisfy it. This filter may be an "about" function or an equality expression.
- **Context**: The context for an element is an absolute XPath expression denoted by a list of child steps with a numerical index e.g. "/article[1]/bdy[1]/sec[1]/p[4]"
- **ReturnElement**: A ReturnElement is an element (qualified by the document name and a context) that satisfies the full path expression of a query (or query fragment) not including any path expression in a filter. The context of the ReturnElement is the one returned by the query engine to the user.
- **SupportElement**: A SupportElement is an element (qualified by the document name and a context) that satisfies the full path expression of a query (or query fragment) including any path expression in a filter. The context of the ReturnElement is not returned to the user but can be used to "support" the validity of the ReturnElement (in other words: shows why the ReturnElement was in fact returned).

The search engine was designed to operate on the <Title> element of CAS topics. It operates in the same manner for both strict (SCAS) and vague (VCAS) interpretation of the queries. The only difference is in the definition of equivalence tags:

SCAS Equivalent tags:

- **Article,bdy**
- **p|p[1-3]|ip[1-5]|ilrj|item-none**
- **sec|ss[1-3]**
- **h|h[1-2]a?|h[3-4]**
- **l[1-9a-e]|dl|list|numeric-list|numeric-rbrace|bullet-list**

VCAS Equivalent tags:

- **Article,bdy,fm**
- **sec|ss[1-3]|p|p[1-3]|ip[1-5]|ilrj| item-none**
- **h|h[1-2]a?|h[3-4]**
- **yr|pdt**
- **snm|fnm|au**
- **bm|bibl|bib|bb**
- **l[1-9a-e]|dl|list|numeric-list|numeric-rbrace|bullet-list**

4.2 Parsing the Query

We used the Programmar[2] parser development toolkit to generate a parser for XPath[3] queries. Programmar accepts a Backus Naur Form (BNF) grammar as input and is able to generate a parser that can parse an instance of that query into a *parse tree*. The Programmar library then provides an API to access and walk the parse tree that it constructed.

We used the XPath BNF grammar as defined by the W3C as input to the Programmar IDE. Some small modification to the BNF syntax was made in order to make the task of walking the parse tree and gathering the required information simpler.

Our approach was to walk the parse tree and construct an abstract syntax tree, which represents that same query but at a higher level of abstraction than the parse tree generated by the Programmer toolkit. Representing the query at a higher level of abstraction meant that implementing the query engine that processes that query was made simpler.

4.3 The Abstract Syntax

The abstract syntax was contained within a separate module that is kept independent of the QueryEngine that processes it. Thus we allow for the possibility that the abstract syntax for XPath queries may be utilised in other applications. For example it would be possible to implement a more traditional XPath processor on top of this abstract syntax. Therefore there is a dependency from the Query Engine to the Abstract Syntax package but no reverse dependency.

The basic structure of an XPath query (in the abstract syntax) is that it consists of a Path that contains a list of Steps. This is consistent with the terminology used by the XPath standard. Steps must contain a node test – and may also contain zero to many filters (or predicates).

4.4 Evaluateable Fragments

Once the XPath parser has constructed the abstract syntax, the query engine performs one further transformation on the query before executing. The path, or list of steps, must be broken down into EvaluateablePathFragments. Each step in the query that contains an *EvaluatableExpression* will be treated as the last step in an EvaluateablePathFragment.

An *EvaluatableExpression* is a step filter that can be evaluated by the QueryEngine.

In our implementation we are using an index of inverted lists that map a *term* to a list of *contexts* (full absolute XPath path plus document name). Therefore, for a filter to be *evaluateable* it must filter based on some term that can be looked up in the index. For example the filter:

/article/bdy[count()=1]

would not be *evaluateable* in our system as no terms is given in the filter. However the filter:

/article//yr[. = "1999"]

is evaluateable as the term "1999" will be in the index.

As an example, the query:

//article[//yr='1999']//sec[about(./,'DEHOMAG')]

would be broken down into two fragments:

1. **//article[//yr = "1999")]**
2. **//article//sec[about(//p, 'DEHOMAG')]**

Notice that the second fragment contains the full path including the "article" step.

Next each EvaluatablePathFragment is evaluated – the eval() method will return a set of nodes whose *contexts* match the full path for that fragment. For example fragment 2 above may return a node with the context:

/article[1]/bdy[1]/sec[2]

4.5 Merging Fragments

After each fragment is evaluated independently, we will have a list of node sets (one for each fragment) that must be merged. For example when merging the two sets from the above fragments, we will wish to include only those elements returned from the first fragment if they also have a descendent node contained in the set returned from the second fragment. In fact, what we need to return are elements with a context that matches the full path of the last fragment (in the case above they must have a context that matches //article//sec – the last named element in the context must be "sec"). What is meant by "including elements from the first fragment" is that the *SupportElements* for those *ReturnElements* in the first set will be added to a descendant *ReturnElement* (if it exists) in the 2nd set.

For example: let us say that the first set contains a ReturnElement with the context "/article[1]" and that ReturnElement has an attached SupportElement of "/article[1]/fm[1]/yr[1]" (for the purposes of this example assume that all contexts are in the same document.) Then let us say that the second set contains a ReturnElement of "/article[1]/bdy[1]/sec[2]". This element is supported by /article[1]/bdy[1]/sec[2]/p[3]. In this case the ReturnElement in the 2nd is a descendant of the ReturnElement in the 1st set – so we can merge the supports from the 1st ReturnElement into the supports of the 2nd and we will end up with a ReturnElement ("/article[1]/bdy[1]/sec[2]") that has 2 supports ("/article[1]/fm[1]/yr[1]" and "/article[1]/bdy[1]/sec[2]/p[3]").

When merging sets we must determine whether to do a strict merge or a union merge. For example if we need to merge the 2 fragments above, fragment 1 is "strict" – all elements that we merge from fragment 2 must also have an ancestor "article" element that contains a "yr" element for "1999".

The last fragment will always require a strict merge. This is because of the requirement stated above, that all elements returned by the query must have a context that satisfies the full path of the query.

However, a Union merge can be appropriate when we are merging two fragments where neither are the last fragment in the query, and both are non-strict (for example both only contain "about()" filters. In this case all ReturnElements will be retained, whether an element returned from the second fragment is a descendant of some element from the first fragment or not.

4.6 Support Elements

Support elements are elements that were found to contain at least one instance of a term that was specified in the filter. The element that contains this term must satisfy the full path for that filter including the context path.

In our example above the first filter (first fragment) looks for occurrences of the term "1999" in elements whose context matches the path "//article//yr". If we find that the term "1999" occurs in an element with the context "/article[1]/bdy[2]/sec[1]/p[1]" this is not a valid support for this filter. However, if we find a single occurrence of "1999" in the context "/article[1]/fm[1]/yr[1]" this would be a valid support.

Once we have removed all supports that do not represent valid supports (according to the filter), we then can create the return elements for this filter. In this case the return path is "//article" so the return element would have the context "/article[1]" with an attached support element with the context "/article[1]/fm[1]/yr[1]" and having one "hit" for the term "1999". It is possible that a return element contains more than one support element. For example, if within the same document we find another element with the context "/article[1]/fm[1]/yr[2]" that contains 2 hits on the term "1999" we would add another support element to the return element and record 2 hits on it. (This example is spurious as in the case of an equality constraint you actually only want to find one hit on the term. However it would make sense in the context of the "about()" filter).

4.7 Ranking

Previous works on document ranking in text retrieval are too numerous and diverse to mention in the INEX context. However, some relevant work has been done on ranking schemes of XML [7]. Many of them apply techniques used in classical Information Retrieval such the vector space model and apply them to structured documents, taking into account that relevance should be usually judged on a level smaller than that of a document

The approach we adopted in ranking was a multi-stage sorting process.

- First sort by f*ilter satisfaction*.
- For ReturnElements that satisfy the same number of filters - sort by number of distinct terms and phrases that were hit.
- For ReturnElements with the same number of filters satisfied and the same number of distinct terms - calculate a score based on total number of terms hit adjusted by a factor that penalises terms that are very common in the document collection.

5.7.1 Filter Satisfaction

A ReturnElement is considered to have satisfied a filter where it is a valid ReturnElement for that filter, and it has a least one SupportElement that has recorded a hit for at least one term in the filter. A valid ReturnElement is one whose context matches the path expression of the filter.

In its simplest form, the filter satisfaction algorithm will rank higher a ReturnElement that has satisfied a greater number of filters. There are a number of refinements to this rule:

- Where two filters appear as *Predicates* to different *Steps* in the query expression (e.g. //article[//yr = “1999”] //sec[about(./, 'DEHOMAG')]), each one of these filters that is satisfied will count towards the overall *filter satisfaction count.*
- Where two filters appear in the same Predicate and they are and-ed together (e.g. //article//sec[[//yr = “1999”] **AND** about(./, 'DEHOMAG')]), each one of these filters that is satisfied will count towards the overall *filter satisfaction count.*
- Where two filters appear in the same Predicate and they are or-ed together (e.g. //article//sec[[//yr = “1999”] **OR** about(./, 'DEHOMAG')]), if both filters are satisfied only one will be counted towards the overall *filter satisfaction count.*
- If any unwanted terms (prefixed by a minus) are hit in a SupportElement for the ReturnElement, then the *filter satisfaction count* will be reduced by a count of 2.

5.7.2 Distinct terms and phrases

This algorithm is a second stage sort after the *filter satisfaction* sort. Where two ReturnElements have the same *filter satisfaction count,* the distinct terms algorithm is applied to determine their relative rank. Here we rank ReturnElements based on the number of distinct terms and phrases that they satisfy.

If a SupportElement has recorded hits for a particular term, its containing ReturnElement will have it’s *distinct terms and phrases count* incremented by one. Take for example the query:

//article[about(.//st,'+comparison') and

about(.//bib,'"machine learning"')]

Let us take the case where we have two ReturnElements that satisfy both filters. The first ReturnElement has supports that hit the terms “comparison” and “machine”. The second ReturnElement has supports that hit the terms “comparison”, “machine” and “learning”. In this case the second ReturnElement will be ranked higher. Note that it does not matter how many times each term is hit – it only matters if a term was hit at least once, or not at all.

The *distinct terms and phrases count* secondly takes into account the number of phrases that a ReturnElement has supports for. For example, take the query and the second ReturnElement we discussed above. If this ReturnElement also contained a support for the phrase “machine learning” - that is to say a context was found where the words “machine” and “learning” appear directly adjacent to each other – the *distinct terms and phrases count algorithm* will increment the count by one.

5.7.3 Scorer penalizes frequent terms

The final stage algorithm of the 3 stage sort is only invoked where two ReturnElements have the same *filter satisfaction count* and *distinct terms and phrases count.* This algorithm calculates a score based on the total number of instances that terms were hit by SupportElements. The total number of hits for a term is normalized based on heuristic that takes into account how frequently that term occurs in the entire documents collection. This normalization factor is calculated as follows:

- *Hits*: Total number of instances that this term appears in the ReturnElements supports.
- *TF (TermFrequency)*: Count of number of times this term appears in total document collection

- *TFC (TermFrequencyConstant)*: A constant (determined using heuristics)
- *Score*: The ranking score for this ReturnElement
- *Terms*: The set of terms the score is based on
- i: Denotes the term
- *SM (ScarcityMultiplier)* = 1 + (*TF* / *TFC*)
- *Score* = ? $^{\text{i in } Terms}$ (*hits*$_i$ * (1/ *SM*$_i$))

4.8 Discussion on Ranking

Our overall ranking strategy was based on a series of heuristics.

5.8.1 Filter Satisfaction

It is clear that our strategy places a high degree of importance to whether a particular collection of query terms are aggregated into one filter or if they are put in separate filters. For example, let us take the following two queries:

- //article[about(.,'clustering distributed') and about(., 'java')]
- //article[about(.,'clustering distributed java')]

Whilst these filters may appear logically equivalent, our filter satisfaction algorithm will mean that lists returned from each query formulation will vary significantly in how they are sorted. With the first query, the term “java” is raised to the same level of importance as that of both the other terms (“clustering” and “distributed”). By contrast, with the second query, a result that hits “clustering” and “distributed” (but not “java”) will rank equal to a result that hits “distributed” and “java” (but not “clustering”). However, if the first query formulation is used the second result would be ranked higher as it satisfies two filters whereas the first result only satisfies one.

We believe this ranking strategy works well due to the psychology involved in creating these two filters. It can be inferred that when a query writer aggregates terms into one filter he/she considers all terms so aggregated of equal importance. In contrast, where a query writer puts terms in separate filters they are indicating that whilst each filter should be treated of equal importance, terms contained in separate filters are not necessarily of equal importance.

The second thing worth discussing about the filter satisfaction algorithm is the way it treats or-ed filters versus the treatment for and-ed filters. Let us take another two filters by way of example:

//article[about(.,'clustering) and

about(.,’distributed')]//sec[(about(‘java’)]
//article[about(.,'clustering) or
about(.,’distributed')]//sec[(about(‘java’)]

Further, let us assume we have *returnElement1* that hits the terms “clustering” and “distributed” and *returnElement2* that hits the terms “clustering” and “java”.

In this case query 1 will rank *returnElement1*and *returnElement2* equal (both with a *filter satisfaction count* of 2). However query 2 will treat these quite differently. The *returnElement2* will still have a *filter satisfaction count* of 2 but the *returnElement1* will have a *filter satisfaction count* of only one.

Again we believe this makes intuitive sense. The second query construction implies that the user wants one of “clustering” or “distributed” to be hit – they don’t care which – and if they are both hit then this is not as important as if “java” is also hit. It is interesting to note that the following query would be equivalent to the second query:

//article[about(.,'clustering distributed')]//
sec[(about(‘java’)]

One final thing to note about this algorithm is how it treats unwanted terms (i.e. terms preceded by a minus sign). The algorithm is very harsh in how it treats the occurrence of such terms (by deducting 2 from the overall *filter satisfaction count*). However, We have found this works well in practice as the specification of such unwanted terms by the query writer appears to indicate a very strong aversion to that term.

5.8.2 Distinct Terms and Phrases

The *distinct terms and phrases* algorithm is important in two respects:

- It places a greater importance on the number of distinct terms hit, than on the total number of instances that a term or terms are hit. (This can also be said about the *filter satisfaction* algorithm).
- Phrases are given prominence by the fact that they in effect count as an additional distinct term.

Let us consider the consequences of first point above. Take as an example the filter “//article[about(.,'clustering distributed java')]”. Let us say that a ReturnElement records hits on the term “clustering” and “distributed”; both terms with 100 instances of this term occurring in the return’s supports – a total of 200 recorded hits. Then let us take another ReturnElement that records just the one instance of a hit on each of “clustering”, “distributed” and “java”. It may surprise that this second ReturnElement will be ranked higher when it only recorded 3 separate hits versus the 200 of the first ReturnElement.

However, we believe this strategy has worked quite well in reality. What we have found that this in effect gives a greater prominence to those terms that do not occur frequently – that is it weights infrequent terms more heavily than frequent terms. This makes intuitive sense as an infrequent term that appears in a query is more likely to aid the precision of the recall than frequent terms. The more frequent a term is in the overall document collection the less value it has to determining the requirements of the user.

As regards the 2nd point above about giving phrases prominence, this should be self explanatory. Phrases occur much less frequently than individual terms, so it makes sense to treat them with a level of importance equivalent to the individual terms.

5.8.3 Scorer penalizes frequent terms

Finally we discuss the algorithm that is invoked where the above two algorithms still cannot separate two equally ranked ReturnElements. It is only in this final stage algorithm that we take into account how "strong" the support is for a ReturnElement – that is how many instances of hits on terms have been recorded in a ReturnElement's SupportElements.

As per our discussion for the *distinct terms and phrases* algorithm, here we also wish to penalize infrequent terms. The algorithm we developed to do this was refined by running a series of experiments and running our own assessment on the results to see if the modified algorithm improved the results. The *TermFrequencyConstant* gives us the ability to adjust the *normalization factor* for penalizing frequent terms.

4.9 Exceptions

Some INEX topics included conditions that could not be easily evaluated in the absence of external knowledge. For instance, a conditions such as **about[.//yr,2000].** Such a condition can be easily evaluated if a user, or an external schema can be consulted, in which the meaning of "about" in relation to <yr> can be determined. Furthermore, in practical terms, the implementation must take account of the type of the element (e.g, is it numeric or alphanumeric?).

The treatment of equality functions involving years (i.e. a "yr" tag) is straightforward: a string comparison is made between the value in the tag and the constant. However, the treatment of inequality functions (i.e. those involving inequality operators "<", ">", "<=", ">=") is more complex. The greater than operator is undecideable as the upper range of year values to search the index for is unbounded. The less than operator may be decideable if we take the year 1 as the lower bound - but in this case the practical consequence of having to search the index for upwards of 1,990 terms is that we need to define a more reasonable lower bound. As such, we allowed for the lower and upper bound of year terms to be configured via our configuration file. This results in a managable range of year terms for which we have to search the index for any reasonable year based inequality predicate. The "about" was also defined in a configuration file (3 years either side of specified "about" year).

5. Experimental Results

The system was only designed for Content and Structure queries (CAS). Only the <Title> element was used in topic evaluation. The system was not designed to take advantage of information contained in the <Description> and <Keywords> elements of a Topic.

5.1 Strict Content and Structure

The best results were obtained with the SCAS query and strict quantization metric. The average precision was 0.26 (the submission was ranked **3rd**.) With the Generalized quantization metric the system was ranked 8th. These results are somewhat surprising given that we only used the <Title> element of a topic. One would have expected the use of additional keywords from the <Description> and <Keywords> elements to assist retrieval and ranking.

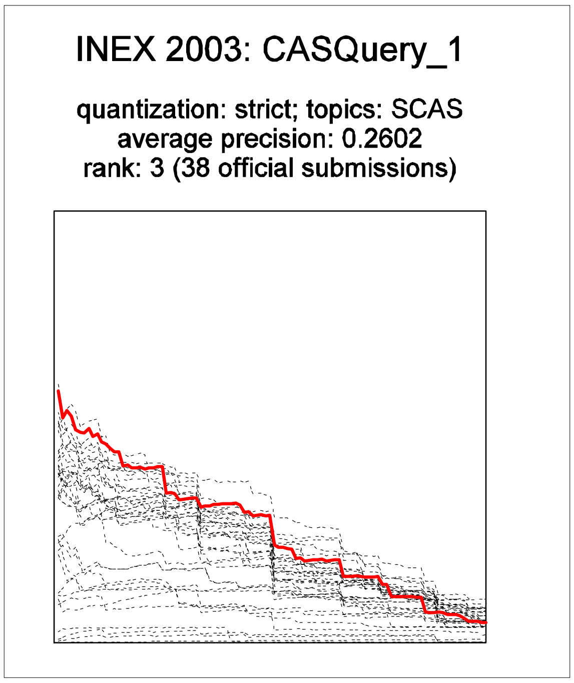

Figure 2: Retrieval results for Strict Content and Structure (SCAS) topics, quantization Strict

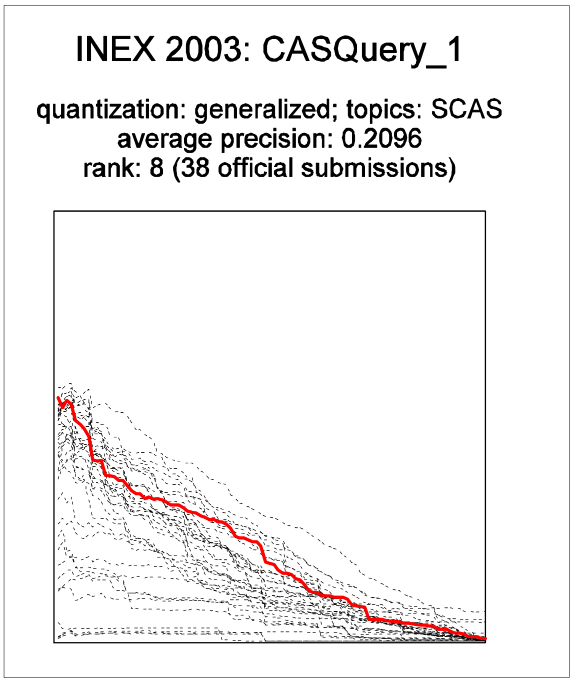

Figure 3: Retrieval results for Strict Content and Structure (SCAS) topics, quantization Generalized.

5.2 Vague Content and Structure

Results for VCAS are not available at the time of writing this paper.

6 Discussion

There is no question that the formulation of the <Title> element of an XML topic at INEX 2003 is not end user oriented. However, it does allow for exact specification of structure and content constraints. We were able to implement a search engine that evaluates CAS <title> expressions with good accuracy and reasonable response time. Furthermore, we were able to construct the search engine on top of a generic XML inverted file system. This allows the application of the system to XML collections without explicit reference to the underlying XML Schema (or DTD). It seems however that in the definition of INEX CAS Topics the authors did not always specify the intent of the topic (as evident in the topic's narrative) in an accurate manner. This ultimately must have lead to low precision (across all submissions from all participants).

We were not able to solve the problem in a completely generic fashion because some topics' structural constraints could not be easily interpreted in a generic manner (e.g treatment of about conditions over <year>). This problem can be overcome to some extent with the use of an XML Schema in future evaluations at INEX.

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Applying the IRStream Retrieval Engine to INEX 2003

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ABSTRACT

Last year, in the context of the INEX evaluation initiative, we could show that our retrieval system IRStream is successfully applicable as a retrieval engine for XML-documents. Nevertheless, we have to point out that IRStream can be further optimized in many directions.

In the present paper we show, how IRStream was extended and improved for its application to INEX 2003 in order to achieve better retrieval results. Furthermore, we present some first retrieval results, which demonstrate the impact of the improvements of IRStream concerning the quality of the retrieval result.

1. MOTIVATION

Last year, as a participating organization at the INEX evaluation initiative [11], we applied IRStream to the collection of XML documents provided by INEX. Hereby, we investigated the usability of IRStream for structured text documents. By the application of IRStream as retrieval system for XML-documents, we have recognized that IRStream can be further improved and optimized in many respects.

As two of the main drawbacks of IRStream we have identified the absence of a component for an automatic generation of queries based on topic data and the problem that IRStream sometimes provided wrong granules as the result of a query. Therefore we decided to improve and extend IRStream in order to avoid these drawbacks.

In this respect is intended to provide a powerful framework to search for components of arbitrary granularity – ranging from single media objects to complete documents. IRStream combines traditional text retrieval techniques with content-based retrieval for other media types and fact retrieval on meta data. In contrast to other retrieval services which permit set-oriented or navigation-oriented access to the documents, we argue for a *stream-oriented* approach. In the following paper, we shortly describe the significant features of this approach and describe the system architecture of IRStream. Furthermore, we present the application of an extended and improved version of our IRStream retrieval engine as a retrieval system for XML documents in the context of INEX 2003 [4].

The paper is organized as follows: In section 2 we will give a short overview of the ideas and main components of IRStream. The architecture of our IRStream implementation is presented in section 3. Section 4 shows how we improved our retrieval system IRStream in order to use it as a retrieval engine for XML documents in the context of INEX 2003. In section 5 we present some first experimental results concerning the improved version of IRStream. Section 6 concludes the paper.

2. STREAM-ORIENTED QUERY PROCESSING

"Stream-oriented" means that the entire query evaluation process is based on components producing streams, one after the other. First, there are components creating streams given a base set of objects and a ranking criterion. We call these components *rankers*. Other components consume one or more input streams and produce one (or more) output stream(s). *Combiners*, *transferers* and *filters* are different types of such components.

2.1 Rankers

The starting point for the stream-oriented query evaluation process are streams generated for a set of objects based on a given ranking criterion. For example, text objects can be ranked according to their content similarity compared to a given query text and images can be ranked with respect to their color or texture similarity compared to a given sample image.

Such "initial" streams can be efficiently implemented by access structures such as the M-tree, the X-tree, the LSD^h-tree, or by approaches based on inverted files. All these access structures can perform a similarity search in the following way: (1) the similarity search is initialized and (2) the objects are taken from the access structure by means of some sort of "getNext" method. Hence, the produced streams can be efficiently consumed, one after the other.

2.2 Combiners

Components of this type combine multiple streams providing the same objects ranked with respect to different ranking criteria. Images are an example of media types, for which no single comprehensive similarity criterion exists. Instead, different criteria addressing color, texture and also shape similarity are applicable. Hence, components are needed which merge multiple streams representing different rankings of the same base set of objects into a combined ranking.

Since each element of each input stream is associated with some type of retrieval status value (RSV), a weighted average of the retrieval status values in the input streams can be used to derive the overall ranking [3]. Other approaches are based on the ranks of the objects with respect to the single criteria [12, 7]. To calculate such a combined ranking efficient algorithms, such as Fagin's algorithm [1, 2], Nosferatu [14], Quick Combine [5] and J^* [13] can be deployed.

2.3 Transferers

With structured documents, ranking criteria are sometimes not defined for the required objects themselves but for their components or other related objects. For example, searching for images where the text in the "vicinity" (for example in the same section) should be similar to a given sample text. In such situations the ranking defined for the related objects has to be transferred to the desired result objects.

To put it more precisely, we are concerned with a query which requires a ranking of objects of some desired object type ot_d (image for example). However, the ranking is not defined for the objects of type ot_d, but for related objects of type ot_r (text for example).

We assume that the relationship between these objects is well-defined and can be traversed in both directions. This means that we can determine the concerned object - or objects - of type ot_d for an object of type ot_r and that we can determine the related objects of type ot_r for an object of type ot_d. The characteristics of these traversal operations depend on the database or object store used to maintain the documents. In objectrelational databases join indices and index structures for nested tables are used to speed up the traversal of such relationships. For a further improvement additional path index structures can be maintained on top of the ORDBMS (cf. section 3).

Furthermore, we assume there is an input stream yielding a ranking for the objects of type ot_r. For example, this stream can be the output of a ranker or combiner.

To perform the actual transfer of the ranking we make use of the fact that each object of type ot_r is associated with some type of retrieval status value (RSV_r) determining the ranking of these objects. As a consequence, we can transfer the ranking to the objects of type ot_d based on these retrieval status values. For example, we can associate the maximum retrieval status value of a related object of type ot_r with each object of type ot_d. Another possibility would be to use the average retrieval status value of all associated objects of type ot_r. In [10] you will find a detailed description of an algorithm called "RSV-Transfer", which is used by IRStream to perform the transfer of rankings between different object types.

2.4 Filters

Of course, it must be possible to define filter conditions for all types of objects. Accordingly, it is necessary that filter components are used for our stream-oriented approach. These filter components are initialized with an input stream and a filter condition. Then only those objects from the input stream which fulfill the given filter condition are passed to the output stream.

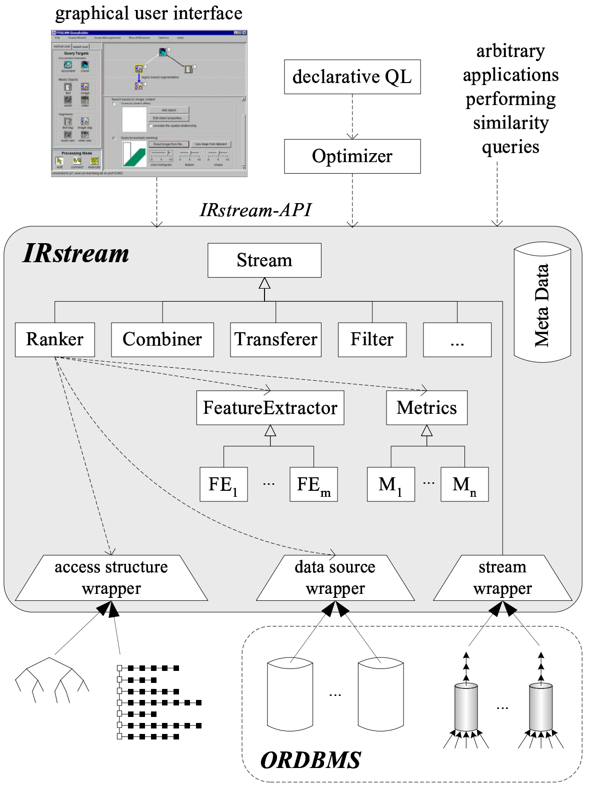

Figure 1: Architecture of the IRStream system

3. THE IRSTREAM ARCHITECTURE

The architecture of our IRStream system is based on the idea that the data is maintained in external data sources. In our implementation, an ORDBMS is used for this purpose. The stream-oriented retrieval engine is implemented in Java on top of this data source and provides an API to facilitate the realization of similarity based retrieval services. Figure 1 depicts this architecture.

The core IRStream system — shaded grey in figure 1 — comprises four main parts: (1) Implementations for rankers, combiners, transferers, and filters. (2) Implementations of various methods for the extraction of feature values as well as corresponding similarity measures. (3) A component maintaining meta data for the IRStream system itself and applications using IRStream. (4) Wrappers needed to integrate external data sources, access structures and stream implementations.

Feature Extractors and Similarity Measures

A feature extractor receives an object of a given type and extracts a feature value for this object. The similarity measures are methods which receive two feature representations — usually one representing the query object and an object from the database. The result of such a similarity measure is a retrieval status value.

Ranker, Combiner, Transferer, Filter, . . .

All these components are subclasses of the class "Stream".

The interface of these classes mainly consists of a specific constructor and a `getNext` method.

For example, the constructor of a *ranker* receives a specification of the data source, a feature extractor, a similarity measure and a query object. Then the constructor inspects the meta data to see if there is an access structure for this data source, this feature extractor, and this similarity measure. In this case, the access structure is employed to speed up the ranking. Otherwise, a table scan with a subsequent sorting is performed.

For the construction of a *combiner* two or more incoming streams with corresponding weights have to be defined. Here it is important to note that combiners such as Fagin's algorithm or Quick Combine rely on the assumption that random access is supported for the objects in the input streams. The reason for this requirement is simple. When these algorithms receive an object on one input stream, they want to calculate the mixed retrieval status value of this object immediately. To this end, they perform random accesses on the other input streams. Unfortunately, some input streams are not capable of such random access options, or a random access would require an unreasonable high effort. In these cases, other combine algorithms — such as Nosferatu or J^* — have to be applied.

For the construction of a *transferer*, an incoming stream, a path expression and a transfer semantics have to be defined. In our implementation, references and scoped references provided by the underlying ORDBMS are used to define the path expressions.

To construct a *filter*, an incoming stream and a filter predicate have to be defined.

Meta Data

This component maintains data about the available feature extractors, similarity measures, access structures, and so forth. On one hand, this meta data is needed for the IRstream system itself in order to decide if there is a suitable access structure for example. On the other hand, the meta data is also available via the IRstream-API for applications.

Wrapper

IRstream makes the extension of the retrieval service in various directions possible by the use of wrappers and interfaces: *Data source wrappers* are needed to integrate systems maintaining the objects themselves into our retrieval system. At present, objectrelational databases can be used via JDBC. Whereas *access structure wrappers* can be used to deploy access structures originally not written for our system. For example, we incorporated an LSD$^{\text{h}}$-tree written in C++ via a corresponding wrapper. In contrast, the *stream wrapper interface* is used to incorporate external sources for streams into our system. It can be used to incorporate external stream producers. At present, the text module of the underlying ORDBMS is integrated via a stream wrapper.

On top of the IRStream API various types of applications can be realized. An example is a graphical user interface where the user can define the query as a graph of related query objects [9]. Another possibility is to implement a declarative query language on top of the API. At present, we are working on a respective adaptation of our POQL$^{\text{MM}}$ query language [6, 8].

4. EXTENSIONS AND IMPROVEMENTS OF IRSTREAM FOR INEX2003

In INEX 2003 every retrieval system had to be able to perform an automatic query generation from topic data. While a topic is interpreted as a representation of an information desire, a query in this context is an internal representation for the system's retrieval process. Thus, the first extension of IRStream was to integrate a query generation step into this retrieval process. An evaluation of last year's results shows that one of main problems of IRStream02 was the determination of a fitting granule of retrieval results for CO-topics, and furthermore an automatic processing of structural constraints of CAS-topics, as well as automatically generating multiple results from one document (e.g. a list of authors). To solve these problems, the retrieval process of the system was completely redesigned, which is described in this section.

To determine fitting granules for retrieval results (and their corresponding identifying paths), a retrieval system has to be able to perform two tasks: First, to extract (possibly several) fragments of one document and to determine their unique paths (including node indices). In this case a path expression is given as part of the query, which describes a structural constraint for result granules, as is the case with CAS-topics. Second, the system must be able to process queries which do not contain a constraint regarding the result granule (CO-topics). In this case, the decision on the fitting granule is to be made automatically within the retrieval process.

4.1 Automatic query generation

The queries used internally by a retrieval system, generated from the topic data, may influence the quality of retrieval results significantly. In order to compare the results of different retrieval systems or even the result of a retrieval system in various development states, the influence of manual (pre-) processing must be eliminated. Therefore an automatic query generation was added to the IRStream system, which was also a requirement for retrieval systems participating in INEX 2003. For reasons of performance, two different approaches for CO- and CAS-topics were used, although every CO-topic may be converted into CAS-format by interpreting a CO-topic title as `//[about(.,'CO-title')]`. The different retrieval processes for these two topic types will be described later in this section.

The general architecture is the same for both variants. A wrapper-class *Topic* parses a topic file and provides means of access via a Java-API. The system is thereby also prepared for changing topic-formats, which will result in additional sub-classes of this wrapper. The methods provided by *Topic* are used by a *QueryBuilder* component specialized in CO-topics or CAS-topics respectively. This component

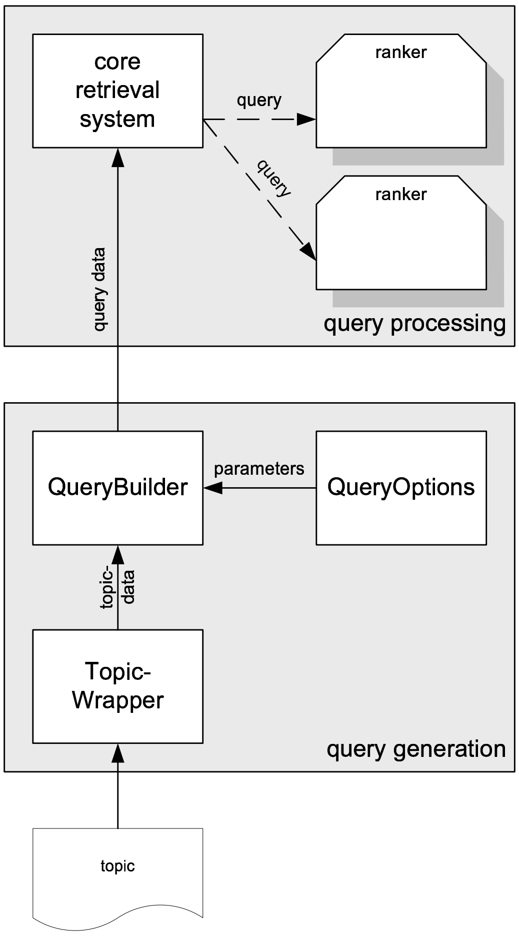

Figure 2: Architecture of query generation

creates the queries internally used by the *Rankers* of the core-retrieval system. To configure the query generation, a *QueryOptions* class is used, which contains all kinds of parameters used in the generation process. Figure 2 gives an overview of the general architecture and the differentiation between query generation and query processing.

Every query may make use of any of the following three topic parts: the *title*, the *description* and the *keywords*. Within the topic title, terms may further be categorized in must-terms (marked by a `+`), must-not terms (marked by a `-`) and terms not marked at all. For each part or each category of terms, the *QueryOptions* class contains parameters about:

Consideration: Shall these terms be considered for query generation at all?

Weighting: What weight shall be associated to these terms (1-10)?

Stemming: Shall the stemming operator of the underlying ORDBMS be used for these terms?

Connectors: Which connecting operator (OR, AND, ACCUMulate) shall be used to connect terms of this class or between classes of terms?

Compound terms: Which way shall compound terms be treated?

4.2 CAS-topics

A CAS-topic contains structural constraints as well as content information, so that three logic parts of a CAS-topic may be identified: First, a constraint regarding the granule of result elements. Second, content and structure information about the result element itself — i.e. its inner context —, which shall be called *content constraint.* Third, there may be content and structure information about the result element's parent or sibling elements — i.e. the element's environment —, which shall be called *structure constraint.*

The differentiation between content and structure constraint may easily be done by looking at the syntax of a CAS-topic title:

```
[node [filter]]* target-node filter
```

Every filter (which corresponds to constraints) before the target-node belongs to the structure constraint, while the filter given for the target-node contains the content constraint.

The title of a CAS-topic contains a path expression that must be matched by the path of a result element. For the automatic query generation, this path expression is simply the concatenation of all nodes. Normally, there are several elements within a document with matching paths, since the path expression may contain wildcards and does not have to use node indices. Thus, a retrieval system not only has to find relevant documents and determine fitting sub-elements of that element, but it also has to determine relevance scores for each sub-element. Therefore we inserted a new table into the underlying ORDBMS which contains every addressable element of the document collection, i.e. every element that matches the XPath-expression `//*`, which are about 8 mio elements. Each table entry consists of an element with all its sub-elements and their textual content, its unique path expression, and its path expression without indices. To determine the unique path of an element, which is needed for the creation of the submission-file, this data can simply be read from this table. To fulfill the structural constraint of a CAS-topic regarding the result granule, only a selection of those elements is evaluated whose path matches the path expression given in the topic title. Apparently, this approach implies a high degree of redundancy, since the table contains every textual content multiple times. Further developments of IRStream will address this problem, probably by making extended use of the transferer functionality.

The content constraint includes every information that is given about the result element itself. That may be content only, but also constraints concerning the internal structure of an element, like a section having a title about `information retrieval`:

```
/article/bdy/
    sec[about(.,//st,'"information retrieval"')]
```

The crucial factor of this logic part of the topic is that every information needed is within the result element itself and thus may be addressed via the table mentioned above.

The structure constraint includes every information given about the environment of the result element, i.e. its sibling and parent elements. This may include both structure and content information which is not contained in the result element itself and therefore cannot be addressed via the table mentioned above, since the table entries are decoupled from their environment. To fulfill this constraint, a document as a whole has to be evaluated, i.e. it refers to a whole article instead of a result element only.

By looking at an example (topic 77), the retrieval process of IRStream for CAS-topics and the integration of a query generation step into this process will be depicted. The title of topic 77 states:

```
//article[about(.//sec,'"reverse engineering"')]//
    sec[about(.,'legal') OR about(.,'legislation')]
```

The concatenation of all nodes is `//article//sec`, which is the given path expression that all result elements have to fulfill. Therefore only elements with the fitting granule will be ranked in the query process, which is implemented via a corresponding `WHERE`-clause.

The content constraint, referring to the result element itself, is contained in the last filter. It says that the result element has to be about concepts of `legal` or `legislation`. The query generation component successively reads all about-clauses and their connectors. Each about-clause is translated into a corresponding `INPATH`-clause of the ORDBMS, which reads `(terms INPATH path)` and includes any given structural constraints. In this example, `(legal INPATH /sec)` would be the resulting query part. The `INPATH`-clauses, their connectors and the result element's path expression form the main part of the content query, which is applied to the table containing every addressable element.

The structure query on the other hand has to be applied to a table of whole articles, which contain the complete structure information of a document. The query generation is done accordingly, reading each filter successively and connecting the resulting `INPATH`-expressions. The last filter in the topic-title may or may not be part of the structure query. Not including it means that some articles are probably marked relevant that do not contain any elements that satisfy the content constraint. IRStream therefore considers the content query to be a part of the structure query.

In order to get a result ranking, these two queries have each to be processed by a ranker-component and then be joined into a final ranking. These two rankers create streams of two different object types — article (structure query) and element (content query) —, which cannot directly be combined by a combiner-component. Therefore a transferer-component is needed, which transfers the ranking of an article to all its sub-elements. A special filter-component filters all elements whose path does not fulfill the given path expression. The output of this filter is a stream of elements,

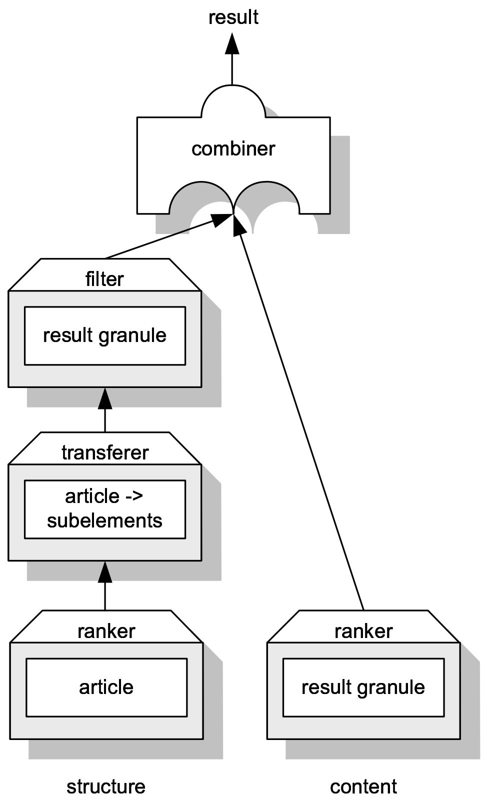

Figure 3: CAS-topic processing

and thus a combiner can finally merge the two streams into a result ranking. This procedure is shown in figure 3.

Obviously, this (general) procedure can be optimized, because the transferer creates hundreds of elements that are immediately eliminated by a filter. Therefore the task of ranking, transferring and filtering was integrated into a specialized component `InexRanker`, which relocates the transferring-process into the DBMS. The three logical steps described above can thereby be performed by a single SQL-query:

1. ranking an article in reference to the structure query

2. transferring the RSV to all sub-elements, identified via foreign key relationship

3. selection of those elements that fulfill the given path expression

4.3 CO-topics

The special challenge while processing CO-topics is that the retrieval system has to decide autonomously, which granule of the result elements is the most fitting. For INEX 2003, the procedure for handling CO-topics is based on the table mentioned above, which contains every addressable element including all its textual content and that of its sub-elements. A single ranker-component simply creates a ranking of all those elements, and an element's filename and unique path may be read from this table. The aim of this approach was to evaluate whether it is worthwhile basing further optimizations on it, which are obviously possible, since this table contains about eight million elements, every layout-tag (italic, bold etc.) being contained.

For CO-topics, four characteristics can be identified. Based on these, the general applicability of this approach is to be shown:

CO-topics do not contain structural information

The elements in the table used are decoupled from their structural environment and are treated as single documents. No structure information is needed for this query processing.

CO-topics do not contain constraints regarding the granule of result elements

By this procedure, elements of all granules are ranked likewise, so that every granule may be contained in the result ranking. Possible optimizations will be addressed in section 6.

An ideal result element satisfies the information need completely

A retrieval system cannot validate a complete answering of an information need, but this requirement has to be considered in the process of determining relevance scores. Regarding an XML-document as being a tree of elements, that one element obviously fulfills that requirement best, which is superior to all elements which contain relevant information. If several paragraphs are marked as relevant, for example, their corresponding section seems to be the best fitting element. The calculation of a *score*-value that is done by the underlying ORDBMS provides an according evaluation, because it is in principle based on absolute term frequencies. Thus, superior elements normally get a relevance score which is equal to or greater than that of their child elements.

An ideal result element is specific about the topic's theme

For INEX 2003, IRStream did not eliminate multiple result elements within a branch of the document tree, the consequences of which with respect to retrieval effectiveness has not yet been evaluated, but it will be addressed in the near future. If several elements of a branch have the same RSV-score, it is obviously the smallest element that conforms best to this requirement. It remains to be seen whether elimination of such duplicates or considering document lengths will improve retrieval effectiveness.

The query generation for CO-topics is similar to that of CAS-topics, but here only one query has to be created, and no structural information has to be included. Terms in the title of CO-Topic may be marked by a + (declared as must-terms). The IRStream query generation allows to interpret these markings as strict or vague. A strict interpretation means that only those elements may be relevant that contain all must-terms. Therefore these terms are connected to each other by `AND`-operators, and must-terms and all other terms are each encapsuled by brackets which are also connected by an `AND`-operator. Interpreting these terms as vague, other connecting operators may be used, like `ACCUMulate` or `OR`.

5. EVALUATION OF THE NEW IRSTREAM ENGINE AT INEX 2003

With the runs submitted to INEX 2003, two things were to be looked at: First, we wanted to see, whether our interpretation of CAS-topics and thus the differentiation between content and structure constraints would lead to good results compared to those of the other participating retrieval systems. Second, we wanted to get an estimation of how applicable our approach for processing CO-topics is.

Figures 4 and 5 show the recall/precision graphs for IRStream's CAS-run — with strict and generalized quantization — in comparison to all officially submitted retrieval runs. Rank 12 of 38 for strict quantization and rank 10 of 38 for generalized quantization seem promising that the chosen query architecture forms a solid basis for further efforts.

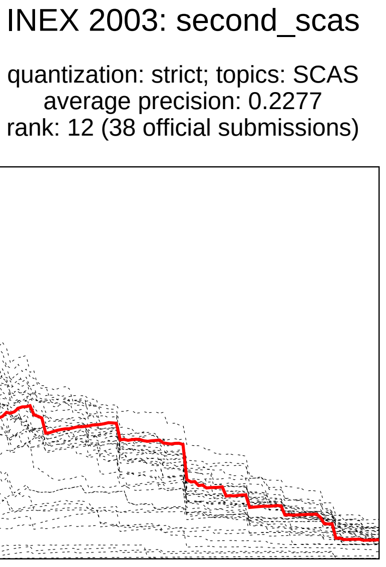

Figure 4: summary CAS strict

The recall/precision graphs for IRStream's CO-run are shown in figures 6 and 7. Rank 10 of 56 for strict and rank 7 of 56 submissions for generalized quantization indicate that further efforts to optimize our approach seem to be worthwhile.

In order to compare the results of IRStream02 and IRStream03 — and thus to evaluate the effect of the system changes — we used the new system to create a retrieval run on the topics of INEX 2002. Since the topic syntax for CAS-topics has changed, only those topics were processed in this run which could be converted to the new syntax. Topics without explicitly stating a target element or those with multiple target elements do not conform to INEX 2003 syntax and thus were omitted.

Figures 8 to 11 show that — especially considering the re-

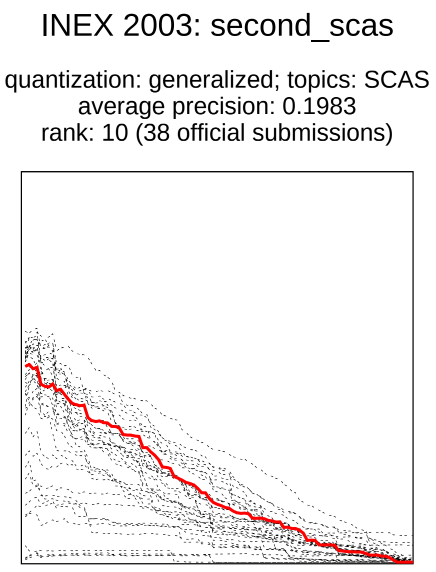

Figure 5: summary CAS generalized

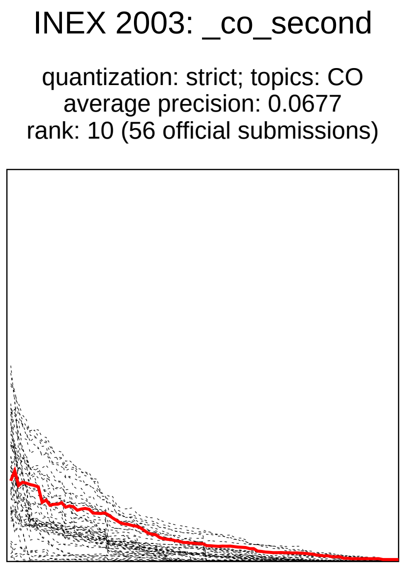

Figure 6: summary CO strict

call — the results of IRStream03 are noticeably better than those of IRStream02, which is mainly caused by a more vague interpretation and processing of topic data. Due to the manual optimization of the queries used in IRStream02, its precision at low recall values is slightly better than that of IRStream03, which uses a fully automated query processing.

6. CONCLUSION

In this paper, we have presented an improved version of our retrieval system called IRStream, which was successfully used in the context of INEX 2002. The main idea of IRStream is to complement traditional query processing techniques for queries dominated by similarity conditions. The IRStream retrieval engine has been implemented as a prototype in Java on top of an ORDBMS and first experimental results achieved with this prototype are promising.

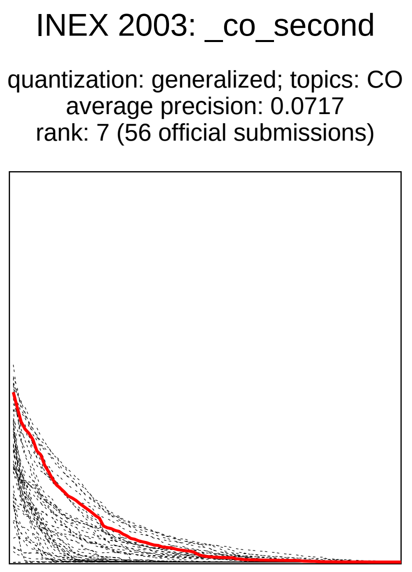

Figure 7: summary CO generalized

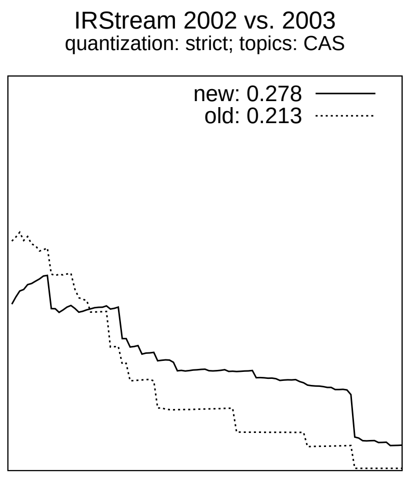

Figure 8: improvement CAS strict

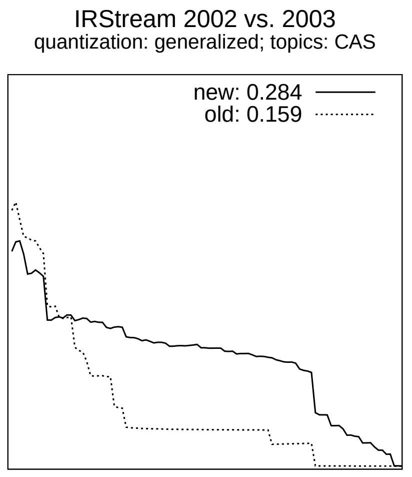

Figure 9: improvement CAS generalized

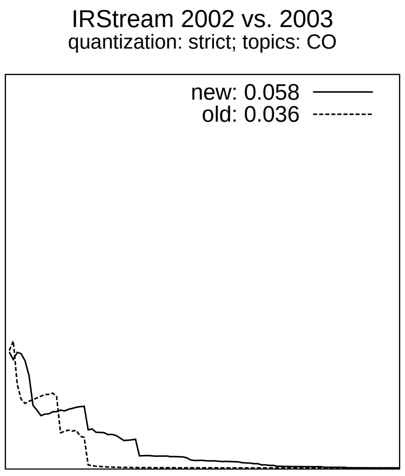

Figure 10: improvement CO strict

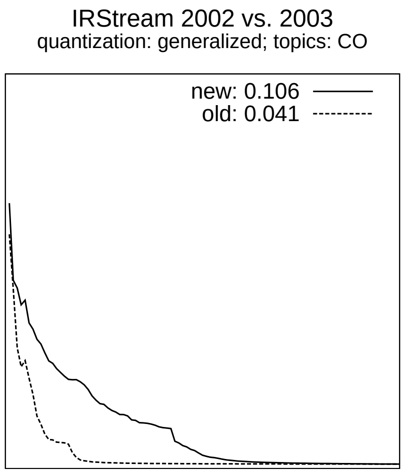

Figure 11: improvement CO generalized

With regard to INEX2003 IRStream was extended and improved in several respects. IRStream now supports automatic query generation as well as the automatic detection of the best fitting result granule for a given query.

In the near future, we will develop a query language for this approach and consider optimization issues regarding the interaction between the underlying ORDBMS and the IRStream system. Last but not least, IRStream should build a good basis for the integration of further query criteria — like context information or domain specific thesauri — into the query execution in order to improve the precision of the system.

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Distributed XML Information Retrieval

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ABSTRACT

In this paper we describe the implementation of a distributed search engine for XML document collections. The system is based on a generic P2P collaborative computing framework. A central server coordinates query and search results distribution. The server holds no documents nor does it hold any indexes. The document collection is distributed amongst multiple PC based workstations, where it is also indexed and searched. The system is scalable to databases several orders of magnitude larger than the INEX collection, by using a system of standard networked PCs.

Keywords: P2P, INEX, XML, Distributed Database, Information, Retrieval, Inverted File, XPath, Assessment, Evaluation, Search Engine

1. Introduction

Web search engines such as Google are enormously valuable in allowing ordinary users to access information on a vast array of topics. The enormity of the information being searched and the massive number of clients wishing to make use of such search facilities means, however, that the search mechanisms are inherently constrained. The data being searched needs to be a priori indexed. Searching is limited to finding documents that contain at least one occurrence of a word from a list of words somewhere within its body. The exact relationship of these words to one another cannot be specified. These limitations mean that it is often difficult to specify exactly what you want, consequently clients are overwhelmed by an avalanche of query results – if users don't find what they are looking for in the first couple of pages of results they are likely to give up.

XML documents contain rich structural information that can be used by information retrieval system to locate documents, and part thereof, with much greater precision than text retrieval systems can. However, systems capable of searching XML collections by content are typically resource hungry and are unlikely to be supported extensively on central public servers for some time to come, if at all.

Peer to Peer (P2P) file sharing systems such as KaZaA, Gnutella and Napster enable documents to be searched and accessed directly from end user's PCs, i.e., without needing to *publish* them on a web server, but again the indexing for retrieval is a priori. This is fine if you are searching based on well defined metadata keys such as song title or performer, but not if you are trying to search based on the content of the data.

The greatest degree of search specificity is achieved if the search engine can potentially access the content of the entire collection for each and every query. Obviously this is infeasible for huge document collections such as the entire WWW. If, however, we limit ourselves to smaller collections such as documents archived by a "community" of individuals that are collaborating on some project or share some common interest, then such a precise Information Retrieval paradigm is feasible and highly desirable.

The P2P framework that we propose is based on *search agents* that visit the workstations of participating individuals to perform custom searches. Individuals wishing to perform a search can choose from a library of "standard" search agents, or they can implement their own agent that implements an arbitrarily sophisticated search algorithm. The agents execute on the individual workstations within our P2P host environment that "sand-boxes" them, preventing them from doing "harm" to the workstations and allowing the workstation owners to control exactly which "resources" can be accessed. Resources potentially accessed include files, directories and databases. The key advantages of our system compared to web search engines such as Google are:

- Arbitrarily sophisticated algorithms can be used to perform highly selective searches, since the query is known before the actual document collection is scanned.
- The documents don't have to be explicitly published to a central server – they are accessed in place. This saves time and effort and means that working documents can be made immediately available from the time they are created, and work can continue on those documents locally while still being externally accessible.
- Volunteers have the option to only partially publish documents. This means they allow a client's search agent to examine their documents, but they limit the response that such search agents can return to the client. The response could be as limited as saying "Yes - I have a document that matches your query". In most cases, the agent will return some form of URL which uniquely identifies the matching document, but our framework doesn't in itself provide a mechanism for the client to retrieve that document from the volunteer. The exact mechanism by which such documents are retrieved is beyond the scope of this paper, but it could for example be a manual process, whereby the owner of the volunteer workstation will access each such client request based on the identity of the client and the document being retrieved. This might happen, for example, in a medical setting with doctors requesting patient records from other doctors, or in a law enforcement setting with police agencies requesting criminal histories from other jurisdictions.

The remainder of this paper is organized as follows. In section 2 we describe the system underlying the distributed search engine. In section 3 we describe the XML search engine that is distributed and executed by search agents on the distributed database. In section 4 we discuss the results of testing the systems against the INEX collection. In section 5 we discuss and summarize the lessons learnt from the INEX exercise.

2. System Architecture

Our system is termed P2P in that the actual searching is performed on peer nodes. The internal architecture of our system is, however, client/server based - for a number of reasons. The underlying architecture of our system is illustrated in Figure 1. The client PCs that make up the "leaves" of system belong to the individuals in the community and can play two distinct roles; they can be a *searcher* or they can *volunteer* to be searched. A *searcher* is a PC that submits queries to the system. The *volunteers* are the PCs on which the documents reside and on which the queries are processed. Individual PCs can play either or both of these roles at various points in time. PCs volunteer themselves to be searched typically only when they are otherwise idle. This is a form of cycle stealing, as the execution of the search agents may consume considerable CPU time and memory bandwidth of the machine while it is running.

The clients of the system - the searchers and the volunteers come and go over time; the *search server* is the only part of the system that remains constant. It acts as a central point of contact for searchers wishing to submit queries and for volunteers willing to be searched. It also acts as a repository for queries waiting to be processed and query results waiting to be retrieved. At the point in time when a searcher submits a query, there may be some volunteers "currently connected" to the server that would be willing to process that query immediately. In such a case some results may be able to be returned to the searcher almost immediately (allowing of course, for the time to perform the search on the volunteer machines - which can be arbitrarily long depending on the complexity of the search algorithm and the size of the document collection being searched on each PC).

Often, however, the relatively small set of set of volunteers that are currently connected, will either produce no results for the query, or at least will produce no results that are satisfactory to the searcher (note that this is made more probable by the high degree of query specificity that is possible with an agent based search framework). In such a case, we assume the searcher will often be willing to wait (minutes, hours, days or perhaps even weeks) for other volunteers to connect to the system and hopefully contribute interesting new results. This is the key difference between our distributed search engine and traditional cycle stealing systems. In a traditional cycle stealing system, all volunteers are considered equal – once a computational task has been carried out by one machine there is no point if her volunteer machine repeat that

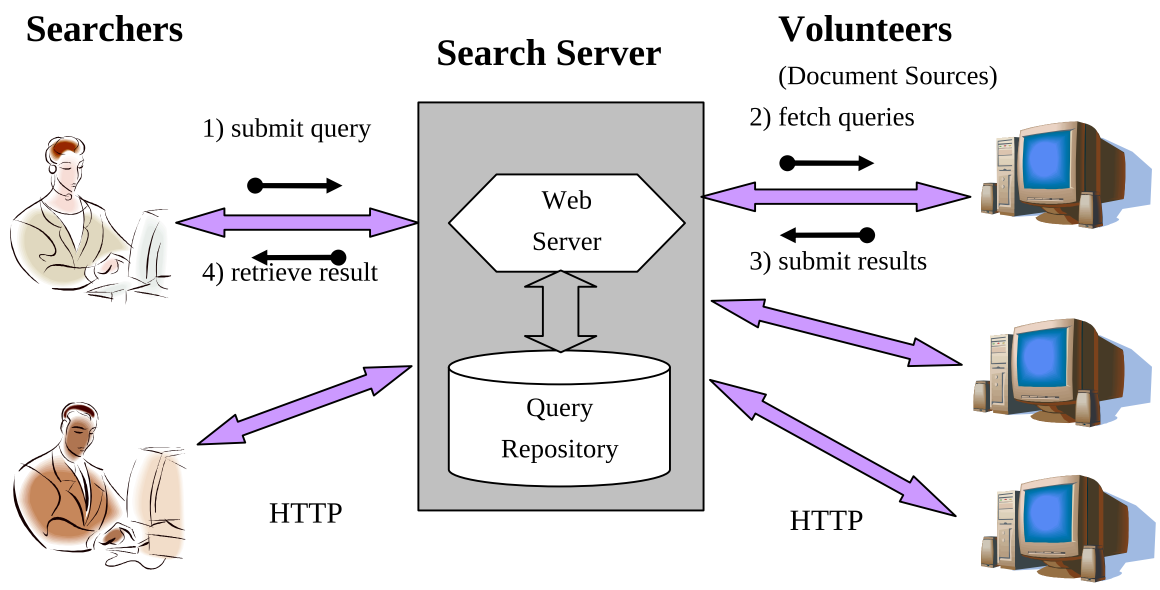

Figure 1: System Architecture

same computation. In our distributed search system, however, each PC is assumed to archive a different set of documents – so even if a query has been processed on one volunteer, it still makes sense to keep that query around for other volunteers to process when they connect later.

Having a query and results *repository* allows the submission of queries and results to be separated in time from the fetching and processing of those queries and results. Having a central server means that once a client has submitted a query, it can disconnect from the system, and only reconnect much later when it expects to find a significant collection of results. More importantly, the wide spread use of corporate firewalls will often mean that PC's performing searchers cannot directly communicate with many potential volunteers and vice versa. Having a central server that is able to receive HTTP requests from anywhere on the Internet has the effect of providing a gateway for searchers and volunteers to work together who would otherwise be unable to communicate. Note, installing a web server on all searcher and volunteer PC's would *not* achieve the same effect – a HTTP request message generally can not be sent to a machine behind a firewall, even if that machine hosts a web server.

The search server exposes interfaces to searchers and volunteers as SOAP web services transported using HTTP. Searchers can submit queries and fetch results and volunteers can fetch queries and submit results. All communication is initiated by either the searchers or the volunteers, and connections are not left open; i.e, the server can't push either queries or results to the searchers or the volunteers - they must request them. From the volunteer's perspective, the server is stateless. The server maintains *neither* a list of currently "connected" volunteers, nor a list of all potential volunteers. Anyone can volunteer at any time (subject to any authentication that the server may implement to ensure that the volunteer is a member of "the community"). When a volunteer connects to the server (after having been "disconnected" for a period of time) it receives a list of all queries that have been submitted to the server since that volunteer last connected. Each volunteer is responsible for keeping a "time-stamp" (in reality a sequence number allocated by the server) that represents the point in time at which that volunteer last requested queries from the server. In this way, the server is spared from maintaining information specific to each volunteer yet is able to respond to requests from individual volunteers in a personalized manner.

The time period that a query remains on the server is determined by a number of factors. Firstly, the searcher can specify a "time-to-live" when they submit the query. This may be overridden by the server which may dictate a system wide maximum "time-to-live" for all queries. Individual volunteers may also implement their own policies, such as refusing to process queries that are older than a certain date. Finally, the searcher can manually retract a query from the server as soon as they have received satisfactory result(s) to their query or if they realize that the query was incorrect or too inexact.

3. The XML Search Engine

The search engine is based on an XML inverted file system, and a heuristic approach to retrieval and ranking. These are discussed in the following sections.

3.1. The XML Inverted File

In our scheme each term in an XML document is identified by 3 elements. File path, absolute XPath context, and term position within the Xpath context.

The file path identifies documents in the collection ; for instance :

C :/INEX/ex/2001/x0321.xml

The absolute Xpath expression identifies a leaf XML element within the document, relative to the file's root element:

/article[1]/bdy[1]/sec[5]/p[3]

Finally, term position identifies the ordinal position of the term within the Xpath context.

One additional modification that we adopted allowed us to support queries on XML tag attributes. This is not a strictly content search feature, but rather structure oriented search feature. For instance, it allows us to query on the 2nd named author of an article by imposing the additional query constraint of looking for that qualification in the attribute element of the XML author element. The representation of attribute values is similar to normal text with a minor modification to the Xpath context representation – the attribute name is appended to the absolute Xpath expression. For instance:

article[1]/bdy[1]/sec[6]/p[6]/ref[1]/@rid[1]

Here the character '@' is used to flag the fact that "rid" is not an XML tag, but rather an attribute of the preceding tag <ref>. An inverted list for a given term, omitting the File path and the Term position, may look something like this:

Context
Xpath
article[1]/bdy[1]/sec[6]/p[6]/ref[1]
article[1]/bdy[1]/sec[6]/p[6]/ref[1]/@rid[1]
article[1]/bdy[1]/sec[6]/p[6]/ref[1]/@type[1]
article[1]/bm[1]/bib[1]/bibl[1]/bb[13]/pp[1]
article[1]/bm[1]/bib[1]/bibl[1]/bb[14]/pdt[1]/day[1]
article[1]/bm[1]/bib[1]/bibl[1]/bb[14]/pp[1]
article[1]/bm[1]/bib[1]/bibl[1]/bb[15]
article[1]/bm[1]/bib[1]/bibl[1]/bb[15]/@id[1]

In principle at least, a single table can hold the entire cross reference list (our inverted file). Suitable indexing of terms can support fast retrieval of term inverted lists. However, it is evident that there is extreme redundancy in the specification of partial absolute Xpath expressions (substrings). There is also extreme redundancy in full absolute Xpath expressions where multiple terms in the same document share the same leaf context (e.g. all terms in a paragraph). Furthermore, many Xpath leaf contexts exist in almost every document (e.g. /article[1]/fm[1]/abs[1]).

We have chosen to work with certain imposed constraints. Specifically, we aimed at implementing the system on a PC and base it on the Microsoft Access database engine. This is a widely available off-the-shelf system and would allow the system to be used on virtually any PC running under any variant of the standard Microsoft Windows operating system. This choice implied a strict constraint on the size of the database – the total size of an Access database is limited to 2Gbyte. This constraint implied that a flat list structure was infeasible and we had to normalise the inverted list table to reduce redundancy.

3.2 Normalized Database Structure

The structure of the database used to store the inverted lists is depicted in Figure 2. It consists of 4 tables. The ***Terms*** table is the starting point of a query on a given term. Two columns in this table are indexed - The ***Term*** column and the ***Term_Stem*** column. The ***Term_Stem*** column holds the Porter stem of the original term. The ***List_Position*** is a foreign key from the ***Terms*** table into the ***List*** Table. It identifies the starting position in the inverted list for the corresponding term. The ***List_Length*** is the number of list entries corresponding to that term. The ***List*** table is (transparently) sorted by Term so that the inverted list for any given term is contiguous. As an aside, the maintenance of a sorted list in a dynamic database poses some problems, but these are not as serious as might seem at first, and although we have solved the problem it is outside the scope of this paper and is not discussed any further. A search proceeds as follows. Given a search term we obtain a starting position within the List table. We then retrieve the specified number of entries by reading sequentially.

The inverted list thus obtained is *Joined* (SQL) with the ***Document*** and ***Context*** tables to obtain the complete de-normalised inverted list for the term. The XPath context is then checked with a regular expression parser to ensure that it satisfies the topic's <Title> XPath constraints. The retrieval by ***Term_Stem*** is similar. First we obtain the Porter stem of the search term.

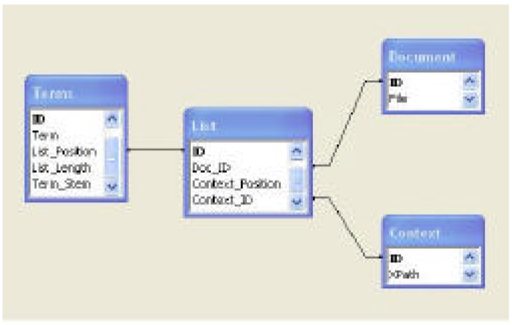

Figure 2: Database Schema for the XPath based Inverted XML File.

Then we search the list by ***Term_Stem*** – usually getting duplicate matches. All the lists for the duplicate hits on the ***Terms*** table are then concatenated. Phrases and other proximity constraints can be easily evaluated by using the ***Context_Position*** of individual terms in the ***List*** table.

With this normalization the database size was reduced to 1.6GByte and within the Microsoft Access limits. This is of course a trade-off in performance since costly join operations may be necessary for the more frequent terms.

3.3 Searching the Database

The database structure enables the identification of inverted lists corresponding to individual terms. Each term that appears in a filter of an INEX <Title> element has an associated Xpath context. Terms that appear in a <keywords> element of a topic have the default context of /article. With simple SQL statements it is easy enough to retrieve inverted lists for terms that satisfy a filter.

3.3.1 SCAS topics

Our search strategy for SCAS topics consists of several steps, as follows.

We start by fragmenting the INEX <Title> element into several sub-queries, each corresponding to a filter on the path. So, for instance:

<title>//article[about(.//st,'+comparison')/ bm[about(.//bib,'machine learning')]</title>

is transformed to a set of 2 individual queries:

S|//article|//article//st|+comparison
R|//article/bm|//article//bm//bib|machine learning

This formulation identifies two sub-queries, each with 4 parts delimited by a '|'. The **S** denotes a support element and the **R** denotes a Returned Element. The support element has the Xpath signature **/article**. The return element has the XPath signature **/aticle/bm**. The support element filter looks for elements with the Xpath signature **//article//st,** containing the term "**comparison**". The returned element filter looks for elements with the Xpath signature **//article/bm//bib,** containing the phrase "**machine learning**".

Strict compliance to the XPath signature of the various elements is enforced. However, this is moderated by the use of equivalent tags.

SCAS Equivalent tags:

- **Article,bdy**
- **p|p[1-3]|ip[1-5]|ilrj|item-none**
- **sec|ss[1-3]**
- **h|h[1-2]a?|h[3-4]**
- **l[1-9a-e]|dl|list|numeric-list|numeric-rbrace|bullet-list**

Each of the elements is scored in the following way – we count the number of times that each term in the filter is found in the element. If more than one term is found then the term counts are multiplied together. This has the desired heuristic that elements containing many search terms are scored higher than elements having fewer search terms.

The score of a returned element is the sum of the scores of all its support elements. So in the example above, the score of a **//article/bm** element is the sum of all the corresponding **//article//st** elements (within the same <article>) and all **//article/bm//bib** elements (within the same <article> and same <bm>). At one extreme a returned element may be supported by numerous elements from all filters. At the other extreme it may only have support in one term of the returned element filter. We accept all such return elements as candidates for results. However, the returned elements are sorted first by the number of support filters that they satisfy and then by their score.

Topics that make use of AND clauses and OR clauses in the <Title> are handled by generating separate query for each clause. We do not distinguish between AND and OR and effectively allow ranking to take care of it. The heuristic justification is that if all terms appear then the score should be higher regardless of whether AND or OR were used. Also, if AND was specified, but only satisfied by some of the terms, we still want the partially matching elements as potentially valid results – after all, this may be the best that we can find.

The <Keywords> element of topic is also used – it defaults to a query on the entire <article> and considered a support to all returned elements within the same article.

3.3.2 VCAS topics

The VCAS queries were treated in exactly the same manner as SCAS queries, except that we expanded the equivalence tag interpretation.

alent tags:

- **Article,bdy,fm**
- **sec|ss[1-3]|p|p[1-3]|ip[1-5]|ilrj|item-none**
- **h|h[1-2]a?|h[3-4]**
- **yr|pdt**
- **snm|fnm|au**
- **bm|bibl|bib|bb**
- **l[1-9a-e]|dl|list|numeric-list|numeric-rbrace|bullet-list**

3.3.2 CO Topics

The CO topics were handled in the same manner as CAS topics. However, all terms from both the <Title> and <Keywords> elements of the CO topic were combined to form a single query – after removing duplicate terms. The return element was assigned the default XPath signature //* which means that any element in the article was returnable (subject to support). For instance, topic 91 –

<title>Internet traffic</title>
<keywords>internet, web, traffic, measurement, congestion </keywords>

is transformed to the following query:

R|//*|//article|Internet,traffic,web,measurement, congestion

Every element with the context of //article (this includes descendents) and which contains at least one of the terms in the query is suitable for return. However, since only leaf nodes in the XML tree contain terms (with very few exceptions) there is a need to associate a score with other non-leaf elements in the tree in order to qualify them for selection. The search engine propagates the score of matching elements upwards, recursively, to ancestor nodes, in the following manner. If an ancestor has a single child it receives half the child's score. If it has multiple children it receives the sum of their scores. In this manner, for instance, a section with multiple scoring paragraphs receives a score higher than any of its paragraphs and will be ranked higher. A section having only one scoring paragraph will be ranked lower.

3.3.4 Selection by Year

Selection by year was treated as an exception. The search engine expands conditions with respect to years to allow for a range of years. It allows up to 5 years below for a Less Than condition, up to 5 years above for a Greater Than condition, and 2 years either side for an about condition. Equality is treated strictly. This is necessary for two reasons. The inverted list structure does not support range queries so it is necessary to translate such conditions to explicit values that can be searched. It is also not possible to interpret the *about* condition over <year> without some pre-conceived idea of what might be a reasonable year range.

3.3.4 Term expansion

The search engine can optionally expand keywords in one of two ways. It can perform plural and singular expansion, or it can use the full porter stem (pre-stored in the database). In the case of phrases, the program also attempts to construct an acronym. So for instance, the phrase "Information Retrieval" generates the additional term "IR". A common writing technique is to introduce an acronym for a phrase and thereafter use the acronym for brevity. For instance, at INEX, we defined "Strict Content and Structure" as "VCAS". Subsequent references are to VCAS only. So the idea here is to try and guess acronyms. We use several simple rules that attempt to manipulate the phrase initials to construct a few acronyms. If an acronym thus generated is found in the inverted list it is used as an additional term.

4. Results

Two aspects of the system were tested. The precision/recall values were measured through the standard INEX evaluation process. The performance of the distributed search engine was also tested on a distributed database.

4.1 Performance

The system was tested as a stand alone search engine in a single PC and on a distributed configuration. On a single PC (Pentium 4, 1.6GHz, 500MB RAM) the search times for topics varied between 5 seconds and one minute, depending on the number of terms and their frequency in the database.

The database can be distributed in a logical manner by placing each of the 18 journals on a different PC. Each search engine was set to return the N best results. We used a threshold N=100, but this is a run-time argument. The communications overhead of the system is about 5 seconds (pretty much fixed, given a reasonably fast connection.) The search over a single journal is very quick and takes less than 3 seconds. The INEX collection can thus be searched in less than 10 seconds even for the most elaborate topics. The total search time is pretty much upper limited by the longest search time on any of the distributed components. Nevertheless, results arrive asynchronously, so the user can view early results before the entire distributed search is complete.

The system scales up well. If the full database is duplicated on several PCs the search time is virtually constant – as long as the number of results returned is reasonably capped.

Results are ranked independently by each distributed search component. Consequently, the results can be displayed in order, either globally, or within each Journal. A difference between the single complete database and the distributed database results can arise if there are useful results in one journal that are ranked below the allowed threshold N. However, this difference will only affect the lower end of the ranked list and in any case this problem can be easily circumvented. An obvious variation is to determine the return threshold by rank rather than by count. In this manner poor results can be avoided while better results are allowed to arrive in larger numbers from fruitful searches of distributed database compartments.

5.2 Precision/Recall

The better results were obtained in the SCAS track with plural/singular term expansion. It scored an average precision (generalized) of 0.195 (rank 12/38). The Porter stemming expansion of terms produced somewhat lesser results with an average precision of 0.186. Without term expansion the results had an even lower score with an average precision of 0.174.

VCAS results are not available at the time of writing this paper.

In the CO track results were similar. The better results were obtained with full Porter stemming, with an average precision (generalized) of 0.0525 (rank 14/56). Somewhat lesser, but essentially similar results were obtained with plural/singular expansion with an average precision of 0.0519. Without term expansion the average precision was 0.0505.

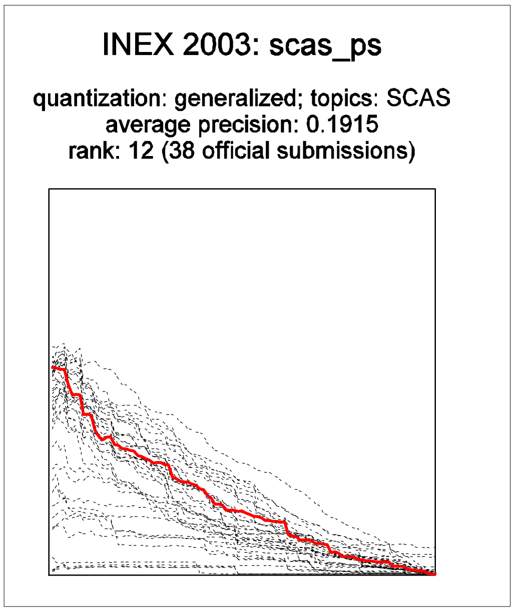

Figure 3: Plural/Singular expansion

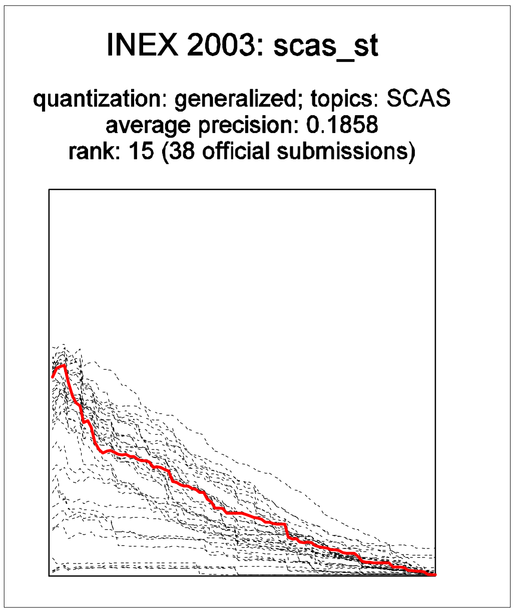

Figure 4: Full Porter stemming

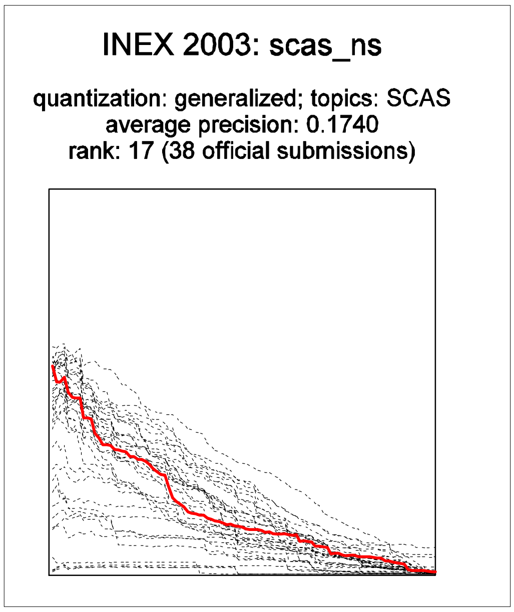

Figure 5: Without Term expansion

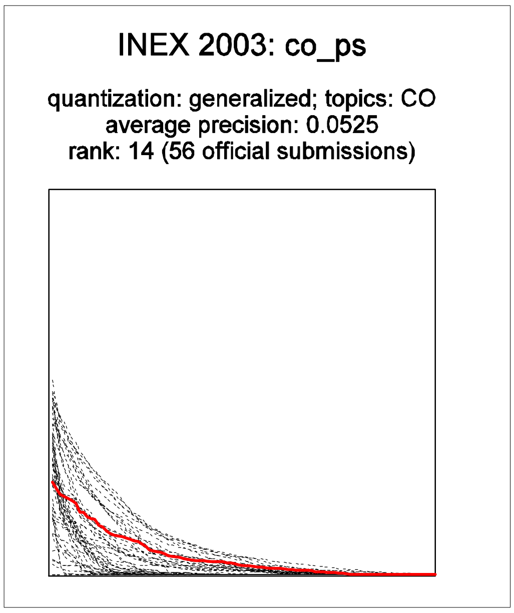

Figure 6: Full Porter stemming

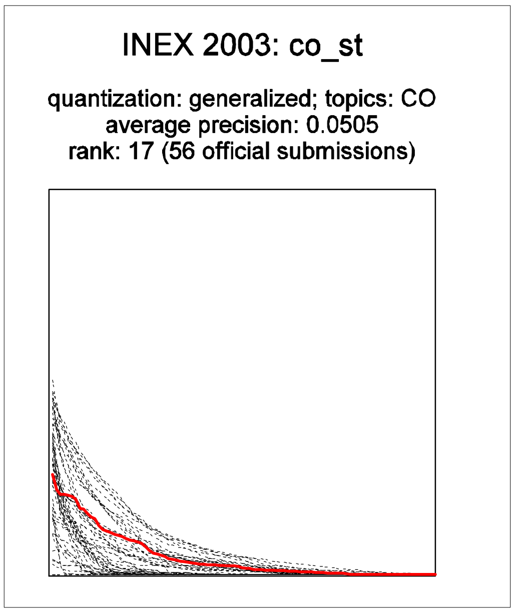

Figure 8: Without Term expansion

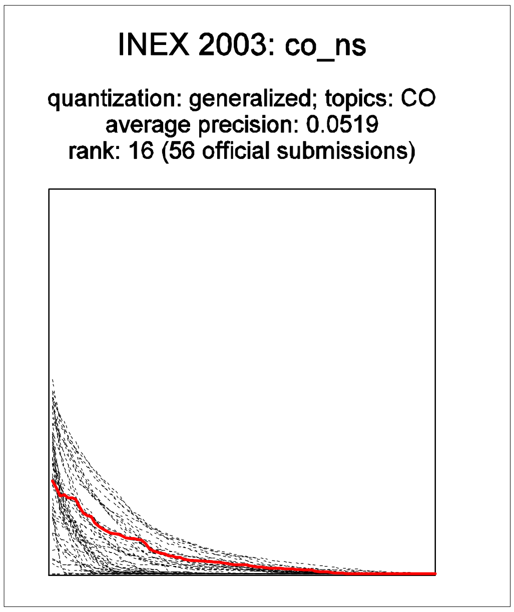

Figure 7: Plural/Singular expansion

5. Discussion

The search engine that was developed and tested performs reasonably well in terms of precision/recall. It performs very well in terms of speed, and scales almost linearly.

Inspection of our results suggests that while the system was able to retrieve the most significant <article> elements, it fell short in terms of ranking the various descendents. With CAS queries the loose interpretation of AND, OR, and equality constraint might have contributed to violations of topic <title> XPath constraints leading to selection of undesirable elements. With CO queries the ranking heuristics that we used were generic. We only took account of abstract tree structure considerations. It might have been advantageous to also apply heuristics that are specific to the INEX collection and perceived intent of topic authors (in general, not specifically). For instance, paragraphs might be better units of retrieval than sections. More analysis and experimentation with ranking is required.

6. REFERENCES

[1] Proceedings of the First Workshop of the Initiative for the Evaluation of XML Retrieval (INEX), DELOS Network of Excellence on Digital Libraries, ERCIM-03-W03

[2] "XML Path Language (XPath) Version 1.0" http://www.w3.org/TR/xpath

RMIT INEX experiments: XML Retrieval using Lucy/eXist

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ABSTRACT

This paper reports on the RMIT group's approach to XML retrieval while participating in INEX 2003. We indexed XML documents using Lucy, a compact and fast text search engine designed and written by the Search Engine Group at RMIT University. For each INEX topic, up to 1000 highly ranked documents were then loaded and indexed by eXist, an open source native XML database. A query translator converts the INEX topics into corresponding Lucy and eXist query expressions, respectively. These query expressions may represent traditional information retrieval tasks (unconstrained, CO topics), or may focus on retrieving and ranking specific document components (constrained, CAS topics). With respect to both these expression types, we used eXist to extract final answers (either full documents or document components) from those documents that were judged highly relevant by Lucy. Several extraction strategies were used that differently influenced the ranking order of the final answers. The final INEX results show that our choice for a translation method and an extraction strategy leads to a very effective XML retrieval for the CAS topics. We observed a system limitation for the CO topics resulting in the same or similar choice to have little or no impact on the retrieval performance.

Keywords

XML Search & Retrieval, eXist, Lucy, INEX

1. INTRODUCTION

During INEX 2002, different participants used different approaches to XML retrieval. These approaches were classified into three categories [1]: extending well known full-text *information retrieval* (IR) models to handle XML retrieval; extending *database management systems* to deal with XML data; and *XML-specific*, which use native XML databases that usually incorporate existing XML standards (such as XPath, XSL or XQuery). Our modular system utilises a combined approach using traditional information retrieval features with well-known XML technologies found in most native XML databases.

Lucy[1] is RMIT's fast and scalable open source full-text search engine. Lucy follows the content-based information retrieval approach and supports Boolean, ranked and phrase queries. However, Lucy's smallest unit of retrieval is a whole document, thus ignoring the structure specified using the document schema as in the XML retrieval approach. Indeed, when dealing with information retrieval from a large XML document collection, sections that belong to a document, or even smaller document components such as paragraphs, may be regarded as appropriate units of retrieval. Accordingly, it is important to have an IR-oriented XML retrieval system that will be able to identify and rank these units of retrieval.

eXist[2], an open source XML database, follows the XML-specific retrieval approach. It is the XML-specific approach that deals with both the content and the structure of underlying XML documents and incorporates keyword, Boolean and proximity search. Most of the retrieval systems that follow this approach use databases specifically built for XML. These databases are often called *native XML databases*. However, most of these systems do not support any kind of ranking of the final answers, which suggests a need of applying an appropriate retrieval strategy to determine the relevance of the answers to a given retrieval topic.

The XML retrieval approach we consider at INEX 2003 is that for many retrieval topics, one way of obtaining satisfactory answers is to use either *proximity* or *phrase search* support in XML retrieval systems. That is, a final answer is likely to be relevant if it contains (almost) all of the query terms, preferably in a desired order. The native XML databases, as explained above, provide all the required support to enable this functionality. However, when a native XML database needs to load and index a large XML collection, the time required to extract the most relevant answers for a given query is likely to increase significantly. Moreover, the XML database needs to determine a way to somehow assign relevance values to the final answers. Accordingly, it would be more efficient if the XML database has to index and search a smaller set of XML documents that may have previously been determined *relevant* for a particular retrieval topic. The database would then need to decide upon the most effective strategy for extracting and ranking the final answers. We have therefore decided to build a system that uses a combined IR/XML-specific retrieval approach. Our modular system effectively utilises Lucy's integrated ranking mechanism with eXist's powerful keyword search extensions. The INEX results show that our system produces effective XML retrieval for the content-and-structure (CAS) INEX topics.

[1]http://www.seg.rmit.edu.au/lucy/

[2]http://exist-db.org/

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<!DOCTYPE inex_topic SYSTEM "topic.dtd">
<inex_topic topic_id="117" query_type="CO" ct_no="98">

<title>
Patricia Tries
</title>

<description>
Find documents/elements that describe
Patricia tries and their use.
</description>

<narrative>
To be relevant, a document/element
must deal with the use of Patricia Tries
for text search. Description of the standard
algorithm, optimised implementation and use
in Information retrieval applications are all
relevant.
</narrative>

<keywords>
Patricia tries, tries, text search,
string search algorithm,
string pattern matching
</keywords>

</inex_topic>
```

Figure 1: INEX Topic 117

2. INEX TOPICS

As in the previous year, INEX 2003 has used the same set of XML documents that comprises 12107 IEEE Computer Society articles published within the period 1997-2002 and stored in XML format. INEX 2003 also introduced a new set of ad-hoc retrieval topics which in contrast to the previous year were differently formulated. Revised relevance dimensions, *exhaustivity* and *specificity*, for assessing the relevance of the retrieval topics were also introduced.

Two types of XML retrieval topics are explored in INEX: content-only (CO) topics and content-and-structure (CAS) topics. A CO topic does not refer to the existing document structure. When dealing with CO topics, an XML retrieval system should follow certain rules that will influence the size and the granularity of a resulting document component. Not every document component can be regarded as a meaningful answer for a given query. Some of them are too short to act as meaningful answers while some of them are too broad. Thus, if an XML retrieval system shows poor performance (in terms of its effectiveness), the rules that decide upon the answer size and granularity should be changed accordingly.

A CAS topic, unlike a CO topic, enforces restrictions with respect to the existing document structure by explicitly specifying the type of the unit of retrieval (section, paragraph, or other). When dealing with CAS topics, an XML retrieval system should (in most cases) follow the structural constraints described in the topic, which will result in answers having the desired (or similar) structure. In this case, the size and the granularity of a final answer are determined in advance.

The rest of this section describes INEX topics 117 and 86, which are respectively the CO and CAS topics proposed and assessed by our group. Some issues were observed during our relevance assessments for these topics. Our final results at INEX 2003 show that these issues, when addressed correctly, significantly improve the performance of an XML retrieval system. We also discuss the implications of these INEX topics for using the combined Lucy/eXist retrieval system and report other comments and suggestions.

2.1 INEX Topic 117

Figure 1 shows the INEX CO topic 117. This topic searches for documents or document components focusing on algorithms that use Patricia tries for text search. A document or document component is considered relevant if it provides description of the standard/optimised algorithm implementation or discusses its usage in information retrieval applications.

Our first observation is that this topic (unintentionally) turned out to be a difficult one, since:

- *Patricia* (usually) represents a person's first name, rather than a data structure;
- *tries* is a verbal form, and
- keywords like *text*, *string*, and *search* appear almost everywhere in the INEX IEEE XML document collection.

The relevance assessments were long and difficult, mainly because there were too many answers (due to *Patricia* and *tries*), there were not many highly relevant answers, and the few somewhat relevant answers were hard to evaluate consistently both for exhaustivity and specificity.

For this and similar topics, it appears that the only way to obtain satisfactory results is to use either *proximity* operators or *phrase search* support in full text retrieval systems. In the context of XML, an interesting question is whether the granularity of XML document components can be used as the proximity constraint. For example, it is more likely that paragraphs containing few of the query keywords will be regarded more relevant than a document that contains all keywords in different sections. On the other side, since users expect meaningful answers for their queries, the answers are expected to be rather broad, so retrieved document components should at least constitute a section, possibly a whole document. Accordingly, an XML retrieval system should follow an effective *extraction strategy* capable of producing more relevant answers.

2.2 INEX Topic 86

Figure 2 shows the INEX CAS topic 86. This topic searches for document components (sections) focusing on electronic

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<!DOCTYPE inex_topic SYSTEM "topic.dtd">
<inex_topic topic_id="86" query_type="CAS" ct_no="107">

<title>
//sec[about(.,'mobile electronic payment system')]
</title>

<description>
Find sections that describe technologies
for wireless mobile electronic payment systems
at consumer level.
</description>

<narrative>
To be relevant, a section must describe
security-related technologies that exist
in electronic payment systems that can be
implemented in hardware devices.
The main interests are systems that can be
used by mobile or handheld devices.
A section should be considered irrelevant
if it describes systems that are designed
to be used in a PC or laptop.
</narrative>

<keywords>
mobile, electronic payment system,
electronic wallets, e-payment, e-cash,
wireless, m-commerce, security
</keywords>

</inex_topic>
```

Figure 2: INEX Topic 86

payment technologies implemented in mobile computing devices, such as mobile phones or handheld devices. A section will be considered highly relevant if it describes technologies that can be used to securely process electronic payments in the mobile computing devices.

In order to consistently assess the relevance of the resulting document components (for this topic, most of these components were sections), two assessment rules were applied: document components focusing *only* on mobile computing devices were considered irrelevant, and document components focusing on security issues *in general* were also considered irrelevant.

It is evident from the above rules that for a document component to be considered marginally, fairly or highly relevant, it should *at least* contain a combination of some important words or phrases, such as *mobile*, *security*, *electronic payment system*, *e-payment*, and so on. In this sense, the issues encountered while assessing INEX CAS topic 86 were very similar with the ones discussed earlier for INEX CO topic 117. The only difference is that for this topic, the unit of retrieval is known in advance (`<sec>` identifies the type of document component to be retrieved), although by no means this should be regarded as a mandatory constraint, since the INEX DTD specifies different types of document components that may be regarded as sections (such as `sec`, `ss1`, or `ss2`). It is therefore reasonable to expect that the extraction strategy previously applied to the CO topics would lead to more effective results for the CAS topics. The final INEX results for the CAS topics shown later in Figure 5 confirm this expectation.

2.3 Implications of INEX topics

It is evident from the previous observations that using either Lucy or eXist will partially satisfy the information need expressed with both the CO and the CAS topics. Lucy supports phrase search and ranking, however proximity support is limited, and the unit of retrieval is a whole document. eXist supports proximity operators and phrase search, and additionally allows final answers containing any of the query terms. However, it does not rank the final answers, and unless explicitly specified in the query, it does not impose additional constraints on the granularities of the returned answers. We identify later that this missing feature represents a serious system limitation for the CO topics. Accordingly, we decided to take into account the positive aspects of both systems and build a modular system that incorporates a combined approach to XML retrieval. Section 3 describes our approach in detail.

2.4 Other comments and suggestions

As a result of our active INEX participation this year, particularly while creating the INEX topics 86 and 117 and assessing the relevance of corresponding documents and document components, we observed some additional issues.

- In proposing a retrieval topic, should a participant make a statement about what XML retrieval feature he/she is trying to evaluate?
- Should the INEX initiative start making a classification of these various features? The features that we refer here might include, for example, usefulness of existing links and references in XML documents, proximity search, selection criteria, granularity of answers, and so on.

Although the INEX 2003 assessment tool was much better than the one used in 2002, the assessment task is still very time consuming. We suggest whether less answers could be pooled for assessment and whether the assessment tool could be furthermore improved to reduce some interaction required by users. The last suggestion might for example include less required “clicks” and the ability to select a group of answers as irrelevant (regardless whether they represent documents or document components).

3. MODULAR SYSTEM ARCHITECTURE

For INEX 2003, we decided to build a modular system that uses a combined approach to XML retrieval, comprising two modules: the Lucy full-text search engine and the eXist native XML database. Before we explain our approach in detail, we briefly summarise the most important features of both modules.

3.1 *Lucy* search engine

Lucy is a compact and fast text search engine designed and written by the Search Engine Group at RMIT University. Although Lucy primarily allows users to index and search HTML[3] (or TREC[4]) collections, we have successfully managed to index and search the entire INEX IEEE collection of XML documents. However, Lucy's primary unit of retrieval is a whole document and currently it is not capable of indexing particular document components, such as `<author>`, `<sec>`, and `<p>`. Lucy has been designed for simplicity as well as speed and flexibility, and its primary feature, which is also evident in our case, is the ability to handle a large amount of text. It implements an inverted index structure, a search structure well researched and implemented in many existing information retrieval systems. Witten et al. [8] provide a detailed explanation for efficient construction of an inverted index structure such as implemented in Lucy.

Lucy is a fast and scalable search engine, and incorporates some important features such as support for Boolean, ranked and phrase querying, a modular C language API for inclusion in other projects and native support for TREC experiments. It has been developed and tested under the Linux operating system on an Intel-based platform, and is licensed under the GNU Public License.

3.2 *eXist*: a native XML database

Since January 2001, when eXist [3] started as an open source project, developers are actively using this software for various purposes and in different application scenarios. We use eXist as a central part of our modular XML retrieval system. eXist incorporates most of the basic and advanced native XML database features, such as full and partial keyword text searches, search patterns based on regular expressions, query terms proximity functions and similar features. Two of eXist's unique features are efficient index-based query processing and XPath extensions for full-text search.

Index-based query processing. For the purpose of evaluating XPath expressions in user queries, conventional native XML database systems generally implement top-down or bottom-up traversals of the XML document tree. However, these approaches are memory-intensive, resulting in slow query processing. In order to decrease the time needed for processing the queries, eXist uses an inverted index structure that incorporates numerical indexing scheme for identifying the XML nodes in the index. This feature enables eXist's query engine to use fast path join algorithms for evaluating XPath expressions. Meier [3] provides detailed technical explanation of this efficient index-based query processing implementation in eXist.

XPath extensions for full-text searching. Standard XPath implementations do not provide very good support for querying document-centric XML documents. Document-centric documents, as oppose to data-centric ones that usually contain machine-readable data, typically include mixed content and longer sections of text. eXist implements a number of XPath extensions to efficiently support document-centric queries, which overcome the inability of standard XPath functions (such as `contains()`) to produce satisfactory results. For example, the `&=` operator selects document components containing *all* of the space-separated terms on the right-hand side of the argument. `|=` operator is similar, except it selects document components containing *any* of the query terms. In the next section we provide examples of the way we used these operators in the INEX topic translation phase.

eXist is a lightweight database, completely written in Java and may be easily deployed in several ways. It may run either as a stand-alone server process, or inside a servlet-engine, or may be directly embedded into an existing application.

3.3 A combined approach to XML retrieval

Section 2 observes the implications of the INEX topics that influenced our choice for a combined approach to XML retrieval. However, due to the advanced retrieval features described previously it becomes evident that using eXist alone should suffice in satisfying the XML retrieval needs. Indeed, some applications have shown that eXist is already able to address real industrial needs [3]. Despite all these advantages, we were not able to use eXist as the *only* XML retrieval system for two main reasons: first, we were using eXist version 0.9.1, which did not manage to load and index the entire IEEE XML document collection needed for INEX, and second, although we could retrieve relevant pieces of information from parts of the IEEE document collection, eXist does not assign relevance values to the retrieved answers. Accordingly, since *ranking* of the retrieved answers is not supported, we decided to undertake a combined XML retrieval approach that utilises different *extraction strategies* to rank the answers. With respect to a specific extraction strategy, a document component may represent a highly ranked answer if it belongs to a document that has previously been determined relevant for a particular retrieval topic.

Figure 3 shows our combined approach to XML retrieval. The system has a modular architecture, comprising two modules: Lucy and eXist. We use INEX topic 86, as shown in Figure 2, to explain the flow of events.

First, the INEX topic is translated into corresponding queries understandable by Lucy and eXist, respectively. Depending on the type of the retrieval topic (CO or CAS), the topic translation utility follows different rules. For the INEX CO topics, such as topic 117 shown in Figure 1, queries that are sent to both Lucy and eXist include only terms that appear in the `<Keywords>` part of the INEX topics. For the INEX CAS topics, as shown in Figure 3, query terms that appear in both `<Title>` and `<Keywords>` parts of the INEX topics were used.

For example, we use the query terms from the `<Keywords>` part of the INEX topic 86 to formulate the Lucy query:

```
.listdoc
'mobile "electronic payment system"
"electronic wallets" e-payment e-cash wireless
 m-commerce security'
```

[3]http://www.w3.org/MarkUp/
[4]http://trec.nist.gov/

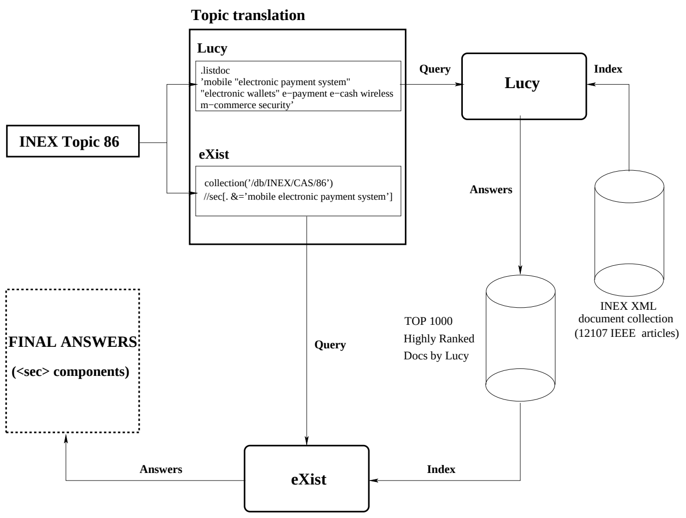


Figure 3: A modular system architecture.

However, before submitting a query to the system, the INEX document collection needs to be indexed. We use Lucy to create an inverted index from all the documents in the large IEEE XML collection. We then search this indexed data by entering the queries derived from the translation rules, as explained above. For the purpose of ranking its answers for a given query, Lucy uses a variant of the Okapi BM25 [5] probabilistic ranking formula. Okapi BM25 is one of the most widely used ranking formula in information retrieval systems. It is thus expected that, for a given INEX topic, Lucy will be able to retrieve highly relevant XML documents early in the ranking. Therefore, for each INEX topic, we retrieve (up to) 1000 highest ranked XML documents by Lucy. It is our belief that the information contained in these documents is sufficient to satisfy the information need expressed in the corresponding INEX topic. However, at this phase of development, Lucy's only unit of retrieval is a whole document. Accordingly, for a particular INEX topic, we still have to extract the relevant parts of these highly ranked documents. Wilkinson [7] shows that simply extracting components from highly relevant documents leads to poor system performance. Indeed, there may be cases when a section belonging to highly ranked document is irrelevant as opposed to a relevant section belonging to lowly ranked document. However, we believe that the retrieval performance of a given system may be improved using a suitable *extraction strategy.* We implemented several extraction strategies using eXist's XPath extensions. We provide examples how we use these XPath extensions while translating INEX topic 86 as follows.

For INEX CAS topics in general, and INEX topic 86 in particular, the terms that appear in the `<Title>` part are used to formulate eXist queries. However, since a document component is likely to be relevant if it contains *all* or *most of* the query terms that appear in the `<Title>`, we undertake several extraction strategies while implementing our INEX runs. The extraction strategies are described in detail in Section 4, were we also explain how we constructed our INEX runs. In general, these strategies depend on the combined usage of Boolean `AND` and `OR` operators, identified by the `&=` and `|=` operators in eXist, respectively. In that sense, the INEX topic 86 may be translated either as:

```
collection('/db/INEX/CAS/86')
//sec[. &='mobile electronic payment system']
```

if one wants *all* query terms to appear in the resulting section, or:

```
collection('/db/INEX/CAS/86')
//sec[. |='mobile electronic payment system']
```

if one wants *any* of the query term to appear in the resulting section.

We follow the first translation rule for our example in Figure 3. Final answers will thus constitute `<sec>` document components (if any) that contain all the query terms. By following this rule, we reasonably expect these document components to represent relevant answers for the INEX topic 86. On the other hand, it is clear that if the second translation rule is applied for the same topic, it may produce very many irrelevant answers as well as some further relevant answers. Accordingly, it is very important to decide upon the extraction strategy that will yield in highly relevant answers for a given INEX topic. We discuss the results for different extraction strategies in the following section.

4. INEX RUNS AND RESULTS

The retrieval task performed by the participating groups in INEX 2003 was defined as ad-hoc retrieval of XML documents. In information retrieval literature this type of retrieval involves searching a static set of documents using a new set of topics, which represents an activity very commonly used in library systems.

Within the ad-hoc retrieval task, INEX 2003 defines additional sub-tasks. These represent a *CO* sub-task, which involves content-only (CO) topics and a *CAS* sub-task, which involves content-and-structure (CAS) topics. The CAS sub-task comprises a *SCAS* sub-task and a *VCAS* sub-task. The SCAS sub-task requests that the structural constraints in a query must be *strictly* matched, while *VCAS* allows the structural constraints in a query to be treated as *vague* conditions.

For each topic belonging to a particular sub-task up to 1500 answers (full documents or document components) were required to be retrieved by the participating groups. In order to assess the relevance of the retrieved answers, the revised relevance dimensions (exhaustivity and specificity) need to be quantized in a single relevance value. INEX uses two quantization functions: *strict* and *generalised.* The strict function can be used to evaluate whether a given retrieval method is capable of retrieving highly relevant and highly focused document components, while the generalised function credits document components according to their *degree of relevance* (by combining the two relevance dimensions, exhaustivity and specificity).

Our group submitted 6 official runs to INEX 2003, 3 for each CO and SCAS sub-task, respectively. Figures 4 and 5 show

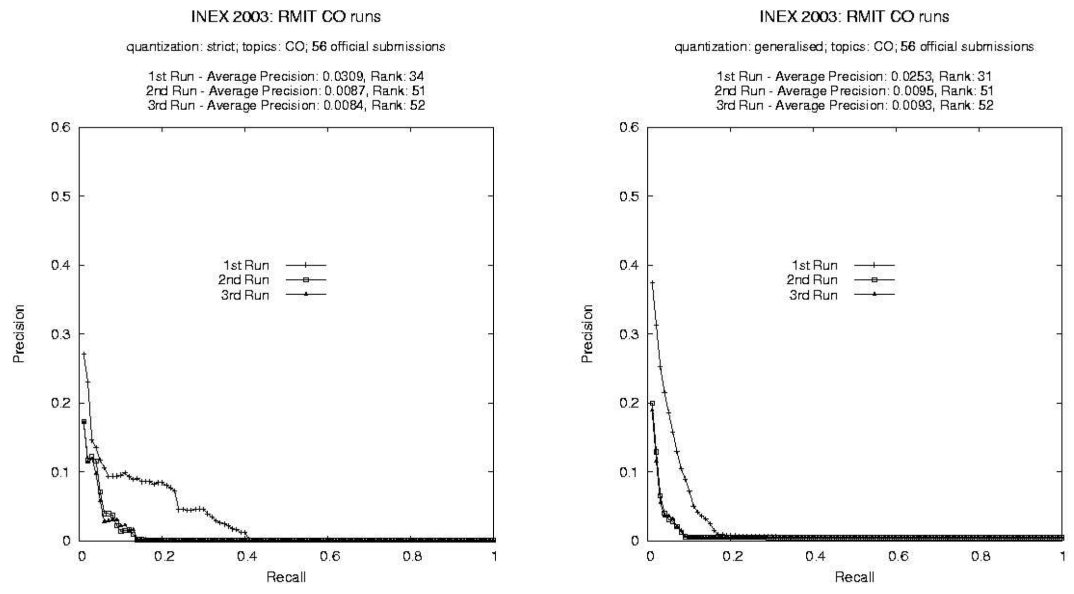


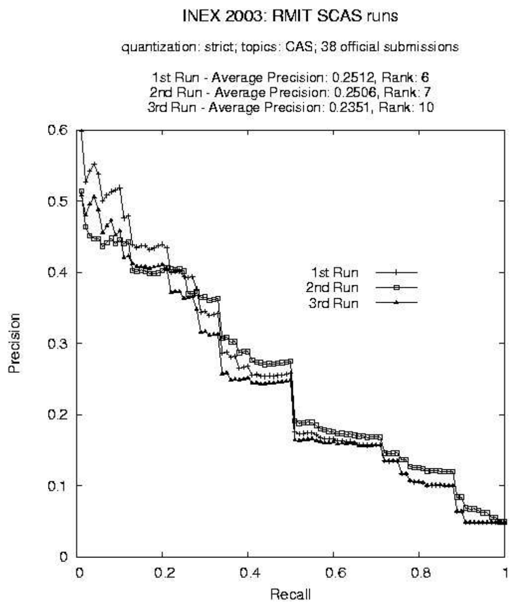
Figure 4: Results for the RMIT CO runs using both strict and generalised quantization functions

the results for both the CO and SCAS runs when both strict and generalised quantization functions are used. The rankings of the runs are determined according to the average precision over 100 recall points considering each corresponding INEX topic. Two of our three runs for each sub-task were automatically constructed while one was manually. The automatic runs were constructed using the translation rules explained in the previous section. We manually constructed the other runs in order to produce more meaningful queries for each INEX topic. Each run was constructed by using elements in the following answer lists: [A] that uses eXist's `&=` (logical `AND`) operator and enforces strict satisfaction of logical query conditions (the elements that belong to the answer list [A] will therefore represent document components containing *all* the query terms or phrases); [B] that uses the `|=` (logical `OR`) operator, "relaxes" the query conditions and allows for document components containing *any* of the query terms or phrases; and a combined answer list that contains the elements in the answer list [A] followed by the elements in the answer list [B–A].

Three retrieval runs were submitted for the CO sub-task. We constructed the first CO run by retrieving the 1500 highest ranked documents for each INEX topic. As described in the previous section, the `<Keywords>` part of each INEX topic was automatically translated as an input query to the Lucy search engine. The final rank of a document was then determined by its similarity with the given query as calculated by Lucy using a variant of Okapi BM25. As shown in Figure 4 this run performed better than the other two CO runs in both cases when strict and generalised quantization functions are used, which suggests that a whole document is often likely to be considered a preferable answer for an INEX CO topic.

For the other two runs, for each INEX CO topic we first used Lucy to extract (up to) the 1000 highest ranked documents. Then we used eXist to index and retrieve the final answers from these documents. We reasonably expected that the most relevant document components required to be retrieved for each INEX topic were very likely to appear within the 1000 highest ranked documents. Since the CO topics do not impose constraints over the structure of resulting documents or document components, we used the `//**` eXist construct in our queries. The "`**`" operator in eXist uses a heuristic that retrieves answers with different sizes and granularities. For our second CO run, the `<Keywords>` part of each topic was automatically translated as an input query to the eXist database, and its final answer list includes only elements from the answer list [B]. We used the manual translation process for our third run, where the final answer list includes the elements in the answer list [A] followed by the elements in the answer list [B–A]. Although we expected the third run to perform better than the second, Figure 4 shows that both these runs performed poorly in both cases when strict and generalised quantization functions are used, regardless of choices for the translation method and the extraction strategy. At this phase of development, the heuristic implemented in the "`**`" operator in eXist is not able to determine the most meaningful units of retrieval nor influence the desired answer granularity for a particular CO topic. Next we show that this is not the case for the CAS topics, where the type of the unit of retrieval is determined in advance and the choices for the translation method and the extraction strategy have a significant impact on the system's performance.

Three runs were submitted for the SCAS sub-task. As discussed previously, both `<Keywords>` and `<Title>` parts from INEX CAS topics were used to generate the input queries for Lucy and eXist, respectively. Our first SCAS run was automatic and its final answer list includes the elements in the answer list [A] followed by the elements in the answer list [B-A]. The queries for the second SCAS run were manually constructed and its final answer list includes the elements from the same answer lists as for the first run.



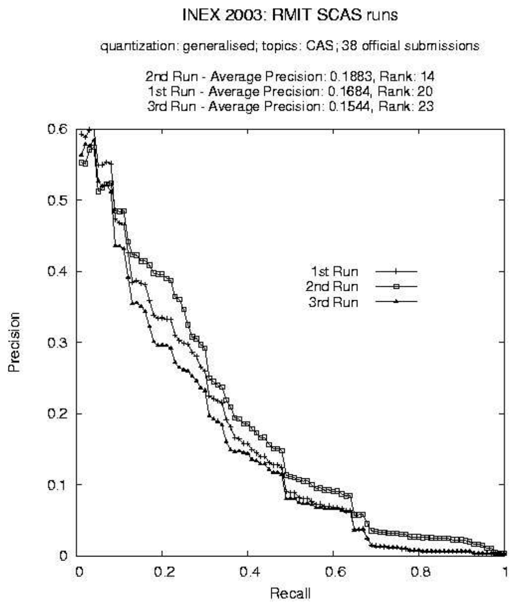


Figure 5: Results for the RMIT SCAS runs using both strict and generalised quantization functions

Figure 5 shows that these runs performed relatively better when using a strict quantization function compared with the runs from other participating groups at INEX 2003. Since the type of the unit of retrieval is determined in advance for the SCAS runs, the choice of the extraction strategy implemented in both runs appears to be very effective for retrieving highly exhaustive and highly specific document components. It can be observed that our system performs slightly more effective for the first than for the second run (6th compared to 7th out of 38 systems), and the first run performs better for recall values lower than 0.2. However, the choice of the translation method has an effect on the system's performance for recall values greater than 0.3, where the second run performs better than the first run. Figure 5 also shows that the choice of the extraction strategy is not as effective when using a generalised quantization function, where marginally/fairly exhaustive or marginally/fairly specific document components are regarded as partly relevant answers. Indeed, the ranks for both runs when evaluated using the generalised quantization function are not among the ten highest ranked INEX runs. In this case, the choice of the translation method results in second run performing better than the first run overall.

The third SCAS run was automatic, however its final answer list includes only the elements from the answer list [B]. By choosing this strategy we reasonably expected some irrelevant answers in the final answer list, but we hoped to find more relevant components in highly ranked documents. Indeed, as Figure 5 shows, irrespective of whether a strict or a generalised quantization function is used, our retrieval system is ranked lower for the third SCAS run compared to the previous two runs.

5. LIMITATIONS OF OUR SYSTEM

Previous sections describe the XML retrieval approach that we implemented while participating in INEX 2003. However, during different phases of our INEX involvement, particularly while constructing the INEX runs and assessing the relevance of retrieved results, we observed several system limitations. Although they can and should be considered as a weakness of our approach, the fact that we are able to identify them influences our future research directions. Some of these limitations include the following.

No IR ranking of the final answers. The choice of implementing an extraction strategy that may influence the rank of a final answer suggests that our system does not consider an IR ranking score for a particular answer. Although for a given INEX topic Lucy ranks the XML documents in a descending order of their query similarity, the unit of retrieval represents a whole document, and there is no support for existing XML technologies. eXist, on the other hand, has a tight integration with existing XML development tools and technologies, but does not rank the final answers according to their query similarity. We have thus decided that a particular extraction strategy should influence the final ranking score for a resulting document or document component. We have decided upon different extraction strategies while we constructed our INEX runs, and have shown that for the CAS topics some of them have a significant impact on the retrieval performance of our modular system.

Complex usage. Since our system has a modular architecture that incorporates a combined IR/XML-specific oriented approach to XML retrieval, its usage is very complex. It comprises two different retrieval modules (Lucy and eXist), each having different internal architectures and rules of use. Instead, it would be preferable to have only one system that incorporates the best features from the above modules.

Significant space overhead. The size of the INEX IEEE XML document collection takes around 500MB disk space. The inverted index file maintained by Lucy additionally takes

20% of that space. For each topic, (up to) 1000 XML documents are indexed by eXist, which adds up to approximately 12% of the space for the INEX collection. Although both Lucy and eXist implement efficient retrieval approaches, it becomes evident that their combination leads to significant disk space overhead. As for the previous limitation, one system that can deal with the above issues would also be preferable.

6. RELATED WORK

Even before INEX, the need for information retrieval from XML document collections had been identified in the XML research community. As large XML document collections become available on the Web and elsewhere, there is a real need for having an XML retrieval system that will efficiently and effectively retrieve information residing in these collections. This retrieval system will need to utilise some form of an XML-search query language in order to meet the growing user demand for information retrieval. Thus, the needs and requirements for such a query language have to be carefully identified and appropriately addressed [4].

At INEX 2002 the CSIRO group proposed a similar approach to XML retrieval. Their XML retrieval system uses a combination of a selection and a post-processing module. Queries are sent to PADRE, the core of CSIRO's Panoptic Enterprise Search Engine[5], which then ranks the documents and document components on the basis of their query similarity. In contrast to Lucy, whose primary unit of retrieval is a whole document, PADRE combines full-text and metadata indexing and retrieval and is capable of indexing particular document components, such as `<author>`, `<sec>` and `<p>`. Different "mapping rules" determine what metadata field is used to index the content of a particular document component. A post processing module was then used to extract and re-rank the final answers from documents and document components returned by PADRE [6].

In an effort to reduce the number of document components in an XML document that may represent possible answers for a given query, Hatano et al. [2] propose a method for determining the preferable units of retrieval from XML documents. We consider investigating these and similar methods for improving the effectiveness of our system for the CO topics.

7. CONCLUSION AND FUTURE WORK

We have described the combined approach to XML retrieval that we used during our participation in INEX 2003. Our retrieval system implements a modular architecture, comprising two modules: Lucy and eXist. For each INEX topic, we used Lucy, a full-text search engine designed by the Search Engine Group at RMIT, to index the IEEE XML document collection and retrieve the top 1000 highly ranked XML documents. We then indexed those documents with eXist, and implemented different topic translation methods and extraction strategies in our INEX runs. The INEX results show that these methods and strategies result in an effective XML retrieval for the CAS topics. Since our system is not yet able to identify the preferred granularities for the final answers, the methods and strategies are not as effective for the CO topics. Further investigations need to be done in order to improve this functionality.

We have also observed several limitations of our modular system. In order to overcome these limitations, we intend to investigate more effective ways to use and combine the most advanced features of Lucy and eXist. It is our belief that they will result in more accurate and interactive XML retrieval.

[5]http://www.panopticsearch.com

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ABSTRACT

This paper describes the retrieval approaches proposed by IRIT in the INEX'2003 evaluation initiative. The primary approach uses Mercure system and different modules to perform content only and content and structure queries. The paper also discusses a second approach based on a voting method previously applied in the context of automatic text categorization.

Keywords

Information Retrieval, XML retrieval, connectionist model, voting method, automatic text categorization

1. INTRODUCTION

XML (eXtensible Markup Language) has recently emerged as a new standard for representation and data exchange on the Internet [29]. If this tendency goes on, XML will certainly become a universal format and HTML (Hypertext Markup Language) will disappear in aid of XML. Consequently, the information retrieval issue in XML collections becomes crucial.

A growing number of approaches are dealing with structured documents like XML. They can be divided into three main groups: database, XML-oriented specific approaches and IR approaches. The database community considers XML collections as databases, and tries to develop models for representing and querying documents, according to the content and the structure of these documents. Many languages have been developed for querying and updating these databases [1][18][24][30][11]. XML specific oriented approaches estimate the relevance of document parts according to the relevance of their structurally related parts. They are also named aggregation-based methods [8][15][7][13] [16]. In IR approaches, traditional IR models are adapted to be used on structured collections [17][20][22].

In this paper, we present two IR approaches applied to structured documents retrieval, within the context of INEX'2003: the first approach uses Mercure information retrieval system, while the second one is based on a voting method used initially for automatic text categorization. Section 2 presents the INEX initiative. Section 3 describes the Mercure model, and the INEX search approach with Mercure system is reported in section 4. Section 5 and 6 present first the voting method defined in the context of categorization and then the adaptations we integrated within the INEX'2003 context.

2. THE INEX INITIATIVE

2.1 Collection

INEX collection, 21 IEEE Computer Society journals from 1995-2002, consists of 12 135 (when ignoring the volume.xml files) documents with extensive XML-markup. All documents respect the same DTD.

2.2 Queries

As last year, participants to INEX'2003 have to perform two types of queries. CO (Content Only) queries are requests that ignore the document structure and contain only content related conditions, e.g. only specify what a document/component should be about. CAS (Content and Structure) queries contain explicit references to the XML structure, and restrict the context of interest and/or the context of certain search concepts. Both CO and CAS topics are made up of four parts: topic title, topic description, narrative and keywords.

Within the ad-hoc retrieval task, three sub-tasks are defined: (1) the CO task, using CO queries, (2) the SCAS task, using CAS queries, for which the structural constraints must be strictly matched, (3) the VCAS task, also using CAS queries, but for which the structural constraints can be considered as vague conditions.

3. MERCURE SYSTEM

Mercure is a full-text information retrieval system based on a connectionist approach and modeled by a multi-layer network. The network is composed of a query layer (set of query terms), a term layer (representing the indexing terms) and a document layer [4].

Mercure includes the implementation of retrieval process based on spreading activation forward and backward through the weighted links. Queries and documents can be used either as inputs or outputs. The links between layers are symmetric and their weights are based on the *tf-idf* measure inspired by OKAPI [23] and Smart term weighting.

The query-term links are weighted as follows :

$$q_{ui} = \begin{cases} \dfrac{nq_u * qtf_{ui}}{nq_u - qtf_{ui}} \text{ if } (\mathrm{nq_u} > qtf_{ui}) \\ qtf_{ui} \text{ otherwise} \end{cases} \quad (1)$$

Where:

- q_{ui} : the weight of the term t_i in the query u
- qtf_{ui}: the frequency of the query term t_i in the query u
- nq_u: the number of terms in the query u

The term-document link weights are expressed by :

$$d_{ij} = \frac{tf_{ij} * (h_1 + h_2 * \log(\frac{N}{n_i}))}{h_3 + h_4 * \frac{dl_j}{\Delta_l} + h_5 * tf_{ij}} \quad (2)$$

Where:

- d_{ij} : term-document weight of term t_i and document d_j
- tf_{ij}: term frequency of t_i in the document d_j
- N: total number of documents
- n_i: number of documents containing term t_i
- h_1,h_2,h_3,h_4 and h_5: constant parameters
- Δl : average document length
- dl_j :number of terms in the document d_j

The query evaluation function computes the similarity between queries and documents.

Each term node computes an input value: $In(t_i) = q_{ui}$

and an activation value: $Out(t_i) = g(In(t_i))$, where g is the term layer activation function.

Each term node propagates then this activation value to the document nodes through the term-document links. Each document node computes an input value: $In(d_j) = \sum_i Out(t_i) * d_{ij}$ and an activation value: $Out(d_j) = g(In(d_j))$, where g is the document layer activation function.

Documents are then ranked by ascending order of their activation value.

The ranking function (activation) is modified to take into account term proximity in a document [14]. Thus, documents having close query terms compute a new input value:

$$In(d_j) = \sum_i (Out(t_i) * d_{ij}) * \sum_i \frac{\alpha}{prox_{i,i-1}} \quad (3)$$

Where:

- α is a constant parameter so that $\frac{\alpha}{prox_{i,i-1}} \geq 1$. α is set to 4 for INEX'2003 experiments.
- $prox_{i,i-1}$ is the number of terms separating the query terms t_i and t_{i-1} in the window of α terms in the document. The query terms are ranked according to their position in the query text.

In other words, documents having close query terms (i.e. no more than α words separate two consecutive query terms in the document content) increase their input value.

In addition, we have implemented two modules that are used to process structured documents. The aim of these modules is to filter the most specific[1] and exhaustive[2] elements of the documents returned by Mercure [15].

The first module, which is *content-oriented* (we will call it *CO-module*), deals with queries composed of simple keyword terms. It browses through documents retrieved by Mercure, and finds elements answering the queries in the most specific and exhaustive way. Element types that can be retrieved are pre-specified by the administrator of the system, according to the DTD of the documents. For example, the administrator can decide that the CO-module will only return *article* or *section* elements. The CO-module performs as follow: for each document retrieved by Mercure, it searches occurrences of query terms in all pre-specified elements. It returns the elements containing the greatest number of query terms. If more than *k* elements are supposed to be the most specific and exhaustive, the module returns the whole document.

The second module, which is *content-and-structure*-oriented (we will call it *CAS-module*), performs queries containing both explicit references to the XML structure and content constraints. These queries can be divided into two parts : a target element and a content constraint on this target element. As the CO-module, the CAS-module browses documents returned by Mercure, and returns specific elements (e.g. target elements) containing the greatest number of query terms specified in the content constraints. If the target elements do not contain any of the terms of the content constraints, the document retrieved by Mercure is removed from the list of results.

Thus, the main difference between the two modules is the way they process the documents structure. In the CO-module, elements that can be returned are pre-specified by the administrator of the system. The user only gives keywords and cannot express structural conditions in his query. Using the CAS-module, users explicitly give a target element and content constraints on this target element.

As a result for both modules, we obtain a ranked list of elements/documents.

4. THE INEX SEARCH APPROACH WITH MERCURE SYSTEM

4.1 Indexing the INEX database and the queries

The INEX collection was indexed in order to take into account term positions in the documents. Terms are stemmed with Porter algorithm and a stop-word list is used in order to remove non-significant terms from the index. No structural information is kept in the index.

For both types of queries, terms are also stemmed with Porter algorithm and terms appearing in the stop-word list are also removed. However, depending on their type, queries are indexed in two different ways.

4.1.1 Indexing CO queries

CO queries are indexed using title field of queries. We simply remove terms preceded by minus (which means that the user does not want these terms appear in the results) and keep all the other terms.

4.1.2 Indexing CAS queries

CAS queries are first indexed using terms in the content constraints of the title field and terms of the keyword field, in order to build queries *for Mercure system*. They are then re-indexed *for the CAS-module*. Indeed, as explained before, the

[1] An element is specific to a query if all its information content concerns the query.

[2] An element is exhaustive to a query if the element contains all the required information.

CAS-module needs the target element of queries in order to process them. Let us take some examples of CAS queries:

Top.	Title field	Description
63	//article[about(.,'"digital library"') AND about (.//p,'+authorization +"access control" + security')]	Relevant documents are about digital libraries and include one or more paragraphs discussing security, authorization or access control in digital libraries.
66	>/article[.//yr <='2000'] //sec[about(.,'"search engines"')]	The user is looking for sections of articles published before 2000, which discuss search engines.
84	//p[about(.'overview "distributed query processing" join')]	The user wants paragraphs that give an overview about distributed query processing techniques with a focus on joins implementations.
90	//article[about(./sec,' +trust authentication "electronic commerce" e-commerce e-business marketplace') //abs[about(.,'trust authentication')]	The user wants to find abstracts or article that discuss automated tools for establishing trust between parties on the internet. The article should discuss applications of trust for authenticating parties in e-commerce.

Table 1: Examples of CAS queries

All the content constraints occurring in the *about* predicates are first indexed for Mercure system, even though they are not on the target element (in topics 63 and 90 for example). Targets elements (*article* for topic 63, *section* for topic 66, *paragraph* for topic 84 and *abstract* for topic 90) are then indexed for CAS-module.

About 20% of the CAS topics (like topic 66) contain a constraint on the year of publication. This constraint is also stored and will be used to filter results of the CAS- module.

4.2 Retrieval

In both cases (CO queries and CAS queries), a first search is performed with Mercure search engine using the content part of the queries. As a result, a ranked list of 1000 documents is selected for each query. Then, the CO- module is used to process the results of CO queries, and the CAS-module is used for CAS queries. Both modules return a ranked list of elements/documents, derived from the first ordered list of documents returned by Mercure system.

4.2.1 Retrieval with CO queries

According to the DTD, we have decided to allow the CO-module to return only *section* or *abstract* elements. Indeed, section and abstract elements are supposed to be large enough to be exhaustive and small enough to be specific.

If the CO-module finds more than two relevant elements (k =2) within a given document, the whole document is returned.

4.2.2 Retrieval with CAS queries

The CAS-module browses documents returned by Mercure, and returns target elements containing the greatest number of query terms specified in *all* the content constraints of CAS queries. If no occurrence of terms contained in the content constraints is found in target elements, the document returned by Mercure is removed from the list of results. Indeed, the target element always have a content constraint.

Then, if the query contains a year constraint, elements returned by the CAS-module are filtered, according to the article publication date .

4.3 Submitted runs

The first goal of our experiments in INEX'2003 is to test whether a full-text information retrieval system can be easily adapted to structured retrieval and to evaluate how suitable are the full-text IR based techniques for such kind of retrieval. Our approach can be compared to the fetch and browse method proposed in [5]. No static structure is used a priori and so, all types of XML documents can be processed. The second goal of our experiments is to measure the effect of term positions in INEX query types.

Five runs performed with Mercure have been submitted to INEX'2003:

- *Mercure2.co_ti* was performed for the CO task. Only title field of queries was used for indexing
- *Mercure2.pos_co_ti* was also performed for the CO task, using only title field of queries. Term positions were used by Mercure to process queries
- *Mercure2.cas_ti* was performed for the SCAS task. Only title field of queries was used for indexing
- *Mercure2.pos_cas_ti* was also performed for the SCAS task using only title field of queries. Term positions were used by Mercure to process queries
- *Mercure2.pos_vcas_keyti* was performed for the VCAS task. Both title and keywords fields of queries were used for indexing and terms positions were used by Mercure to process queries.

4.4 First results

4.4.1 CO task

The following table shows the results of the 2 runs performed for the CO task.

Run	**Strict quantization**		**Generalized quantization**	
	Average precision	**Rank**	**Average precision**	**Rank**
Mercure2.co_ti	0.0056	50/56	0.0088	48/56
Mercure2.pos_co_ti	0.0344	28/56	0.0172	41/56

Table 2: Results of the 2 runs performed with Mercure system for the CO task

4.4.2 SCAS and VCAS tasks

The following table shows the results of the 3 runs performed for the SCAS and VCAS tasks.

Run	**Strict quantization**		**Generalized quantization**	
	Average precision	**Rank**	**Average precision**	**Rank**
Mercure2.cas_ti	0.0719	33/38	0.0612	34/38
Mercure2.pos_cas_ti	0.1641	25/38	0.1499	24/38
Mercure2.pos_vcas_keyti	/	/	/	/

Table 3: Results of the 3 runs performed with Mercure system for the SCAS and VCAS tasks

The first result that can be drawn from Table 2 and Table 3 is that runs using term positions are definitely better that simple search for both query types (CO and CAS). Average precision for runs using term positions (*Mercure2.pos_cas_ti* , *Mercure2.pos_vcas_keyti*, and *Mercure2.pos_co_ti*) is about four times higher than average precision of runs performed with a single Mercure search (*Mercure2.cas_ti , Mercure2.co_ti*).

4.5 Discussion and future works

Regarding this year experiments and results, some investigations have to be performed. First of all, for the CO task, elements that can be returned by the CO-module are pre-selected manually. These types of elements are not always necessarily the most exhaustive and specific: it depends on the way the DTD was understood by the document creators. Statistics [12] or aggregation methods [7] [13] may be used to find those elements automatically. Then, the CAS-module is not able to perform all the content and structural constraints. Indeed, it processes only content constraints on the target element and year constraints. For example, in topic 90, the first *about* predicate is on sections, whereas the target element is abstract: the module does not insure that the content constraint on sections is respected. However, topics such as topic 84 are fully treated. According to these remarks, the CAS-module seems to be more adapted to the VCAS task. For this purpose, the run *Mercure2.pos_vcas_keyti* was performed and submitted. Finally, query processing is relatively slow, because the modules have to browse all documents returned by Mercure in order to find relevant elements. Regarding these limitations, an indexing model taking into account the structural and content information of documents seems to be necessary.

Moreover, our approach uses the *idf* measure to compute a retrieval status value for documents (and then documents are browsed to return relevant elements). The *idf* measure is also used in [7] and [26], in order to directly return relevant elements. However, term occurrences in elements do not necessarily follow a Zipf law [31]. The number of term repetitions can be (very) reduced in XML documents and *idf* is not necessarily appropriate [6][10]. The use *of ief (Inverse Element Frequency)* is proposed in [28] and [9]. An indexing scheme storing different IR statistics might be interesting on the INEX collection: thus, combinations of IR and XML-specific approaches could be tested.

5. A VOTING METHOD FOR INFORMATION RETRIEVAL

The proposed approach is derived from a process for textual documents categorisation. This categorisation intends to link documents with pre-defined categories. Our approach focuses on categories organised as a taxonomy. The original aspect is that our approach involves a voting principle instead of a classical similarity computing.

Our approach associates each text with different categories as opposed to most of the other categorisation techniques. The association of a text to categories is based on the Vector Voting method [21]. This method relies on the terms describing each category and their automatic extraction from the text to be categorised. The voting process evaluates the importance of the association between a given text and a given category. This method is similar to the HVV method (Hyperlink Vector Voting) used within the Web context to compute the pertinence of a Web page regarding the web sites referring to it [19]. In our context, the initial strategy considers that the more category terms appear in the text, the stronger is the link between the text and this category.

The association principle between a document and categories is composed of different steps:

– Compute the profile of each category. In automatic categorisation, profiles generally correspond to a set of weighted terms [25][27] which can be obtained by training from previous categorised documents.

– Extract automatically the concepts describing a document and their importance for the document. The extraction is based on a set of rules to treat, for example, document tags, and on processes to treat synonymy and to remove stop words.

– For each category of the hierarchy, compute a score with a voting function which measures the way the category is representative of the text. Different functions can be used as voting function. They are based on measures such as term importance in text and in hierarchy, text size, hierarchy size, number of terms describing a category that appear in the text.

– Sort the winning categories according to their score, and eventually select the best categories (for example, scores greater than a fixed threshold, or n greatest scores).

We have studied different voting functions whose results are presented in [2][3]. The voting function must take into account the importance in the document of each term describing the category, the discriminant power of each term describing the category, the way the category is representative of the document. The function providing the best results is described as follows :

$$Vote(E_H, D) = \sum_{\forall t \in E} \frac{F(t,D)}{S(D)} \cdot \frac{S(H)}{F(t,H)} \cdot e^{\frac{NT(E,D)}{NT(E)}} \quad (1)$$

where

- E_H corresponds to the category E in the hierarchy H,
- D is a document,

$\frac{F(t,D)}{S(D)}$	This factor measures the importance of the term t in the document D. F(t,D) corresponds to the number of occurrences of the term t in the document D and S(D) corresponds to the size (number of terms) of D.
$\frac{S(H)}{F(t,H)}$	This factor measures the discriminant power of the term t in the hierarchy H. F(t,H) corresponds to the number of occurrences of the term t in the hierarchy H and S(H) corresponds to the size of H.
$\frac{NT(E,D)}{NT(E)}$	This factor measures the presence of terms representing the category in the text (importance of the category). NT(E) corresponds to the number of terms in the category E and NT(E,D) corresponds to the number of terms of the category E that appear in the document D

The above function (1) considers as equivalent the importance of a term in the document and the discriminant power of this term in the hierarchy. Applying the exponential function to the third factor (i.e. the presence rate of terms representing the category in the text) aims at accentuating its importance.

The function is completed with the notion of *coverage*. The aim of the coverage is to ensure that only categories enough represented in a document will be selected for this document. The coverage is a threshold corresponding to the percentage of terms from a category that appear in a text . For example, a coverage of 50% implies that at least half of terms describing a category have to appear in the text of a document to be selected.

6. THE INEX SEARCH APPROACH WITH A VOTING METHOD

6.1 Evolution of the categorisation process

From the topic point of view, CO and CAS topics are constituted of different informative parts (title, keywords, description) that can be exploited to construct their profile. Although our method can use all the possible parts we first focused on to the title and keyword parts for the INEX'2003 experiments. For both topic types, stop words are removed and optionally terms can be stemmed using Porter algorithm.

For CAS topics, an additional step identify the structural constraints indicated in a topic. All the structural constraints defined on target elements of topics are taken into account and stored to be processed in a post categorisation step to filter the results of the categorisation step. Only the results having expected XPaths are kept. In structural constraints (for example *about(.//p,'+authorization +"access control" +security') or .//yr <='2000'*), only constraints on the article publication date are taken into account and stored to filter the results. More complex content constraints have not been treated for INEX'2003. Next experiments are planned about the extension of the voting method to take into account such constraints.

From the INEX collection point of view, the documents are considered as sets of text chunks identified by XPaths. For each document, concepts are extracted automatically with the different XPaths identifying the chunks where they appear and their importance in the chunk is calculated. For INEX'2003 experiments, all XML tags have been taken into account.

The voting method is applied without any modification. Topics are considered as categories to which document elements have to be assigned. The result is constituted of a list of topics associated to each chunk of text (identified by its XPath) for each document.

6.2 Experiments

Our experiments aim at evaluating the efficiency of the voting function and estimating the adaptations needed for the categorisation process in a context such as INEX'2003.

Four runs based on the voting method were submitted to INEX'2003. Applying or not a coverage is the main parameter that distinguishes the runs (C50 corresponds to apply a coverage of 50% i.e. half of the terms describing the topic must appear in the text to keep the topic, C0 corresponds to no coverage). No stemming process has been applied for the submitted runs, although it can be added. The tcXX% parameter specifies that only the elements having a score over a given percentage of the best score will be kept (e.g. tc50% indicates that only the elements having a score over the half of the best score are kept in the results).

6.3 Results

The following table shows the preliminary results of the four runs based on the voting method :

Run	**Strict quantization**		**Generalized quantization**	
	Average precision	**Rank**	**Average precision**	**Rank**
VotingNoStemTKCO tc75%C0nonorm	0.0012	54/56	0.0041	56/56
VotingNoStemTKVCAS C50nonorm	/	/	/	/
VotingNoStemTKSCAS tc50%C0nonorm	0.0626	34/38	0.0746	31/38
VotingNoStemTKVCAS tc50%C0nonorm	/	/	/	/

Table 3: Results of the 4 runs performed with the voting method

Results for VCAS topics are not yet known.

6.4 Discussion and future works

Regarding the performed experiments and the obtained results, we can notice that:

- the voting method applied without coverage tends to promote short chunks of text that only have one common term with the topic. Introducing coverage intends to correct this, since short chunks of text that have several common terms with the topic are less frequent than longer ones. We plan to study changes made to the voting function to evaluate their impact on results, notably with regard to the size of text chunks.
- The elementary level has been considered to identify the different chunks of text. This choice leads to miss complex chunks of text constituted of different elementary chunks

with high voting scores. A rebuilding of complex chunk should be integrated in the process.

- Structural constraints defined on the content of topics have not been taken into account. This aspect constitutes the main axis of study to extend the voting method. The main idea is to integrate the constraint when computing the voting score. This will promote relevant text chunks regarding content which respect the structural constraints, without eliminating relevant chunks (regarding content) but that do not satisfy the constraints.

7. ACKNOWLEDGMENTS

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Identifying and Ranking Relevant Document Elements

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ABSTRACT

A method of indexing and searching structured documents for element retrieval is discussed. Documents are indexed using a modified inverted file retrieval system. Modified postings include pointers into a collection-wide document structure tree (the corpus tree) describing the structure of every document in the collection.

Retrieval topics are converted into Boolean queries. Queries are used to identify relevant documents. Documents are then ranked using Okapi BM25 and finally relevant elements are identified using coverage. Search results are presented sorted first by document then coverage.

The design is presented in the context of the second annual INEX workshop.

1. INTRODUCTION

Otago first entered INEX [2] during its second year. There were three objectives: understand the participation process, gain access to this and last year's judgments, and create a baseline for comparing future experiments.

Participation involved design of six topics, generation and submission of search results, and online judging of three topics. Of these, generating the results was the most problematic as it required software changes.

The chosen retrieval engine was designed from the onset for retrieval of whole academic documents in XML [1]. A predecessor can be seen on BioMedNet and ChemWeb [4]. This engine, like that used in the IEEE digital library, returns relevance ranked lists of whole documents – the natural (citable) unit of information in an academic environment. From experience, information vendors are not interested in converting their documents from propriety DTDs into a common DTD or any other format – so software was needed to handle documents in heterogeneous formats.

Boolean searching, field restricting and relevance ranking were already supported, so modifications focused on identifying and ranking document elements. The modified retrieval engine can be thought of as working in three parts. Candidate documents are identified using a Boolean query. Candidates are then ranked using Okapi BM25 [7]. Finally, relevant non-overlapping elements are identified and presented as the result. Although it is easier to understand in three parts, in fact the most relevant elements of the most relevant documents are computed in a single pass of the indexes.

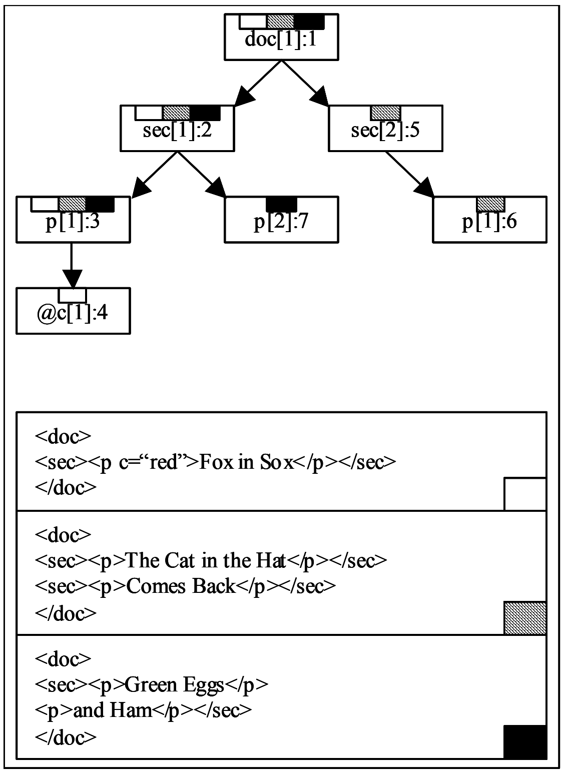
2. INDEXING

Much of the index design has already been described elsewhere [8]. Inverted file retrieval is used. There is one dictionary file and each dictionary term points to a single inverted list of postings.

An unstructured inverted list is usually represented $\{<d_1, f_1>, <d_2, f_2>, \ldots, <d_n, f_n>\}$ where d_n is a document ordinal number and f_n is the frequency of the given term in the given document. For structured retrieval, each $<d_n, f_n>$ pair is replaced by the triple $<d_n, p_n, f_n>$, where p_n is a position in the document. When phrase or proximity searching is required, this triple is replaced with the triple $<d_n, p_n, w_n>$ where w_n is the ordinal number of the term in the collection (starting from 0 at the start of the collection, incrementing by 1 for each term, not incrementing for tags, and not reset at the beginning of each record). On disk the postings are stored compressed.

The p_n value in each posting is a position in the corpus tree. The tagging structure for any one document represents a tree walk. Start at the root of the tree. When an open tag is encountered, the branch labelled with the tag name is followed downwards. When a close tag is encountered, the walk backtracks one branch. For a well-formed XML document, the walk will start and end at the root. This tree-walking property also holds for a collection of well-formed documents. The tree they collectively describe is called the corpus tree and can be built during single pass indexing. As each node is encountered for the first time, a branch is added to the tree and labelled with a unique ordinal identifier, p_n. Terms can lie either at the nodes or the leaves of this tree.

The corpus tree includes every single path in every single document, but is unlikely to match the structure of any one document. In Figure 1, three well-formed documents are given, as is the corpus tree for those documents. For clarity, the branches of the tree are labelled with which document they describe although this information is not computed and not stored.



```
<doc>
<sec><p c="red">Fox in Sox</p></sec>
</doc>
```

```
<doc>
<sec><p>The Cat in the Hat</p></sec>
<sec><p>Comes Back</p></sec>
</doc>
```

```
<doc>
<sec><p>Green Eggs</p>
<p>and Ham</p></sec>
</doc>
```

Figure 1: Three documents and the corpus tree including every path through every document, but not matching the structure of any one document. For the purpose of this figure each document is marked white, gray, or black and each node with which documents include that path. Each node is numbered with the instance of the tag (e.g. p[2]) and the node id, p_n (after the colon).

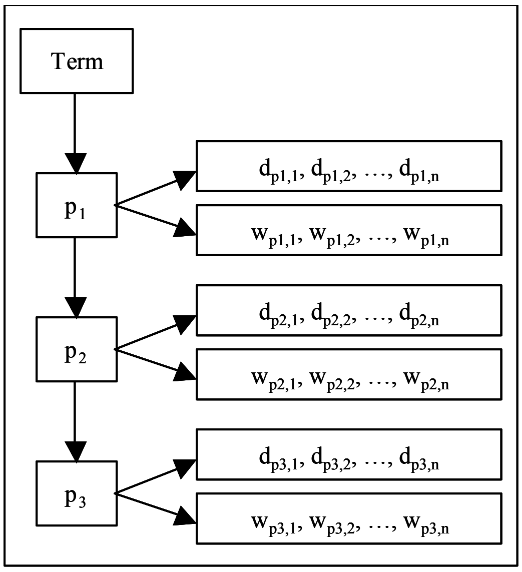

Term
p_1
$d_{p1,1}, d_{p1,2}, \ldots, d_{p1,n}$
$w_{p1,1}, w_{p1,2}, \ldots, w_{p1,n}$
p_2
$d_{p2,1}, d_{p2,2}, \ldots, d_{p2,n}$
$w_{p2,1}, w_{p2,2}, \ldots, w_{p2,n}$
p_3
$d_{p3,1}, d_{p3,2}, \ldots, d_{p3,n}$
$w_{p3,1}, w_{p3,2}, \ldots, w_{p3,n}$

Figure 2: The in-memory postings structure allows quick access to only those postings relevant to the required document elements.

The inverted lists are built and processed using the structure represented in Figure 2. Postings for each term are ordered by increasing p_n. Each p_n points to the list of document ids (the *d*-sublist) and word ids (the *w*-sublist) found at that point in the tree. Each list is held in increasing order and compressed.

To search the collection for a given term, each *d*-sublist is examined in turn. By doing so, documents may not be examined in turn. This does not matter so long as all documents that would be examined are examined. Further, whole documents may not be examined in turn – this, too, does not matter as many ranking functions can be computed piecewise[1]. To field-restrict a term, a restricted set of sublists is examined. The *w*-sublists are used for proximity searching.

Storing and processing the postings in this way has computational advantages. For a field-restricted search, postings not pertaining to the restriction can be skipped. As postings are stored compressed, they need not even be decompressed. Word postings are used only for proximity searching. On disk the *w*-sublists are collected together and stored after all *d*-sublists. They are not even loaded from disk if not needed.

3. SEARCHING

As the retrieval engine starts up, the corpus tree is loaded and an additional structure is created from it, the field list. For each instance of each tag, the list of nodes at or below that node is collected. For each tag, the same is collected. These lists are then merged and sorted.

Table 1: The field list for the corpus tree given in Figure 1.

Field	Restriction
@c	{4}
@c[1]	{4}
doc	{1, 2, 3, 4, 5, 6, 7}
doc[1]	{1, 2, 3, 4, 5, 6, 7}
p	{3, 4, 6, 7}
p[1]	{3, 4, 6}
p[2]	{7}
sec	{2, 3, 4, 5, 6, 7}
sec[1]	{2, 3, 4, 7}
sec[2]	{5, 6}

The field list for the Figure 1 corpus tree is given in Table 1. From this, a search restricted to 'sec' requires postings at or below all 'sec' nodes of the corpus tree, or where $p_n=\{2, 3, 4, 5, 6, 7\}$. To

[1] BM25 cannot, so the lists are merged then processed.

search in ‘p[1]’, the postings are needed where $p_n=\{3, 4, 6\}$. For a search restricted to ‘p[1] in sec’, these two lists are ANDed together (giving $p_n=\{3, 4, 6\}$), and the members of this list are checked against the corpus tree to ensure they satisfy ‘p[1] in sec’ and not ‘sec in p[1]’.

Equivalence tag restrictions are also computed from the field list. The restrictions for each equivalent tag are ORed giving the equivalent restriction. If, for example, ‘p[2]’ and ‘@c’ were equivalent in Table 1, the restriction would be $p_n=\{4, 7\}$.

Several extensions were added to support element and attribute retrieval:

- Attributes are now distinguished from tags by prefixing attributes with an @ symbol. This symbol was chosen because it makes for easy parsing of INEX queries, which use the same symbol.
- The attribute value is considered to be content lying not only within the attribute, but also the tag. For example, “<tag att=“number”> term </tag>”, is equivalent to “<tag> <@att> number </@att> term </tag>”. In this way, a search for “number in tag” will succeed.
- Tags can now be identified not only by their name and path, but also by the tag instance. Where before it was only possible to restrict to paragraph for example, it is now possible to restrict to the second paragraph.

Trotman [8] suggests the corpus tree will be small for real data. In this extended model this no longer holds true. In the TREC [3] Wall Street Journal collection there are only 20 nodes, for INEX there are 198,041 nodes after ‘noise’ nodes are removed (4,789 with attributes and instances also removed).

Table 2: Tags ignored during indexing.

ariel	en	item-text	ss
art	entry	label	stanza
b	enum	large	sub
bi	f	li	super
bq	it	line	tbody
bu	item	math	tf
bui	item-bold	proof	tfoot
cen	item-both	rm	tgroup
colspec	item-bullet	rom	thead
couplet	item-diamond	row	theorem
dd	item-letpara	scp	tmath
ddhd	item-mdash	sgmlf	tt
dt	item-numpara	sgmlmath	u
dthd	item-roman	spanspec	ub

Many tags are used to mark elements too small to be relevant. An example of such a tag is ‘ref’, used to mark references in the text. This tag cannot be relevant to any topic as the contents are simply reference numbers. Some tags were used for visual appearance such as ‘b’ used to mark text in bold. Others were used as typesetting hints such as ‘art’ used to specify the size of an image. If any of these tags, or those in Table 2 were encountered during indexing, tagging was ignored (until the matching close tag), but the content still indexed. Tags in this group were hand selected even though automated systems for choosing such tags have been proposed [5].

4. QUERY FORMATION

The title of the topic is extracted and converted into a Boolean query. This query is used to determine which documents to retrieve. Ranking is computed from the postings for the search terms.

For content and structure (CAS) topics, the target element is computed and stored for later use. The complete path for each about-function is computed by concatenating the about-path to the context-element restricting it. All equivalent paths are then computed by permuting this path with the equivalence tags. This fully specified path now replaces the original about-path and the context-element is removed.

At this point, the topic has been transformed from INEX topic syntax into a query whereby each about-clause is Boolean separated and explicitly field restricted.

```
Create mandatory by ANDing each mandatory term (+)
Create optional by ORing each optional term
Create exclusion by ORing each exclusion term (-)

If all three sub-expressions are non-null, combine:
        mandatory AND (* OR optional) NOT
exclusion

If two sub-expressions are non-null, combine using one of:
        mandatory AND (* OR optional)
        optional NOT exclusion
        mandatory NOT exclusion

If only one sub-expression is non-null, use one of:
        mandatory
        optional
        * NOT exclusion

Where ‘*’ finds all documents
```

Figure 3: Algorithm to convert an about phrase into a Boolean expression.

Examining the about-string, optional, mandatory (+), and exclusion (-) terms are allowed. These terms are converted into a Boolean expression. Optional terms are collected and converted into a sub-expression by ORing (“a b c” → “a OR b OR c"). Likewise, exclusion terms are also ORed. Mandatory terms are collected and ANDed ("+d +e +f" → "d AND e AND f"). These three sub-expressions are then combined to form a complete about-query. The whole algorithm is presented in figure 3.

Separate about clauses are already Boolean separated so these operators are preserved. Finally, all context-elements must be satisfied so these are ANDed together.

For content only (CO) topics, a Boolean expression is computed exactly as for one about-string using the algorithm presented in Figure 3.

5. RANKING

The retrieval engine is a Boolean ranking hybrid. Result sets are computed in two parts; a bit-string of documents satisfying a strict interpretation of the query, and a set of accumulators holding document weights.

5.1 Document Ranking

The Boolean expression constructed above is converted into a parse tree then evaluated. At each leaf, the posting are loaded and converted into a bit-string, one bit per document.

If a given leaf in the parse tree is not tag-restricted, each posting is examined in turn, and the bit at position d_n of each posting is set. Should the leaf be tag-restricted, only those postings for the given tags are examined (see Section 3) and converted.

The bit-strings are combined at the nodes of the parse tree using the operator there. At the root of the tree, the bit-string has set bits for all documents exactly satisfying the query and unset for those that do not.

The accumulator values are the sum of Okapi BM25 scores computed at each leaf of the parse tree. Scores are summed regardless of the operators in the parse tree.

For AND and OR nodes scores are summed because the influence at these nodes is the sum of influences of the children.

For NOT nodes, they are also summed. If a document is excluded from the result set, the accumulator value is irrelevant. If a document is not, it is either re-included through other terms (e.g. mammal OR (dog NOT cat)), or there is a double negative in the query (e.g. cat NOT (dog NOT cat)). In both cases, the document has successfully satisfied a query leaf so receives a positive weight.

5.2 Element Ranking and Selection

The Boolean ranking hybrid engine was extended to include element ranking. Although whole documents are valid as results for CO topics, SCAS topics specify a target element. This targeting establishes the retrieval unit. If the target element is 'sec', this tag must be returned. It essentially directs the retrieval engine to search and rank each given tag instance separately.

Wilkinson [9] suggests that ranking whole documents then extracting elements from these is a poor ranking strategy. The opposite may hold for this collection. A relevant element lies in the greater context of a relevant document. A relevant document will lie in a relevant journal, which, in turn, lies in a relevant collection. To this end, every paragraph of every section of every document is contextually placed so extracting elements from relevant documents may be a good approach.

The coverage of any one posting is computed as those nodes in the document tree at or above the posting. Each posting is already annotated with a pointer into the tree, p_n. To compute the coverage, the tree is traversed upwards from p_n to the root. Coverage is computed for each document with respect to each search term.

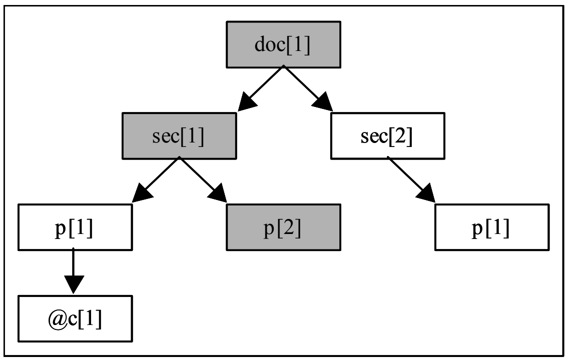


Figure 4: Coverage of a term occurring at p[2]. The coverage includes all those nodes at and above the occurrence node; those parts of the tree that "cover" the term.

In figure 4, the term "ham" occurs at p[2]. The coverage includes all nodes above that point in the document tree. In this example that is sec[1] and doc[1]; all nodes that "cover" the search term – those highlighted in grey.

For each document in the result set, the weighted coverage is computed as the covered branches of the document tree and how many search terms cover that branch. This is computed during a single pass of the indexes by storing the weighted coverage as part of each accumulator.

For the query "eggs and ham" against the documents in Figure 1, the weighted coverage is shown in Figure 5. doc[1] and sec[1] have a weight of 2, while p[1] and p[2] each have a weight of 1.

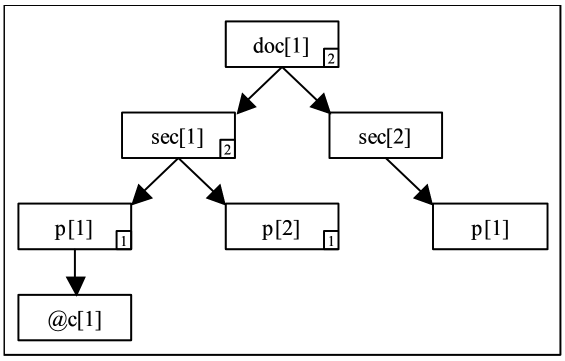


Figure 5: Weighted coverage of each node is the number of search terms that occur at or below that point in the tree. Weighted coverage is shown in the bottom right of those nodes with weights greater than zero.

In any given document, the document root must have the highest weighted coverage, but this can be equal to that of other nodes. For CO topics, all branches of the document tree with coverage less than the root are pruned. The remaining leaves are presented as the result set for that document (in Figure 5, the result is //doc[1]//sec[1]). In this way, the most information dense elements in the document are considered most relevant and no part of any document is returned more than once (overlapping is eliminated).

If a target element is specified in a SCAS topic, all non-target branches are pruned. From the remains, those branches with the highest weighted coverage are presented as the result set for that document.

5.3 Ranking summary

Recall is determined by evaluation of the Boolean expression, documents are then ranked using Okapi BM25, and elements are selected by weighted coverage. As all the metrics needed for ranking are available at search time, the search and rank process is computed in a single pass of the postings.

6. RESULTS

Evaluation results are presented in Table 3.

Table 3: INEX performance measures

Strict	Precision	Rank
CO	0.0243	42nd
SCAS	0.1799	24th
CO-ng-o	0.1359	5th
CO-ng-s	Unknown	Not top 10
Generalized	Precision	Rank
CO	0.0241	34th
SCAS	0.1214	28th
CO-ng-o	0.1542	1st
CO-ng-s	0.1405	5th

The retrieval engine performed badly using the INEX_EVAL measure. This is most likely because this measure treats each tag in a hierarchy as relevant but coverage eliminates overlapping tags – the measure is inappropriate for this retrieval technique.

Good results were shown when performance is measured using INEX_EVAL_NG. NG measures the ratio of relevant to irrelevant information returned. Coverage finds those parts of the document that contain most of the search terms. The correlation between information density and coverage is reflected in the result.

The results show the best performance when generalized quantization is used. This suggests the ordering of the results is not optimal for strict quantization – or the most relevant documents are not ranked before less relevant documents. This may be a consequence of sorting into document order before coverage order.

7. OTAGO AT INEX

The participation process involved the design and contribution of six topics. Of these, four were selected for inclusion in the final topic set. Otago was assigned three of these to assess. The assessment took three people one week each; this was one week per topic.

The retrieval engine described herein was used for designing the contributed topics. This was somewhat problematic as the topic parser was written at the same time the topics were being written, each with few examples.

From the final CAS topic set, 19 required corrections, corrections finally running to 12 rounds! This suggests the topic syntax is unnecessarily complex. See our further contribution [6] for a discussion on a possible language to use for future workshops.

The assessors were overburdened by the multitude of obviously irrelevant documents to assess. Examining some of these documents suggests many retrieval engines were aiming at high recall by retrieving any document containing any of the title terms. In particular, the word 'java' appeared in one topic; this was a somewhat popular research area over the years included in the IEEE collection. The assessment task could be reduced by carefully designing topics (and retrieval engines) to avoid this problem.

8. CONCLUSIONS

Element ranking was added to a Boolean ranking hybrid retrieval engine. Relevant documents were identified using Boolean searching. Documents were ranked using Okapi BM25. Finally coverage was used to rank elements within documents.

The results suggest coverage is a good method of identifying relevant and non-overlapping elements. Performance was best for generalized quantization, so ordering is not ideal. This may be a consequence of presenting results in document order.

9. ACKNOWLEDGEMENTS

In addition to the authors, Yerin Yoo contributed to the assessment task. Without her contribution we would not have been able to complete the task.

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The SearX-Engine at INEX’03: XML enabled probabilistic retrieval

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ABSTRACT

In this paper we describe how we used our „out of the box“ search engine for INEX’03. The *SearX-Engine* integrates structural information into the query language and the retrieval function. It is based on the widely used probabilistic retrieval (TF*IDF) and uses additional indexes on document structure to evaluate queries.

1. INTRODUCTION

Due to the fact that in the real world a huge amount of structured full-text documents is available, there is a growing need to search within those documents. One simple way is to throw away all structural information and use a well known retrieval method to search an unstructured document collection. But if you deal with finding all relevant documents to a user-query, you will be quite happy about every small piece of information you can use to fulfil the user’s information need.

Using the structural information within the documents and maybe the query can help to retrieve more relevant and fewer irrelevant documents. Therefore retrieval systems will do a better job if they take the structure into account. New retrieval algorithms for structured documents have to be designed and implemented.

The main goal of INEX (Initiative for the Evaluation of XML Retrieval) [1] is to promote the evaluation of content-oriented XML retrieval by providing a large test collection of XML documents, uniform scoring procedures, and a forum for organizations to compare their results.

The *SearX-Engine* [2] is a commercial product developed by Doctronic for searching within collections of XML documents. The author of this article is the chief of research and development at Doctronic and is responsible for the main concepts of the *SearX-Engine*. The *SearX-Engine* is integrated into *Xaver*, a multi-channel publishing system for large and structured text collections [3]. *Xaver* is mainly used by professional publishers in the field of law, taxes, or technical documentation.

2. QUERY LANGUAGE

A query in the probabilistic retrieval model can be represented by an unordered set of terms. The user can easily express his information need by specifying some related terms.

To integrate structural assignments and weightings into the query language, we introduce the concept of *roles*. One role (such as ‘author’ or ‘heading’) combines all parts of the collection with a common semantics, so the user does not have to know about the specific structure of the underlying collection.

The mapping from the collection data to structural roles is done at indexing time by the content provider. In our scenario the content provider should be seen as the person who prepares the collection for publishing and retrieval. In the majority of cases this is not the author, but the publisher or a technical service provider. The content provider should know about the content of the collection and the potential end user. Therefore he is qualified to define the roles and any other search parameter.

Not only the user level is simplified by the concept of roles. Roles can also help to search across heterogeneous collections where each one provides its own mapping from collection-specific data structures to general roles. At the implementation level roles can help to keep the index structures and algorithms small and handy, because the structural complexity is reduced.

The user can integrate structural information into his query by assigning query terms to structural roles related to his information need. He can also choose one retrieval role, which determines the parts of the collection that should be returned and ranked.

The *SearX-Engine* also supports a mechanism to weight roles. If a query term is found, the score of this occurrence will be influenced by the structural context. This weighting is often made by the publisher, who can provide his knowledge about the data and the assumed information needs of the users.

The application knows the concept of headings, so structural implications (eg scoring an article title should score all sections within this article) can be expressed. Furthermore the term operators '+' (must have) and '–' (must not have) and phrases are supported.

3. RETRIEVAL FUNCTION

The *SearX-Engine* is based on the well known probabilistic retrieval [4]. Within this framework the score of a document consists of two parts. First the inverted document frequency measure represents the entropy of the term occurring in both document and query. The more documents exist containing the term, the smaller the IDF gets. The second part reflects the term frequency, which has to be normalized by the length of the document. Those two parts of the score can be weighted for different collection characteristics by the tuning factors *C* and *K*.

$$\rho(q,d) = \sum_{t_i \in q \cap d} \left(C + \mathrm{IDF}_i\right) \cdot \left(K + (1-K) \cdot \frac{f_{id}}{\mathrm{maxfreq}_d}\right)$$

$$\mathrm{IDF}_i = \log \frac{N - n_i}{n_i}$$

$$f_{id} = \text{frequency of term } t_i \text{ in } d$$

$$\mathrm{maxfreq}_d = \text{maximum frequency of any term in } d$$

Within collections of structured documents, the retrieval function should not necessarily score an entire document. It should also be able to score smaller (or larger) elements. A structured query contains terms related to roles, and roles can be weighted by the user and the publisher. Therefore we have to extend the retrieval function in a number of ways.

The IDF is replaced by the *inverted element frequency* (IEF) depending not only on a term, but also on a role.

$$\begin{aligned} \mathrm{IEF}(t_i, s_k) &= \log \frac{N_{s_k} - n_{t_i,s_k}}{n_{t_i,s_k}} \\ N_{s_k} &= \text{number of elements having role } s_k \\ n_{t_i,s_k} &= \text{number of elements having role } s_k \text{ and term } t_i \end{aligned}$$

To adapt the IDF, all elements having the same role are handled as a document collection and the entropy over this collection is measured.

The term frequency has to be calculated with respect to the structural conditions in the query and the structural weighting has to be considered.

$$f(t_i, e, s_k) = \sum_{\substack{e' \text{ is descendant-or-self of } e \\ s_k \in \mathrm{roles}(e')}} \mathrm{freq}(t_i, e') \cdot \max(w(s) \mid s \in \mathrm{roles}(e'))$$

Putting the pieces together, the new retrieval function (ignoring the tuning factors *C* and *K*) is:

$$\rho(q, e) = \sum_{\substack{(t_i, s_k) \in q \\ t_i \in e}} \mathrm{IEF}(t_i, s_k) \cdot \frac{f(t_i, e, s_k)}{\mathrm{maxfreq}_e}$$

This formula is able to estimate the relevance of every element to a query with structural assignments and structural weightings.

4. INDEX STRUCTURES

The index structures to evaluate the retrieval function of a query on the collection are quite similar to the well known inverted files [5] used for information retrieval on unstructured texts. There is a lexicon populated with all the terms of the collections, their IEF for each role, and a pointer to the list of postings. The list of postings contains each occurrence for each term. Other than the usual inverted files we have to record the structural context of each occurrence. Because we need to know the complete path of roles from the occurrence to the root of the document structure, integrating the structural information within the list of postings would introduce a huge overhead. Therefore we decided to use a special index for the structure and store links to this index into the list of postings. The structure index is a tree like index structure. It represents the document structure and contains the set of roles for each indexed element and the frequency of the most frequent term of each element. This design reduces the storage requirements, but introduces some runtime disadvantages.

5. INEX'03

To evaluate INEX'03 topics, we made a mapping of the used structural assignments to roles and transformed the topics to our query format described above. Weighting was done to push up hits within article titles, abstracts and keywords. The values of this weighting were guessed by the author and were not calculated from INEX'02 or other collections.

5.1 CO-Topics

For Content-Only queries we decided to rank always whole articles and search for the title and the keywords of the topic description within the whole article. So we did not make any structural assignments besides the weighting. The role *article* is mapped to all articles in the collection.

```
<inex_topic ct_no="35" query_type="CO" topic_id="100">
  <title>+association +mining +rule +medical</title>
  <description>
    Retrieve information about association rule mining in medical databases </description>
  <narrative> We have a medical data mining ... </narrative>
  <keywords>association, mining, rule, medical</keywords>
</inex_topic>
```

$\downarrow$

```
<query name="INEX">
  <retrieval-role><constant value="article"/></retrieval-role>
  <filter/>
  <query-item>
    <role><constant value="article"/></role>
    <terms>
      <constant value="+association +mining +rule +medical association mining rule medical"/>
    </terms>
  </query-item>
</query>
```

5.2 CAS-Topics

The CAS-Mapping is somewhat more difficult because of the CAS topic format introduced in INEX'03.

The last element in the path of the title is taken as the retrieval element. Every about-predicate creates one query item (pair of role and terms). All the paths within the CAS topics are used to build the set of roles needed by the *SearX-Engine*. The XPath for the role mapping is taken as the name.

```
<inex_topic ct_no="14" query_type="CAS" topic_id="63">
  <title>
  //article[about(.,'"digital library"') AND about(.//p,'+authorization +"access control" +security')]
  </title>
  [...]
</inex_topic>
```

$\downarrow$

```
<query name="INEX">
  <retrieval-role><constant value="article"/></retrieval-role>
  <filter/>
  <query-item>
    <role><constant value="article"/></role>
    <terms><constant value=" 'digital library' "/></terms>
  </query-item>
  <query-item>
    <role><constant value="article//p"/></role>
    <terms>
      <constant value="+authorization +'access control' +security"/>
    </terms>
  </query-item>
</query>
```

A Filter on an explicit attribute value in the CAS title (eg /article[.//yr <= '2000']) was translated into a *SearX-Engine* filter to exclude document parts based on attribute values. Therefore we are able to map every CAS query to our query format.

6. EVALUATION

We have submitted two CO and two VCAS runs. Within each track there was one run created automatically and one created manually from the INEX topic description. The results of the CO submissions are shown in figure 1 (automatic) and 2 (manual). Because at this time there are no metrics for the VCAS available, we have treated the VCAS submissions like SCAS. The results are given in figure 3 (automatic) and 4 (manual).

The size of the indexed data was 876MB, that's 111% of the original size of the collection. This size includes all the data, the search indexes, and a phrase index for the efficient evaluation of phrase searches. Each CO topic was evaluated in 20s, each CAS topic in 26s on average (RedHat Linux 8.0 on a P4/2.4GHz). As opposed to an end user query, the given timings contain the construction of the whole result set and the transformation to the INEX submission format.

7. CONCLUSION

We were able to index the INEX document collection and evaluate the INEX topics without any modification of the "out of the box" *SearX-Engine*. The index structures needed by the engine are quite small and each topic could be evaluated fast. The results of the submitted runs show a good retrieval quality. We are satisfied with the overall performance of the *SearX-Engine*.

The INEX'03 was a good exercise to show the flexibility of our *SearX-Engine*. The results of the experiments may influence the future development to improve performance and index sizes on the one hand and the retrieval quality on the other. Without INEX, retrieval quality improvements would be much harder.

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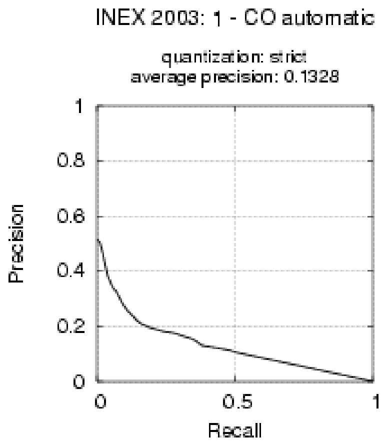

Figure 1. Evaluation of the automatically generated CO runs with `inex_eval_ng` (overlapping considered).

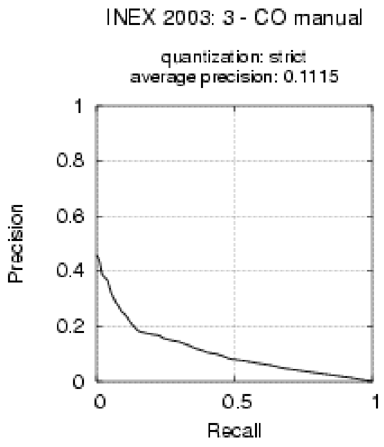

Figure 2. Evaluation of the manually generated CO runs with `inex_eval_ng` (overlapping considered).

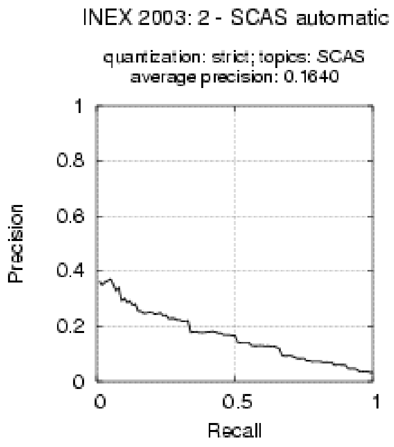

Figure 3. Evaluation of the automatically generated SCAS runs with `inex_eval`.

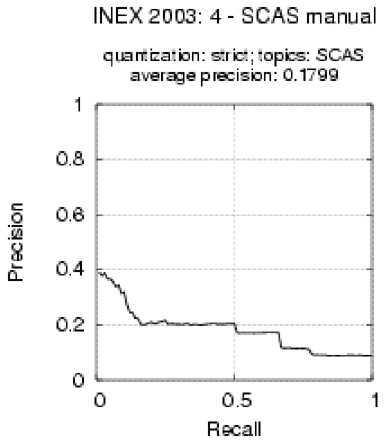

Figure 4. Evaluation of the manually generated SCAS runs with `inex_eval`.

Expected Ratio of Relevant Units: A Measure for Structured Information Retrieval

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ABSTRACT

Since the 60's, evaluation has been a key problem for Information Retrieval (IR) systems and has been extensively discussed in the IR community. New IR paradigms, like Structured Information Retrieval (SIR), make classical evaluation measures inappropriate. A few tentative extensions to these measures have been proposed but are also inadequate. We propose in this paper a new measure which is a generalisation of recall. This measure takes into account the specificity of SIR, when elements to be retrieved are linked by structural relationships. We show an instantiation of this measure on the INEX database and present experiments to show how well it is adapted to SIR evaluation.

1. INTRODUCTION

Information Retrieval systems aim at retrieving documents that are *relevant* to a given user information need. The notion of *relevance* is not only not well defined and ambiguous [13, 9], it is also user specific. The evaluation of IR systems appeared very early as a key problem of IR. Cleverdon experiments on the Cranfield collection [3] were the first experiments that justified the development of entirely automatic IR systems. Evaluation is useful for comparing different systems and is used to justify theoretic and/or pragmatic developments of IR systems.

Many different parameters can be used in order to measure the performance of an IR system like for example time and space taken by the system to answer the query and the user effort to find relevant documents. Swets [14] was the first to clearly define how a metric should be defined in order to provide an objective evaluation of IR systems: a measure should only reflect the ability of the system to discriminate relevant documents from irrelevant ones.

A number of hypotheses are also necessary (even if they are implicit) to develop evaluation measures. We can distinguish two kinds of hypotheses: those which are necessary to the computation of the measure and those which are *priors* on user behaviour. Examples of typical assumptions are the following: (1) the user follows the ordered list of retrieved elements beginning with the first element; (2) a relevant document is still relevant even if the user has already seen the same information in another document higher in the retrieved list. We will make such hypotheses explicit when describing our measure.

There are many different approaches for IR evaluation [15, 1]. The expected search length [4] measures the amount of irrelevant documents a user will consult before finding a certain amount of relevant documents. Some measures are based on the definition of a metric over some predefined statistics [2, 15], some derive from rank correlation [10]. But the most famous measures in IR are recall and precision. *Recall* is defined as the ratio of the number of relevant documents that are retrieved to the total number of relevant documents. *Precision* is the ratio of the number of relevant documents that are retrieved to the total number of retrieved documents.

Raghavan [12] proposed a probabilistic version of recall-precision, which is not inconsistent as standard precision/recall can be, especially when documents are not fully ordered. We will not define more precisely their measure here. Instead, we will detail an extension of precision and recall in the case of a non-binary relevance scale, as it was used to evaluate Structured Information Retrieval systems in the 2002 INEX workshop. This extension was proposed by Kekäläinen and Järvelin [7]. In that case, the set R is defined in a fuzzy way: a document can be more or less relevant. When the document is highly relevant, it will be in the set of the relevant documents with a degree of 1. When the document is not relevant, it will be in this set with a degree of 0. Every value between 0 and 1 will be a measure of the relevance of the document. This scale thus generalises the classic binary scale (relevant/not relevant) that is used in IR. Let us denote $j(d)$ the degree with which the document d belongs to the relevant set of documents for a given query. Then, recall and precision are computed as:

$$\text{recall} = \frac{\sum_{e \in L} j(e)}{\sum_{e \in E} j(e)} \quad (1)$$

$$\text{precision} = \frac{\sum_{e \in L} j(e)}{N} \quad (2)$$

where N is the number of documents in the list, E is the set of documents and L is the set of documents in the list. Those two formulas generalise standard recall-precision: when $j(d)$ takes only the values 0 or 1, they give the same results.

In this paper, we propose a measure to evaluate SIR systems. We will first introduce the new problem of SIR. We will show how standard recall/precision have been extended to evaluate such systems and why this is not well adapted to

SIR evaluation. We will then introduce a new measure which is related to the recall. We will compare our measure and precision/recall extension on stereotypical systems using the corpus provided by INEX[1].

1.1 Evaluation and Structured Information Retrieval

Atomic units are usually documents in classical IR. With the actual growth of structured documents [2], the atomic unit is no more the whole document but any logical element in the document. We will call such an element a *doxel* (for DOCument ELement) in the remainder of this paper. Compared to IR on unstructured collections, Structured Information Retrieval (SIR) should not focus on returning documents but *the smallest doxel that contains the answer to the query.* While that query can be only free text like in standard IR (using the INEX terminology, those are *Content Only* queries, CO in short), a query can also specify both constraints on the structure and on the content (those are called *Content And Structure* queries, CAS in short).

We are interested in the evaluation of systems that answer CAS and CO queries, but we will focus here mainly on CO. We will say that a good answer (the smallest doxel) is SIR-relevant to distinguish this notion from usual relevance.

Our work was greatly influenced by the recent INEX initiative [6]. In this section, we describe briefly how SIR systems were evaluated in INEX 2002, which was the first initiative where a corpus of assessed XML documents was built. We will show why the current evaluation methodology is not well suited for SIR.

Let us first describe the INEX scale used for the user assessments. This scale is neither binary, nor between 0 and 1, but is two-dimensional. The first dimension is related to the extent with which the element is relevant. The relevance does not take into account the non relevant part of the doxel, even if that part is 99% of the doxel. For example, the common ancestor of the whole database *will be considered as highly relevant* even if only a small paragraph is highly relevant. In INEX'02, four levels of relevance were distinguished: the doxel can be *irrelevant* (0) if it does not contain any information about the topic of the request; marginally relevant (1) if it mentions the topic of the request, but only in passing; *fairly relevant* (2) if it contains more information than the topic description, but this information is not exhaustive; highly relevant (3) if it discusses the topic of the request exhaustively.

The second dimension, *coverage,* is specific to structured document evaluation. Document coverage describes how much of the document component is relevant to the request topic. Again, there are four levels: no coverage (N) when the query topic is not a theme of the document component; too large (L) when the topic is only a minor theme of the document component; too small (S) when the topic or an aspect of the topic is the main or only theme of the document component, but the component is too small to act as a meaningful unit of information; finally, exact coverage (E) when the topic is the main theme of the doxel.

[1]Initiative for the Evaluation of XML retrieval, http://qmir.dcs.qmw.ac.uk/INEX/

[2]Where the textual (or multimedia) content of the document is usually organised in a tree

$$\begin{aligned} f_g : J_{\text{INEX}} &\mapsto J_{[0,1]} \\ j &\mapsto \begin{cases} 1 & \text{if } j \in \{3E\} \\ 0.75 & \text{if } j \in \{2E, 3L, 3S\} \\ 0.50 & \text{if } j \in \{1E, 2L, 2S\} \\ 0.25 & \text{if } j \in \{1S, 1L\} \\ 0 & \text{if } j \in \{0N\} \end{cases} \end{aligned}$$

$$\begin{aligned} f_s : J_{\text{INEX}} &\mapsto J_{[0,1]} \\ j &\mapsto \begin{cases} 1 & \text{if } j \in \{3E\} \\ 0 & \text{if } j \notin \{3E\} \end{cases} \end{aligned}$$

Table 1: Quantisations are used to convert an assessment from the INEX scale J_{INEX} to a binary or real scale used to compute recall and precision. In INEX, two quantisations were proposed: f_s is a "strict" quantisation, $f_g$is a "generalised quantisation"

The two dimensions are not fully independent: a non relevant element (0) must have no coverage (N). There are only 10 different values in this scale (and not 16). In the remainder of this paper, J_{INEX} denotes this set of 10 values. Each of these values is a digit (relevance) followed by a letter (coverage). Thus, $2E$ means "fairly relevant with exact coverage". Within this scale, the doxels that should be returned by a perfect SIR system will be all the doxels *with an exact coverage*, beginning with those with high relevance: in the case of the INEX scale, SIR-relevant doxels are those that have an exact coverage. Doxels with too small or too big coverage in this scale are considered *not relevant.* The motivation is that exact doxels *are* the doxels a user is searching for, while "too small" doxels are contained in an "exact" doxel and "too big" doxels contain an "exact" doxel.

2. LIMITS OF CURRENT MODELS

The first measure proposed in INEX 2002 was standard recall and precision (*i.e.* using f_s, see table 1). In this case, only doxels with exact coverage and high relevance (INEX scale) are the relevant elements (for the binary scale). A system that does *always returns a near match* will have a recall and a precision of 0. This should be avoided since the task complexity is very high. Moreover, when one is assessing the corpus one can find it difficult to give the exact match to one doxel rather than to a smaller one. For example, the list element in INEX often contains only one paragraph; the textual content of both elements (list and paragraph) is thus the same. It is impossible to make a choice and if we give an exact coverage to both, a SIR system will have to return both elements in order to have a perfect recall.

In order to cope with that problem, Gövert [5] proposed to add some relevance to neighbouring doxels, using f_g to convert an assessment from the INEX assessment scale to a value between 0 and 1. A highly relevant doxel with an exact match will have a relevance of 1 in the $[0, 1]$ scale. Some of the doxel neighbours will also have a non null relevance: its ancestors – within the document boundary – will have a relevance of 0.75 (too big); some of its children will have a relevance of 0.25 (too small). Non relevant doxel will have a 0 value for relevance. This choice might seem better than the first one, but is still not adequate:

- For every SIR-relevant doxel, there will be a new set of IR-relevant doxels. To give an example of what it implies, consider a system that returns a doxel and two ancestors: this system will have a recall of 2.25, which is better than a system that returns two highly SIR-relevant doxels.
- A system that returns all the SIR-relevant doxels will not be considered as having retrieved all the relevant information: this system will not have a recall of 1.

Those problems are more connected to relevance assessments for free text queries, where there is no constraint on the structure of the retrieved doxels. Nevertheless, the case of structured queries can also be discussed. We will distinguish two different cases:

- The topic formulation does not have any constraint that forbids a doxel and a sub-doxel (a doxel contained in this doxel like e.g. a paragraph in a section) to be both retrieved like for example the query "find a paragraph or a section that talks about cats". Recall/precision are clearly not adapted to this case;
- The topic formulation does not allow a doxel and its sub-doxel to be both retrieved ("chapters that talk about photography"). In this case, we can use standard (or generalised) recall and precision without having any problem.

Classical measures require the definition of the typical behaviour of a system user. This user consults the list of retrieved doxels one by one, beginning with the first returned doxel and continuing in the returned order. In the next section, we propose a measure based on a specific user behaviour, which takes into account the structure of the documents. In particular, we integrated in our measure the fact that a user might explore the doxels which are near the returned doxel in the structure.

In Web-based IR, classical precision/recall can be problematic. Even if the problem is slightly different, some authors have considered using the structural information (hyperlinks) of the corpus. For instance, Quintana, Kamel and McGeachy [11] proposed a measure that takes into account data on the displayed list of documents, on the user knowledge of the topic and also on the links between the documents. They propose to estimate the mean time that a user will spend before finding a relevant document. We follow somewhat the same approach. The main difference is that we rely upon a probabilistic model which makes our measure sound and easily adaptable to new corpora.

3. A MEASURE FOR SIR

We will suppose an ideal situation where assessments in the INEX 2002 corpus *strictly* follow the definition of SIR-relevance (which is not the case). We will thus make the following assumption that a SIR-relevant doxel can only contain SIR-relevant doxels that are less relevant or have a smaller coverage. This constraint states that the same relevant information is assessed with "exact coverage" only one time.

In this section, we describe our measure, beginning with some general hypotheses and its definition. Then we present the probabilistic events and the assumptions we made on them, and finally we show how to calculate our measure.

3.1 Hypotheses

The definition of a measure is based on an hypothetical user behaviour. Hypotheses used in classical measures are subjective but do reflect a reality. In the SIR framework, we will propose a measure that estimates the number of relevant doxels a user might see. We will now describe how a typical user behaves in the context of SIR retrieval. This behaviour will be defined by three different aspects: the doxel list returned by the SIR system, the structure of the documents and the known relevance of doxels to a query. The following hypotheses are similar to that supposed in classical IR:

Order The user follows the list of doxels, beginning with the first returned. He never discourages himself nor does he jump randomly from one doxel to another;

Absolute relevance A doxel is still relevant even if the user has already seen another doxel that contains the same (or a part of the same) information;

Non-additivity Two non relevant doxels will never be relevant even if they are merged.

The three last hypotheses are specific to our measure

Structure browsing The user eventually consults the structural context (parent, children, siblings) of a returned doxel. This hypothesis is related to the inner structure of documents;

Coverage influence The coverage of a doxel influences the behaviour of the user. If the doxel is "too large", then the user will most probably consult its children. If the doxel is "too small", the user will most probably consult the doxel ancestors;

No hyperlink The user will not use any hyperlink. More precisely, he will not jump to another document. This hypothesis is valid in the INEX corpus but can easily be removed in order to cope with hyperlinked corpora.

The measure we propose is the expectation of the number of relevant doxels a user sees when he consults the list of the k first returned doxels divided by the expectation of the number of relevant doxels a user sees if he explores all the

N	Number of doxels in the list consulted by the user
N_R	Number of SIR-relevant doxels that have been seen by the user
L_e	The doxel e is in the list consulted by the user
S_e	The user has seen the doxel e (either in the list or by browsing from a doxel in the list)
$e' \to e$	The user sees the doxel e after he consulted the doxel e'

Table 2: Events

doxels of the database. We denote this measure by ERR (for Expected Ratio of Relevant documents):

$$ERR = \frac{\mathbb{E}\left[N_R/N = k\right]}{\mathbb{E}\left[N_R/N = |E|\right]}$$

This measure is computed for one query. The measure ERR is normalised ($ERR \in [0, 1]$) as $\mathbb{E}\left[N_R/N = |E|\right]$ represents the maximum number of SIR-relevant doxels a user can see in the whole corpus. The measure can thus be averaged over different queries.

3.2 Events

We now have to compute the expectation $\mathbb{E}\left[N_R/N = k\right]$ with the assumptions on the user behaviour we just made. We will introduce some events that are used to formally model the user behaviour and will make some hypotheses on the (probabilistic) relationships between these events. The three different probabilities we introduce are respectively related to the assessments, to the retrieved doxels and to the document structure. The set of events we use in this paper is summarised in table 2.

Events

Let us denote E the set of doxels, e or e' a doxel from E and q a given query. A doxel e can be more or less relevant with respect to the query. We will denote the probability of SIR-relevance of a given doxel by $P(R_e/q)$. The list returned by the SIR system is only partially ordered so that some rearrangements of the list are possible. Depending on the length N of the list, a doxel is then consulted by the user with a probability $P(L_e/q, N = k)$.

When a user consults a doxel e' from the list, he eventually will use the structure to navigate to another doxel e from the document. As it is difficult to make this process deterministic, we will use $P(e' \to e/q)$ as the probability that the user goes from e' to e. Note that this probability depends upon the query, this will be illustrated in the next sections.

We will suppose that the IR user sees the doxel e iff:

- e is in the list;
- e' is in the list and the user browses from e' to e

This event is denoted S_e and we can write:

$$L_e \vee (\exists e' \in E, L_{e'} \wedge e' \to e) \equiv \mathrm{S}_e$$

For simplicity, we will now drop the query q from the formulas, as the measure is computed independently for every new query.

Hypotheses

The following hypotheses are necessary for the computation of the measure. Note that all these assumptions are made knowing the query q and the length of the list N. The first two hypotheses are intuitive. The first hypothesis states that the relevance of a doxel does not depend on the fact the user sees it:

$$P(\mathrm{S}_e \wedge R_e) = P(\mathrm{S}_e)P(R_e) \tag{H1}$$

The second states that the behaviour of a user (going from a doxel in the retrieved list to another doxel, $e \to e'$) does not depend on the fact that the doxel e is in the list (L_e):

$$P(L_{e'} \wedge e' \to e) = P(L_{e'})P(e' \to e) \tag{H2}$$

The third states that the fact that events R or L that are related to different doxels are independent, and that in particular

$$\mathrm{S}_e \wedge L_e \text{ or } \neg(\mathrm{S}_e \wedge L_e) \text{ and } \mathrm{S}_{e'} \wedge L_{e'} \text{ or } \neg(\mathrm{S}_{e'} \wedge L_{e'}) \text{ are independant} \tag{H3}$$

This hypothesis has no intuitive meaning and has been introduced only for allowing the measure computation. Nevertheless, it can be justified by those two statements: the relevance is assigned by the user and thus the probability of SIR-relevance does not depend upon the SIR-relevance of another doxel but on the user assessment (that is denoted by our event q). The second point is that the fact S_e that the user sees a doxel e only depends on the fact that a doxel e' is in the list (which is known when we know the length of the list N which is the case here) and that the user moves from a doxel e' in the list to another doxel e.

The third hypothesis is also a simplification of reality, but is as necessary as the two first. It is related to the probability S_e that the user see a doxel e. The more the user can access this doxel from the retrieved doxels by navigating along the document structure, the more "chanches" he has to see that doxel. As it is not possible to evaluate all the interactions between previously seen doxels and this event, we make the hypothesis that correspond to the "noisy-or". This hypothesis is used to compute the probability of the logical implication $A_1 \vee \cdots \vee A_n \Rightarrow B$ as $1 - P(\neg A_1) \ldots P(\neg A_n)$. We thus state that:

$$\begin{aligned} P(\mathrm{S}_e) &= P\left(\textstyle\bigvee_{e' \in E}(L_{e'} \wedge e' \to e)/N\right) \\ &= 1 - \textstyle\prod_{e' \in E} P\left(\neg(L_{e'} \wedge e' \to e)/N\right. \end{aligned} \tag{H4}$$

In this equation, we assumed that the event $e \to e$ is certain (identity move), that is $\mathrm{P}(e \to e) = 1$ as the logical or is over all doxels in E.

3.3 Theory

In this subsection, we describe how to compute the measure. We now have to derive this measure from the behaviour of a typical user. We will thus introduce a set of probabilities, each of which describes a part of the user behaviour. We will also make several hypotheses in order to make this measure computable. We now describe several hypotheses that are related to the relevance assessments, to the returned list and to the structure of the documents

We want to calculate $\mathbb{E}\left[N_R/N = k\right]$, with $1 \leq k \leq |E|$. We know that by definition,

$$\mathbb{E}\left[N_R/N = k\right] = \sum_{r=1}^{|E|} rP(N_R = r/N = k)$$

The user has seen r SIR-relevant doxels ($N_R = r$) when these two conditions are both met: (1) there exists a subset $\{e_1, \ldots, e_r\} \subseteq E$ of SIR relevant doxels that the user has seen and (2) for every other doxel, either the doxel is not SIR-relevant or the user has not seen it. If one considers the set of all sets A that contains r doxels from E, this condition can be written formally as:

$$N_R = r \equiv \bigvee_{\substack{A\subseteq E\\|A|=r}} \left(\bigwedge_{e\in A} \mathrm{S}_e \wedge R_e\right) \wedge \left(\bigwedge_{e\in E\setminus A} \neg(\mathrm{S}_e \wedge R_e)\right)$$

Events for two different sets are exclusive and using hypothesis (H3) we can state that:

$$\begin{aligned}&\mathbb{E}\left[N_R/N = k\right]\\ &= \sum_{r=1}^{|E|} r \sum_{\substack{A\subseteq E\\|A|=r}} \prod_{e\in A} P(\mathrm{S}_e \wedge R_e/N = k)\\ &\qquad \prod_{e\in E\setminus A} P(\neg(\mathrm{S}_e \wedge R_e)/N = k)\end{aligned}$$

This formula can be reduced, using the hypothesis H1 we obtain:

$$\begin{aligned}\mathbb{E}\left[N_R/N = k\right] &= \sum_{e\in E} P(\mathrm{S}_e \wedge R_e/N = k)\\ &= \sum_{e\in E} P(R_e)P(\mathrm{S}_e/N = k)\end{aligned}$$

Using the definition of S_e and the noisy-or hypothesis, we have

$$P(\mathrm{S}_e/N = k) = 1 - \prod_{e'\in E} P\left(\neg(L_{e'} \wedge e' \to e)/N = k\right)$$

Note that $\mathbb{E}\left[N_R/N = |E|\right]$ can easily be computed as $P(S_e/N = |E|) = 1$. Then, using hypothesis (H2), we finally obtain $ERR(k)$:

$$\frac{\sum_{e\in E} P(R_e) \left[1 - \prod_{e'\in E} (1 - P(L_{e'}/N = k)P(e' \to e))\right]}{\sum_{e\in E} P(R_e)}$$

3.4 INEX

In the last section, we derived the computation of the measure ERR, but we did not instantiate it in a practical case. We now propose a way to compute some of the probabilities for the INEX database[3], namely for a query the probability $P(R_e)$ of relevance of a doxel and the probability $P\left(e \to e'\right)$ that the user browse from a doxel to another.

Computing $P(R_e)$

INEX relevance assessments are given in a two dimensional scale (coverage and relevance). For a given query, we will compute $P(R_e)$ as[4]:

$$P_0(R_e) = \begin{cases} 1 & \text{if } j(e) = 3E\\ 0.5 & \text{if } j(e) = 2E\\ 0.25 & \text{if } j(e) = 1E\\ 0 & \text{otherwise}\end{cases}$$

where $j(e)$ is the assessment of the doxel e for the given query in the scale J_{INEX}. To avoid counting the same relevant information twice, we will furthermore suppose that the probability of SIR-relevance of a doxel is zero whenever the doxel has an ancestor that is relevant with exact match, that is

$$P(R_e) = \begin{cases} 0 & \text{if } \exists e', j(e') \in \{1E, 2E, 3E\}\\ & \text{ and } e' \text{ is an ancestor of } e\\ P_0(R_e) & \text{otherwise}\end{cases}$$

Computing $P(e' \to e)$

To compute the probability that the user jumps from a doxel to another, we will distinguish several relationships between those doxels. Formulas below were only justified by our intuition and can easily be replaced by others. We will denote length(e) the length of doxel e. This length will usually be the number of words contained in the doxel. We will denote by $d(e, e')$ the distance between two doxels. We used the number of words that are between those two doxels: for example, the distance between the last paragraph of section 1 and the second paragraph in section 2 will be the number of words in the first paragraph of section 2 (plus the number of words of the section title). We can now give the formulas, distinguishing four different cases.

e' *and* e *are not in the same document*

We made the hypothesis that the user does not follow any hyperlink:

$$P(e' \to e) = 0$$

e' *is a descendant of* e

We will suppose that the more e' is an important part of e the greater the probability that a user goes from e' to e. e' relevance has an influence on this probability: if the e'coverage is S (or better, E), the probability is higher:

$$P(e' \to e) = \left(\frac{|e'|}{\|e\|}\right)^a$$

where a is $\frac{7}{8}$ when the coverage is exact, $\frac{3}{4}$ when the coverage is too small and $\frac{1}{2}$ otherwise.

[3]Note one can use the same definitions for any corpus of structured documents.

[4]Other functions are of course possible, we chose one that seemed “reasonable” to us

e is in e'
This is a symmetric case. The only difference is the coverage influence: a is $\frac{7}{8}$ when the coverage is exact, $\frac{3}{4}$ when the coverage is too big and $\frac{1}{2}$ otherwise.

Other cases
If in the same document two doxels are one after another (like two sibling paragraphs), we will state that the probability that the user follows the path between the two doxel is proportional to the inverse of the distance between the two doxels:

$$P(e' \to e) = \left(2 + d(e', e)\right)^{-1}$$

4. EXPERIMENTS

4.1 Settings

In this section, we show how the measure discriminates between different IR systems. In order to compare the behaviour of generalised precision-recall versus our measure, we considered six different hypothetical "SIR-systems" which make use of known assessments. These systems exhibit "extreme" behaviours which illustrate a whole set of different situations. The six systems are named:

perfect A system that returns the SIR-relevant doxels

document A system that returns all document in which a SIR-relevant doxel appears

parent A system that returns always the parent of a SIR-relevant document

ancestors A system that returns ancestors of a SIR-relevant document with a score

biggest child The SIR system returns the biggest child (in number of words)

In all these experiments, the score of the doxel was given by the relevance (first dimension of J_{INEX}) of its SIR-relevant doxel: we scored 1 for a doxel which was highly relevant, 0.5 for a fairly relevant doxel and finally 0 for a marginally relevant doxel.

In our experiments, we used all the content only queries for which there were some assessments. We only kept the 1000 first documents returned by the different systems. Given that scores can only take three values, the P/R curve was computed using the Raghavan [12] probabilistic definition of precision and recall (with a step of 0.1). We computed the values at $N = 0...1000$ for our own measure. We averaged our results for P/R and ERR in order to hide the specificities of each assessment. We didn't consider the case of standard precision/recall (e.g. using f_s) as almost all of the models proposed here will have a near null precision-recall curve.

4.2 Results

In figure 1, we present the curves obtained with our measure and in figure 2 the generalised recall/precision (GRP). We will comment on those curves in this subsection: we will point the shortcomings of the GRP and see how our measure corrects the problem. When we analyse those curves, we can at least identify four problems with the GRP:

1. The model **perfect** is not perfect for GRP. This can be seen as it is not the best model and as precision falls very quickly between recall 0.2 and 0.6. This is because when using the generalised quantisation f_g we are adding relevant doxels (for precision/recall) that are not SIR-relevant. Thus, even if the system returns all the SIR-relevant systems, it does not return the other relevant doxels. For our measure ERR, we can see that after almost 400 doxels, model **perfect** has retrieved all SIR-relevant doxels.

2. The model **ancestors** has a higher performance than model **perfect**. This point is related to the previous one: because the model **ancestors** returns more doxels that are relevant (due to the quantisation), recall is better. Due to the limited size of the list and to the 4 possible values for scores, examination of the retrieved doxels shows another thing: every SIR-relevant doxel in the returned list is preceded by a list of its ancestors. We can see this effect with our measure, as the measure increases slowly with the number of the retrieved documents for the model **ancestors**. Our measures also correctly discriminates those two models, as the performance of model **ancestors** is far below the performance of model **perfect**.

3. The model **parent** is much higher than the model **biggest child**. This is not what could be expected, as the parent can contain many irrelevant parts. This effect is due to the fact that doxels with coverage "too small" have a lower value in the real scale than those with coverage "too big". With our measure, model performances are much closer.

4. The model **document** is close to the model **biggest child**. This is not a good property of GRP, since we want a measure that favours systems that retrieved elements of smaller granularity than documents and since the biggest child is very often close to the SIR-relevant doxel (maybe as close as the document). With ERR, this is not the case.

Those four observations show that our measure is better suited to SIR evaluation than GRP. If we consider the theoretic foundations of our measure, it gives some guarantees about its validity.

5. DISCUSSION

In this article, we have described a new measure for SIR systems called the Expected Ratio of Relevant document (ERR). This measure is a generalisation of recall in classical IR: when the probability of going from a doxel to another is always null, the measure reduces to a form of generalised recall. This measure is consistent with SIR, in the sense that it favours systems that find the smallest relevant doxels. Other proposed measures like standard or generalised precision and recall are not good indicators of the performance of a SIR system, as was shown in the last section. Note that results presented here should however be interpreted with care, as we took very specific systems to underline the strange behaviour of GRP. Our measure has the advantage of a sound theoretical foundation and explicitly integrates the structure of the documents in the modelling of user behaviour[5].

The presented measure could also be very easily adapted in order to evaluate performance of systems in the case of web retrieval. Another interesting property is that it could favour systems that provide Best Entry Points to the document structure [8], from which users can browse to access relevant information. In this case, if from a retrieved doxel there is a high probability that the user goes to some (SIR-)relevant doxels, the measure will increase faster than if the doxel is (SIR-)relevant but provides no (structural) links to other (SIR-)relevant doxels.

The last step would have been to provide an extension of precision as we did for recall. But when we tried to follow the probabilistic approach of Raghavan, a number of problems arose[6] and it is still not clear which set of hypotheses could be used to solve the problem. However, the curves we can draw with the proposed measure are informative enough and have good properties, so it could replace or complement the GRP used for the evaluation of SIR-systems.

[5]This behaviour should be empirically validated.

[6]In particular, we need to calculate the probability of finding N_R relevant doxels in the retrieved list if this list has a given length. This probability can only be computed in $O(2^{MR})$where MR is the number of relevant doxels for the query.

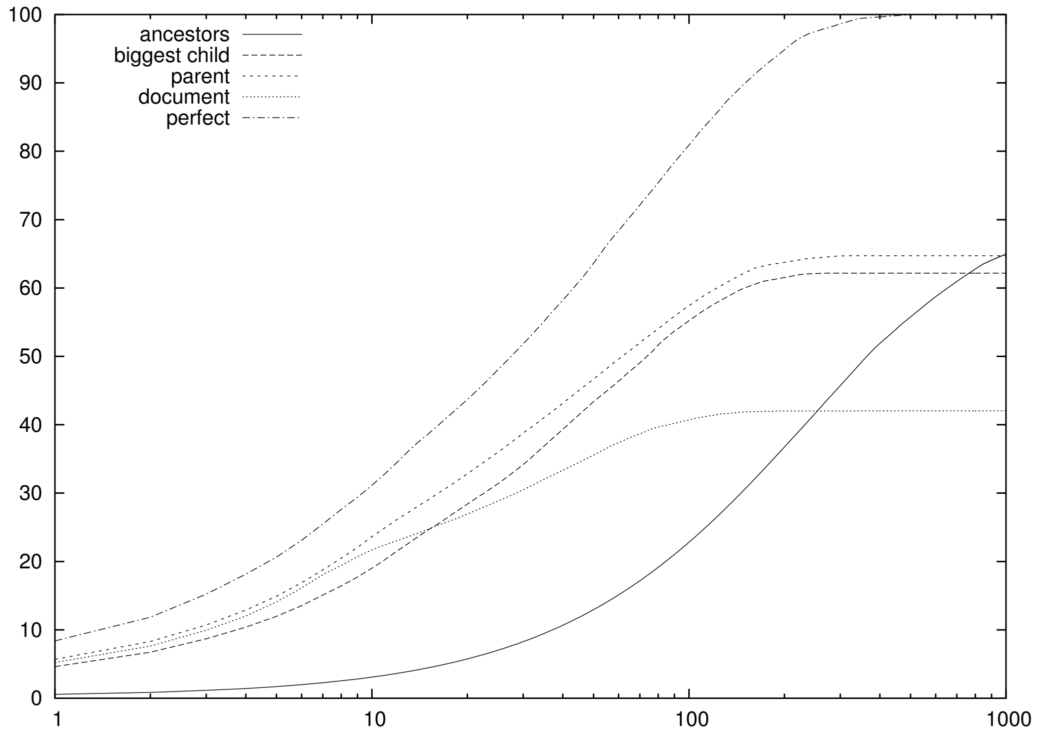

Figure 1: Measure ERR (log-scale for the axis of abscissas). The axis of abscissas represents the length of the list of retrieved doxels. The axis of ordinate represents the measure ERR (in %). The measures are averaged over the queries.

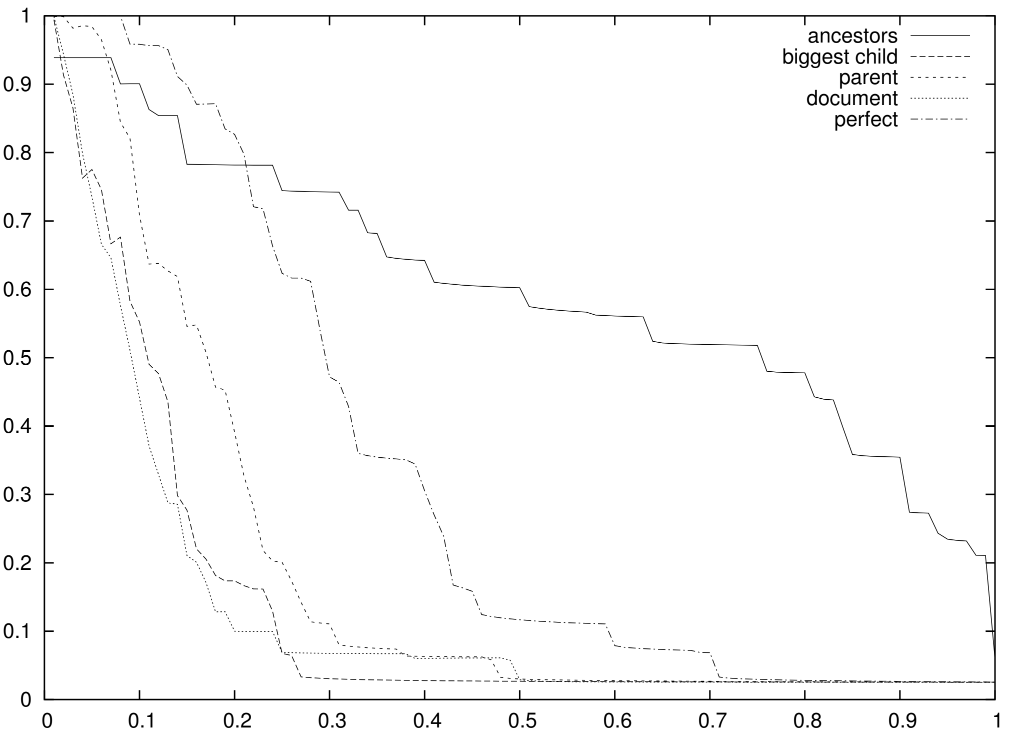

Figure 2: Generalised precision-recall. The axis of abscissas represents recall and the axis of ordinate the precision. Precision are averaged over the queries.

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The Simplest Query Language That Could Possibly Work

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ABSTRACT

The INEX'03 query language proved to be much too complicated for the INEX participants to use well, let alone anyone else. We need something simpler, but not too simple. Something which is basically a hybrid between Boolean IR queries and a stripped down CSS will do the job.

1. INEX NEEDS A QUERY LANGUAGE.

In the INEX conferences, we are trying to develop a data collection and a set of queries with known answers that can provide a solid basis for research and experimentation with XML information retrieval.

In order to communicate between researchers in the same year, we need a common query language. For INEX'02 there was such a language. In INEX'03 there was another. In order to communicate between the researchers who produce the queries in one year and the researchers who use them in later years, we need a stable, well-defined language.

The designer(s) of the INEX'03 query language had every reason to feel pleased. After the INEX'02 query language proved to need revision, surely this was the simplest thing that could possibly work: take an extremely well established XML structural query language (XPath) and add to it a minimal set of features for Information Retrieval.

It seems to be agreed that XPath is not a language for the casual user. But this paper is not concerned with user query languages. The query language we need is a query language for use by researchers who are expert in information retrieval and XML. What counts is whether the query language is suitable *for us*, not users.

Unfortunately, the production of this year's CAS queries proved conclusively that the INEX'03 query language is far too complicated *for us*:

- It proved too hard to use. Of the 30 CAS queries that were selected, 19 (nearly $\frac{2}{3}$), were either syntactically illegal or otherwise wrong. It took no fewer than 12 rounds of correction before we had a completed collection of queries.
- Like many W3C productions, XPath 1.0 is quirky, to put it kindly. It is very powerful in some respects, but there are queries that are very hard to express. For example, *//body//ip1//name* | *//body//ip2//name* is legal, but *//body//(ip1|ip2)//name* is not.
- It proved to be hard to implement. Presumably everyone who submitted a query for consideration had already checked it with some XML IR engine; how else could they have known that the query had about the right number of relevant answers? Yet a large number of queries were syntactically or semantically wrong. That should have been noticed. At least one implementor switched the semantics of the / and // operators.
- It proved to be hard to implement for another reason. XPath is quite powerful, in ways that are not likely to be useful for information retrieval, and yet if XPath was not implemented in full, were we really implementing the INEX'03 query language? This year, it turned out that most of the power of XPath was not needed. It wasn't the simplest thing that could possibly have worked. For example, we[23] found that there were 198,041 nodes in the index after ignoring "noise" tags. Yet if ordinal position was also ignored, there were only 10,522 distinct paths. Not one of this year's selected CAS queries used the ordinal position ([*n*]) feature of XPath.
- XPath has a clear definition of the "string value" of a node; the definition is precise, but given the actual XML markup in the document collection we are working with, it's not the definition we want. For example, if there is one mention of Joe Bloggs in the collection, as ⟨*au*⟩⟨*fnm*⟩*Joe*⟨*/fnm*⟩⟨*snm*⟩*Bloggs*⟨*/snm*⟩⟨*/au*⟩, then the string value is "JoeBloggs" and a search for the word "Bloggs" is guaranteed to miss it.

  Worse, markup that is supposed to enclose numbers very commonly includes punctuation as well; the rules of XPath say that trying to convert such a string value to numeric form is an error. Yet we want to query it.

2. THE INEX'03 QUERY LANGUAGE WAS TOO HARD TO USE.

Every group had to submit 3 CAS and 3 CO queries. These submissions were supposed to have been tested, and known to have a reasonable number (not too high, not too low) of relevant answers. In fact, some answers were provided with each submission. So each submitted query should have been a legal INEX'03 query.

From this pool, 30 CAS and 36 CO queries were selected. Of the 30 CAS queries, 19 had either syntax errors or serious semantic errors. The most common semantic error was using the "child" operator / when the "descendant" operator // was intended.

This is a shocking error rate.

It wasn't just hard to get the queries right in the first place; it was hard to fix them. It took 12 rounds of corrections before we had a workable set of queries, starting from what were presumably the best queries in the first place.

Since a query language based on XPath 1.0 was too hard for us to us, it is impossible to believe that a query language based on the much more complicated XPath 2.0 could be usable by us.

3. WHAT SHOULD WE LOOK FOR IN A QUERY LANGUAGE?

3.1 We want something WE can use.

This paper is not about query interfaces or query languages for end users. This paper is solely concerned with query languages for *researchers* producing or using INEX data. Complexity is not necessarily a problem *for us*, as long as it is useful complexity. Requiring an intimate knowledge of XML or XML related technologies is not necessarily a problem *for us.* Requiring lots of punctuation in just the right places is not necessarily a problem *for us.*

While complexity need not be a problem, we need to take a step back and start with something much simpler than XPath, because it is an empirically established fact that it was too complicated *for us.* It is not likely that the query language we propose in this paper will serve for all time; what does matter is that it should be possible to automatically translate it into whatever richer language may be devised in the future. Simplicity now means easier conversion in the future. So one guiding rule is that nothing should be included in the query language unless it was actually used in this year's or last year's queries.

We do not want to limit INEX participation to experimenters following an "orthodox line" in query languages. Keeping the query language simple keeps the conference open to approaches with as yet unimagined index structures and retrieval techniques. XPath and XPath-like languages penalise such approaches.

3.2 Databases and information retrieval are different.

It is useful to distinguish between *database* query languages and *information retrieval* query languages. They have some similarities, but the differences are fundamental, and mean that an XML database query language is unlikely to be a good foundation for an XML information retrieval query language.

The CODASYL database language, "network" databases, the relational algebra, the relational calculus, SQL, the Object Query Language (OQL) in the ODMG Object Database Standard[4], and various spatial and temporal extensions of relational databases, even the Smalltalk dialect used in Gemstone, all have these fundamental characteristics in common:

- To a large extent, as [9] puts it, this "data is primarily intended for computer, not human, consumption."
- A "database" is made up of elementary values (numbers, strings, dates, and so on) aggregated using a predefined set of container types with precise data structure semantics and labelled with user defined labels (column names, relation names, and so on).
- The user-defined labels have user-defined semantics which the database is aware of only to the extent that constraints are stated.
- Even when there are user-defined structures (classes in ODMG, Gemstone, and SQL3, for example), these may be seen as instances of one of a fixed set of meta-structures. For example, the ODMG standard provides an Object Interchange Format by means of which any object database may be dumped as a text stream; instances of classes all have a fixed format here and it is clear that "class" is a single meta-structure.
- There is a structured query language with a (more-or-less) formal definition which relates any legal query to a precise semantics, by appealing to the data structure semantics of the container types and meta-structures and to any stated constraints.
- A query processor is expected to obey the semantics of any query it accepts *precisely*; it may exploit known properties of the query language to transform a query into one with better performance, typically by using indexes.
- If a query has more than one answer, *all* of the answers are relevant. Someone who doesn't want all of the answers is expected to write a more specific query.

Database query languages are just like programming languages. (Very bad programming languages, some of them, notably SQL.) The person formulating the query is expected to understand the relevant user-defined labels and constraints and to "program" a query which expresses his or her needs. A database query engine is required to obey the query literally, just as a C compiler is required to translate C faithfully, even rubbish. If you ask an ODMG database the OQL query *select p from Persons p where p.address.city = "Dunedin"* and the answer includes a *p* for which *p.address.city = "Mosgiel"*, you will be seriously unhappy, even though Mosgiel is only 10 to 15 minutes' drive from Dunedin.

Since SGML was designed, the SGML slogan has been "a document is a database". For many years there have been SGML document database engines, notably SIM[16]. As XML is a special case of SGML, it is natural to view an XML document as a database.

- The elementary values are strings. The aggregates are labelled attributed tree structures. The data structure semantics is provided by GROVEs, or the DOM. Element type names and attribute names are the user defined labels.

- Constraints are stated by means of DTDs or XML Schemas. XML Schemas in particular express the notion "a database is a document".

What you get, on that view, is a database query language for tree-structured databases.

Information retrieval is very different. Instead of saying "the programmer knows precisely what s/he wants and how that's represented, I must do exactly what s/he says", information retrieval engines say "the user wants to find out about something and has given me a hint about what it is, I must be helpful". If you ask an information retrieval system *"agricultural research Dunedin"* and it comes back with a web page about *"Invermay Agricultural Centre, Mosgiel"*, you are not angry with it for disobeying you but impressed with how clever it was to find something so helpful.

The fact that information retrieval systems regard the user's query as a clue about what the user wants instead of a precise specification has enormous consequences for the design of information retrieval languages. So does the fact that the text they search is itself *not* in a precisely defined language.

When you construct a DTD or Schema for a family of XML documents, you describe how the XML parts fit together. But if you have free text in some of the elements, it remains just as informal as free text on its own.

At one end, we have data without a known precise semantics. At the other end, we have queries that are regarded as clues rather than commands. As Shlomo Geva[13] pointed out in the INEX mailing list, even the Boolean operators are not taken all that seriously by some retrieval engines. If two relational or object database engines holding the same information give different answers to a single query, at least one of them is broken. If two information retrieval engines holding the same document collection give different answers to a query, one of them might be better, but each of them might find something useful that the other doesn't. It certainly doesn't mean that either of them is wrong. All of this makes it hard to design elaborate information retrieval query languages. What earthly use is elaborate precise syntax when you don't have, can't have, and wouldn't want, precise semantics?

Of course we can embed a database query language in an IR query language (find precisely this set of documents and use that as a clue combined with the other clues in the query to find what I really want instead), and we can embed an IR query language in a database query language (give me precisely the answers satisfying a bunch of tests one of which is this clue about what I have in mind). Confusion seems unavoidable; at least we should be clear about which parts are precise and which parts are fuzzy.

3.3 It's all about indexes.

The great strength of Information Retrieval systems is their indexes.

An information retrieval language for XML should exploit this. It should avoid "structural" queries that are hard to handle with plausible index structures. This suggests keeping XML "structure" and IR "content" parts of queries separate, rather than mingling them indiscriminately as XPath does.

This does not mean that we should always be limited to queries that can be expressed in terms of currently known index structures. On the contrary, if someone comes across a reasonable query that is not expressible in the INEX'04 query language, that's a *good* thing, because it suggests a research topic: what kind of index could support this kind of query?

3.4 "Descendant" is more useful than "child".

An extremely common mistake in the INEX'03 queries was using the "child" axis (/) when the "descendant" axis (//) was intended.

The designers of CSS recognised that "descendant" queries were more common when they used the invisible operator to mean "descendant", making "descendant" easier to say than "child".

Consider *//article/bdy/sec/ip1*. That may be what you want, but you might have wanted *//article/bdy/sec/bq/ip1* elements as well, had you known about them. The query *//article//bdy//sec/ip1* is more likely to be what you really mean.

It turns out that *none* of the INEX'03 queries needs "child" at all; in each case "descendant" will do. This frees us to use the simple spelling "/" for "descendant", as many INEX contributors expected.

4. SOME XML QUERY LANGUAGES

The world is awash in query languages for semistructured data, ranging from the complicated (CSS) to the mindbogglingly complicated (XQuery).

4.1 HyTime

HyTime[15, 14, 21] introduced many important things to SGML. One of them was a query language, HyQ[19].

However, the current standard says "HyTime recommends the use of the Standard Document Query Language (SDQL), defined in the DSSSL standard, ISO/IEC 10179:1996 Document Style Semantics and Specification Language, for the queryloc and nmquery element forms. The SDQL language includes equivalents of all the HyTime location address forms."

Early drafts of XPath looked like a stripped down HyQ.

HyQ is all about precise location of points and ranges both in trees and in multimedia coördinate systems. It is quite complicated. But it is worthy of note as one of the two ancestors of most XML query languages. (The other is SQL.)

Because the query language presented here is not semantically like XPath, it would be highly undesirable for it to resemble XPath too much in syntax.

4.2 DSSSL

DSSSL[17] is the SGML version of XSL and XSLT[6]. It contains a Scheme-based query and transformation language. It must be said that DSSSL is incomparably easier to read than XSLT. The Standard Document Query language is basically some datatypes for collections of nodes and some functions that manipulate them. It's a programming language, not an IR query language.

4.3 CSS

A CSS[3] ⟨*selector*⟩ is a collection of ⟨*path*⟩s or-ed together. In each ⟨*path*⟩, the focus is on the rightmost element; it is that element which the following style will be applied to. Working from right to left, an element must be a sibling ('+'), a child ('>'), or a descendant (invisible operator) of the element to its left.

An ⟨*element*⟩ test may check for an element ⟨*name*⟩ or not (⟨*any*⟩ or omitted). It may check whether an element is the '`:first-child`' of its parent. This means that XPath's */*[3 and p]* is expressible as **:first-child+*+p*. But XPath's */p[3]* is not quite expressible; *p:first-child+p+p* does not allow other elements between the *p* elements.

A ⟨*filter*⟩ may check whether an attribute is present, whether it is present and has normalised value exactly equal to a given text, whether it is present and contains a given white space delimited word, or whether it is present, looks like an xml:lang value, and has a given lang code as prefix. The grammar is given in Table 1.

There is no negation anywhere in CSS. You cannot test whether an attribute is present and *not* equal to a string. Paths cannot be negated. Within its limits, CSS seems quite usable.

4.4 XPath

This year's query language was based on XPath 1.0. XPath 1.0 has several uses in W3C standards. One of them is XPointer. XPointer provides a means of pointing *precisely* to a location or range in a document. That is, XPointer, and the underlying XPath, are *database* query languages for XML.

We can get an idea of the complexity of various extensions and relatives of XPath by looking at the sizes of the defining reports; to master any of them requires reading at least this much material. Since the reports are provided in HTML, the page count depends on how you display it. Therefore we normalise the number of screens by the number of screens for XPath 1.0 in Table 2.

The "all up" entries include the Data Model and Functions and Operators documents, which are essential parts of XPath 2.0, XSLT 2.0, and XQuery 1.0. To get page counts for the browser and paper size we used, multiply by left column by about 28.

If XPath 1.0 was too complex for us to master, can any of the other W3C query languages be easier? XML-QL looks as though it might be, but it is not a W3C recommendation, and [9] explicitly says that "...we take a database view, as opposed to document view, of XML. We consider an XML document to be a database ...".

Table 2: Length of Specification (Normalised)

0.5	CSS 2.0 selectors[3]
1.0	XPath 1.0[7]
0.7	XML-QL[10]
1.5	XQL[22]
3.2	XSLT 1.0[6]
4.2	XSLT 1.0 + XPath 1.0 (XSLT includes XPath)
2.4	XQuery 1.0 and XPath 2.0 Data Model[11]
5.8	XQuery 1.0 and XPath 2.0 Functions&Operators[20]
3.1	XPath 2.0[1]
11.3	XPath 2.0 all up
9.0	XQuery 1.0[2]
17.3	XQuery 1.0 all up
10.1	XSLT 2.0[18]
18.3	XSLT 2.0 all up

In fact all of these languages take a database view, making them unsuitable as foundations for an information retrieval query language. Space does not permit thorough discussion of YATL[8], XQL[22], Quilt[5] (Quilt and XPath 1.0 are closely related), YATL[8], or others.

4.5 XIRQL

XIRQL[12] was designed as an "information retrieval" query language, not a "database" query language. However, it extends XQL, so parts of it resemble XPath, including the distinction between "child" and "descendant" which we failed to master. In the INEX collection, it was not clear to most of us what the root actually was, so the ability to refer to the root is not useful to us either.

The abstract of [12] tells us that XIRQL integrates "weighting and ranking, relevance-oriented search, datatypes with vague predicates, and semantic relativism ... by using ideas from logic-based probabilistic IR models." This means that important and attractive as XIRQL is, it is too closely tied to one particular approach to be suitable for INEX.

We propose a much simpler and less capable language, which can be seen as a very small sublanguage of XIRQL, and also of other query languages.

5. THE STRING-VALUE PROBLEM

Practically everything in XPath 1.0 that involves strings is defined in terms of the "string-value" of a node. The rules are spelled out in section 5 of the XPath 1.0 specification. Roughly speaking,

1. The string-value of a text item (parsed character data or CDATA) is the obvious text value.
2. The string-value of an element or of the entire document is the concatenation of the string-values of its text descendants in document order.
3. The string-value of an attribute is its normalised value as spelled out in the XML 1.0 specification. (An XML processor that does not validate cannot be used as the basis for an XPath implementation.)

Table 1: CSS grammar

⟨*selector*⟩	::=	⟨*path*⟩ (⟨*or*⟩ ⟨*path*⟩)*
⟨*or*⟩	::=	‘`,`’
⟨*path*⟩	::=	(⟨*siblings*⟩ ⟨*down*⟩)* ⟨*siblings*⟩
⟨*down*⟩	::=	‘>’ | *empty*
⟨*siblings*⟩	::=	(⟨*element*⟩ ⟨*followed-by*⟩)* ⟨*element*⟩
⟨*followed-by*⟩	::=	‘`+`’
⟨*element*⟩	::=	(⟨*name*⟩ | ⟨*any*⟩ | ⟨*filter*⟩) ⟨*filter*⟩*
⟨*any*⟩	::=	‘`*`’
⟨*filter*⟩	::=	⟨*exists*⟩|⟨*equals*⟩|⟨*word*⟩|⟨*prefix*⟩|⟨*first*⟩|⟨*lang*⟩
⟨*exists*⟩	::=	‘`[`’ ⟨*name*⟩ ‘`]`’
⟨*equals*⟩	::=	‘`[`’ ⟨*name*⟩ ‘`=`’ ⟨*value*⟩ ‘`]`’
⟨*word*⟩	::=	‘`[`’ ⟨*name*⟩ ‘∼=’ ⟨*value*⟩ ‘`]`’
⟨*prefix*⟩	::=	‘`[`’ ⟨*name*⟩ ‘|=’ ⟨*value*⟩ ‘`]`’
⟨*first*⟩	::=	‘`:first-child`’
⟨*lang*⟩	::=	‘`:lang(`’⟨*value*⟩‘`)`’

So ⟨*au*⟩⟨*fnm*⟩*Joe*⟨*/fnm*⟩⟨*snm*⟩*Bloggs*⟨*/snm*⟩⟨*/au*⟩ has string-value “*JoeBloggs*”.

If you go looking for “*Bloggs*” in ⟨au⟩, XPath 1.0 guarantees you won’t find it.

Of course, we don’t have to follow XPath’s definition of string-value. But if we don’t do that, there isn’t much point in following XPath’s complex and limiting syntax either.

This definition of string value goes back to HyTime; every XML-related standard we’ve checked uses essentially the same definition. CSS and XSLT provide means for transforming a document by adding material at the beginning or end of an element’s contents; the string value can be quite different in the transformed document. XPath was too hard; bringing XSLT into it would clearly be inadvisable.

There are three plausible ways around this problem.

- Add an extra space at the end of each text item. This gives the answer “`Joe␣Bloggs␣`”, which will work. In rare cases like “⟨*u*⟩*A*⟨*/u*⟩*ccelerator*” this may break words up, but it will almost always help.
- For items which should be treated as having word breaks, add an attribute in the DTD:

  ```
  <!ATTLIST snm INEXword #FIXED "break">
  ```

  Ensure that there is at least one white space character at the boundaries of every element with INEXword=”break”.
- Allow the indexing software to make the decision just as it does for stemming. Attributes like `INEXword` offer guidance, not rigid command.

The first approach is simpler. If we were seeking the precision of database queries, the second approach would be better. Examples like T⟨scp⟩itle⟨/scp⟩ W⟨scp⟩ords⟨/scp⟩ may make it essential even for us (although the INEXscan attribute should solve this problem). But whichever approach we take, we are divorcing ourselves from XPath.

5.1 Numbers

An XML document contains only strings. Many of this year’s queries involved numeric comparisons. That requires converting strings to numbers. XPath specifies precisely how that is done. (The rules are somewhat different in XPath 2.0, but do not affect the present point.)

The problem is that the INEX’03 document collection is a realistic collection of sloppily marked up text. There are elements such as ⟨*yr*⟩ which are supposed to contain numbers, but also contain punctuation marks and other junk. Trying to convert such a string to a number is an error in XPath. If we want to know whether $yr > 1999$, we do not want our query to be derailed by ⟨*yr*⟩`2000,␣`⟨*/yr*⟩, as it *must* be in XPath.

Not only do we need rules for converting text to numbers that are different from the rules in XPath, we need to interpret comparisons fuzzily. If you ask a database for a record with $date > 1999$ and it reports a record with $date = 1999$, that’s an error. If you ask an information retrieval system for documents with $yr > 1999$ and it returns one with $yr = 1999$, that’s not an error, it’s just somewhat less relevant than one that matches the clue precisely.

6. ARCHITECTURAL FORMS

HyTime was really several interesting standards packaged together. One of the key features presented was the idea of “architectural forms” and of architectural form processing.

Basically, the idea is that a document may be marked up (and validated) according to one DTD, yet processed according to another (traditionally but confusingly called a) meta-DTD. Attributes in the source DTD say how to map the elements and attributes physically present to the ones that ought to be present according to the target DTD. A processing instruction with a special form is used to tell an architectural-form-aware processor which attributes to use for this purpose.

This may sound like XSLT, or, if you are into arcana, like linkage declarations in SGML. In fact it is something much simpler. Elements and attributes may be dropped, renamed, or copied as they are.

Why would you parse in one DTD and process according to another? You might have a formatter that can handle many structures, and a specialised DTD that is only intended to use some of the features. You might have a meta-DTD written using English words for markup, and Swedish users who would like to use Swedish words, so they validate against a DTD which uses Swedish words, but which uses architectural form processing to map to the English version. You might wish to make fine distinctions; for example you might want to use ⟨species⟩ and ⟨foreign⟩ tags in your markup, but they might both be simply mapped to ⟨italic⟩.

With the INEX collection, we have a collection of documents marked up for printing. Some of the distinctions made in the DTD are not important for information retrieval purposes. The INEX'03 rules took this into account. For example, ⟨ip1⟩, ⟨ip2⟩, ⟨ip3⟩, ⟨ip4⟩ were all to be treated by the query engine as equivalent to ⟨p⟩.

That's the wrong time to do it. It had the unpleasant consequence that you asked for p[n] the element you got could be p[m] with $m \neq n$.

It is not the queries which determine which tags are equivalent, but the DTD designer and document collector. The replacement of tags by equivalents should be done before the documents are indexed, so that the index and the query agree about what elements are which. That is just what architectural form processing can do for you.

We may not want to index some elements, either because they do not contain text or because the text is never useful. (We yearned mightily for some way to get rid of ⟨ref⟩ elements during evaluation. They should never have been returned in the first place.)

Some elements may be presentation markup which it is useful to ignore (see Table 2 in [23]). This is especially useful because these are the tags which spoil the simple "add a space after each element" rule for modified string-value. For example, given *⟨st⟩V⟨scp⟩OICE⟨/scp⟩ XML⟨/st⟩* we would like this to be treated as *⟨st⟩VOICE XML⟨/st⟩*. We want to ignore the tags of these elements, but not their contents.

In the spirit of architectural form processing, we can address these issues by adding attribute declarations in the DTD. XML allows us to add attribute declarations without changing the original ones, so xmlarticle.dtd could become

```
<!ENTITY old-dtd PUBLIC "..." "oldarticle.dtd">
%old-dtd;
<!ATTLIST ...>
...
<!ATTLIST ...>
```

with the original xmlarticle.dtd renamed to oldarticle.dtd. It is important that this can be done without touching the original DTD or the original XML files in any way.

The three attributes we want to add are

- INEXscan

  nothing do not index this tag or its descendants

  content do not index this tag; index its content

  element index this tag; do not index its content

  all index this tag and its content

  The evaluation tool should heed this attribute; it would materially reduce the labour of judging.

- INEXname

  if present, the name that is to be used in the index, and in queries, instead of the original element type.

- INEXatts

  a list of pairs of names: *attr* - means "do not index *@attr*, *attr alt* means "index *@attr* under the name *@alt* instead". If an attribute is not in the list, it is indexed as itself.

For example, we might have

```
<!ATTLIST ip1 INEXname NMTOKEN #FIXED "p">
<!ATTLIST ip2 INEXname NMTOKEN #FIXED "p">
<!ATTLIST ip3 INEXname NMTOKEN #FIXED "p">
<!ATTLIST ip4 INEXname NMTOKEN #FIXED "p">
<!ATTLIST scp INEXscan NMTOKEN #FIXED "content">
<!ATTLIST ref INEXscan NMTOKEN #FIXED "nothing">
```

The mapping can be handled by a trivial post-parser.

7. THE SIMPLEST THING THAT COULD POSSIBLY WORK

The following query language was constructed to be just powerful enough to handle the queries people actually wrote. It clearly separates paths and text queries, allowing Boolean combinations of text queries but not of paths.

$$
\begin{array}{lll}
\langle \textit{topic} \rangle & ::= & \langle \textit{about} \rangle \\
 & | & \langle \textit{filtered-path} \rangle \; \langle \textit{star} \rangle^? \; \langle \textit{about} \rangle \\
 & | & \langle \textit{filtered-path} \rangle \; \langle \textit{about} \rangle^? \\
 & & \langle \textit{filtered-path} \rangle \; \langle \textit{star} \rangle^? \; \langle \textit{about} \rangle
\end{array}
$$

An ⟨*about*⟩ is basically a Boolean query plus context for the terms. A ⟨*filtered-path*⟩ describes a path in an XML document; the attributes of elements may be checked. There is no way of marking the "child" relation anywhere, or of specifying ordinal position.

If P and Q match ⟨*filtered-path*⟩ and A and B match ⟨*about*⟩, then A means "answer any elements that are about A"; PA means "answer any instances of P that are about A"; $PAQB$ means "for instances of P that are about A return instances of Q under that P which are about B"; and a missing A imposes no constraint.

⟨*star*⟩ ::= '`/`' '`*`'

A ⟨*star*⟩ may precede the final ⟨*about*⟩. This is to handle the queries which used `//*` in XPath. It means that once an instance of the preceding P or Q has been found, *any* descendant of that instance which fits the last ⟨*about*⟩ may be reported. Such descendants are of course subject to ranking in the same way as any others, elements which are too "dilute" should not be a problem.

⟨*filtered-path*⟩ ::= ⟨*filtered-elem*⟩ ('/' ⟨*filtered-elem*⟩)*
⟨*filtered-elem*⟩ ::= XML-name ⟨*filter*⟩*

An XML-name is any XML identifier, possibly including colons. The time to deal with namespaces will be when we have to. The '/' operator means "descendant", not "child". This is what most people expected '/' to mean in the INEX'03 query language.

⟨*filter*⟩ ::= '[' ⟨*attr-path*⟩ ⟨*range-list*⟩ ']'
⟨*range-list*⟩ ::= ⟨*range*⟩ (',' ⟨*range*⟩)*
⟨*range*⟩ ::= number ('..' number$^?$)$^?$
| '..' number
⟨*attr-path*⟩ ::= ⟨*attr*⟩|⟨*simple-path*⟩
| ⟨*simple-path*⟩ ⟨*attr*⟩
⟨*attr*⟩ ::= '@' XML-name
⟨*simple-path*⟩ ::= XML-name ('/' XML-name)*

A filter compares text with a range of numbers. An ⟨*attr-path*⟩ is followed to find some text; the text may be the (modified) string value of an attribute or the (modified) string value of an element. Spaces and punctuation are trimmed from that modified string value; if the result can be converted to a number, the filter is satisfied to the degree that the number is in one of the ranges.

In a range $x..y$, x is the lower bound and y is the upper bound. It is an error if $x > y$. Missing x means $-\infty$; missing y means $+\infty$.

This query language does not use conventional notation like $<$ or $=$. There are two reasons for that. One is that these queries are supposed to be easy to express in XML, and XML makes it hard to use $<$. The second is that $<$ and $=$ are associated with precise meanings. But this is an information retrieval query language; a value which is not precisely in range may still be somewhat relevant. Since we don't intend the standard meaning of the mathematical signs, we shouldn't use them; it is important not to lie to the user.

⟨*about*⟩ ::= '(' ⟨*or-query*⟩ ')'
⟨*or-query*⟩ ::= ⟨*and-query*⟩ ('|' ⟨*and-query*⟩)*
⟨*and-query*⟩ ::= ⟨*not-query*⟩ ('&' ⟨*not-query*⟩)*
⟨*not-query*⟩ ::= ⟨*text-query*⟩ | '∼' ⟨*text-query*⟩

An IR engine may interpret these Boolean operators the way it would normally interpret any Boolean operators. The conventional precedence of the Boolean operators is followed. They need not be "precise", and although it is tempting to define algebraic identities for this query language, it would be inappropriate. The ampersand is also awkward to express in XML; some other spelling such as ';' could be allowed.

⟨*text-query*⟩ ::= ⟨*basic-query*⟩
| ⟨*basic-query*⟩ ':' ⟨*simple-path-list*⟩
⟨*basic-query*⟩ ::= (⟨*restriction*⟩ ⟨*term*⟩)$^+$ | ⟨*about*⟩
⟨*term*⟩ ::= word | '"' word$^+$ '"' | '’' word$^+$ '’'
⟨*restriction*⟩ ::= empty | '+' | '-'
⟨*simple-path-list*⟩ ::= ⟨*simple-path*⟩(','⟨*simple-path-list*⟩)*

A text query may ask whether a basic query matches the current element, or whether it matches some descendant element. The commas in a simple path list mean "or" just as they do in CSS.

A word is an XML-name that doesn't include any dots, colons, or underscores, or is a pair of such names with an apostrophe in between, or is a number. A sequence of words between matching quotation marks is a phrase. The '+' and '-' restrictions have the same meaning as in the INEX'03 query language.

That's all there is to it. A parser for this language has been built using Lex and Yacc.

Several features that were considered but deliberately excluded:

- Filtering on anything other than a numeric range. In simple cases, this can be handled by the *PAQB* pattern. Complex cases haven't arisen. When they do, it will be important to be clear about whether we want precise matches, so that XHTML documents making extensive use of the "class" attribute could be handled, or information retrieval matches, in which case we could simply have [⟨*attr-path*⟩ ⟨*about*⟩].
- Any kind of language sensitivity. This is what the CSS '|=' predicate is for, and its ':lang" predicate. When the INEX collection includes mixed-language documents, we could perhaps use [:lang *word*].
- Any kind of position checks. It is easy enough to add syntax for this, just copy XPath. What's hard is to interpret it. For example, as the XPath specification points out, "The location path //para[1] does *not mean the same as the location path /descendant::para[1]." Adapting [:first-child] from CSS would make more sense.*
- *Allowing any number of ⟨path⟩⟨about⟩ pairs. There's no difficulty in adding this, it just isn't needed.*
- *Allowing an axis other than "descendant". From a DTD, it is possible to compute a binary relation "can have child", the transitive closure of which is "can have proper descendant". This can be used to check the plausibility of queries. CSS also allows "child" and "sibling", which are similarly checkable. The complex mixing of axes in XPath makes it hard to check; we don't want to go there.*

8. SOME SAMPLE INEX'03 QUERIES

Query 61 //article[about(.,'clustering +distributed') and about(.//sec,'java')]

⇒ article(clustering +distributed & java:sec)

Query 64 //article[about(./, 'hollerith')] //sec[about(./, 'DEHOMAG')]

⇒ article(hollerith) sec(DEHOMAG)

Query 66 /article[./fm//yr &lt; '2000']//sec[about(.,'"search engines"')]

⇒ article[fm/yr ..1999] sec("search engines")

Query 68 //article[about(., '+Smalltalk') or about(., '+Lisp') or about(.,'+Erlang') or about(., '+Java')]// bdy//sec[about(., '+"garbage collection" +algorithm')]

⇒ article(+Smalltalk|+Lisp|+Erlang|+Java) bdy/sec(+"garbage collection" +algorithm)

Query 71 //article[about(.,'formal methods verify correctness aviation systems')]/bdy//*[about(.,'case study application model checking theorem proving')]

⇒ article(formal methods verify correctness aviation systems) bdy/*(case study application model checking theorem proving)

Query 76 //article[(./fm//yr='2000' OR ./fm//yr='1999') AND about(., '"intelligent transportation system"')]// sec[about(., 'automation +vehicle')]

⇒ article[fm/yr 1999..2000]("intelligent transportation system") sec(automation +vehicle)

Query 91 Internet traffic

⇒ (Internet traffic)

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Queries: INEX 2003 working group report

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1. INTRODUCTION

This paper summarizes the discussion of the queries working group at INEX 2003. The group discussed both Content-Only (CO) and Content-And-Structure (CAS) queries. Discussion was however mainly on CAS query syntax, CAS target elements and future CAS data types. The queries working group consisted of: Holger Flörke, Norbert Fuhr, Kenji Hatano, Börkur Sigurbjörnsson, Andrew Trotman, Masahiro Watanabe

Content Only Topics

There was little discussion on CO topics in the working group. This is to be interpreted as a support for leaving the CO topic format unchanged for at least next year.

There was a brief discussion about *query classification*, similar to the classification in [2]. It was considered useful to create a post-hoc classification of the CO queries. Participating groups could then compare their systems performance w.r.t. different types of queries.

Content And Structure Topics

The main discussion was about the complexity of the INEX 2003 CAS queries. It seems that people find it difficult to formulate the XPath-like expressions of the topic title. In the initially distributed (yet reviewed) set of CAS queries, 63% of the queries turned out to be in error [4]. This is in line with research that shows that users have great difficulty with boolean queries, both in databases and information retrieval [3]. Note however that the INEX topics were created by experienced IR researchers. In view of the high error rate there was discussion about syntax clarification, expressiveness restrictions and even a new syntax [4].

The possibility of creating a query generation tool was briefly discussed. The idea was that this tool would help to eliminate mistakes caused by a cumbersome syntax. No details were discussed about the precise functionality of the tool.

There was little discussion about the VCAS task. It is problematic to tell if the CAS queries are suitable for the VCAS task, since the evaluation method for VCAS has not been developed. That is, it is not clear what the task actually is.

In the remainder of this paper we will discuss the two issues which got the most attention from the working group; natural information need in CAS topics; and CAS topic format for INEX 2004.

2. INFORMATION NEED (CAS)

On top of difficulties with the topic syntax, there was also discussion about the difficulty of expressing a natural information need with the current collection. It was questioned whether topic authors add structural constraints because they think it is useful or whether they do it only because they need to write a structured query. The current collection is not very semantically rich and therefore there are limited opportunities for introducing interesting structural constraints.

The working group discussed separately the natural-ness of *target elements* and *structural conditions*.

2.1 Target elements

The working group tried to identify natural target elements for the INEX 2003 collection. The group could identify a few semantically different types of targets.

Textual elements

Textual elements are elements such as sections and paragraphs (`<sec>`, `<ss1>`, `<p>` etc.). It is not obvious which textual tag-name is the most appropriate for a particular query. The question of relevance is more based on the text than the tag-name. It is therefore probably best to leave this problem to the retrieval systems to solve.

Vitaes

Vitaes (`<vt>`) are indeed textual elements, but their semantics is different from the layout semantics of the textual tags in the previous section.

Abstracts

Abstracts (`<abs>`) are also textual elements with a slightly different semantics, since they contain a condensed description of the content of an article, and no detail information.

Bibliographical entries

Bibliographic entries are a different class of answers, since they contain only references to publications, but no real "content" like the textual elements. They represent information needs such as "find references to papers about compression" or "give me all bibliographic details of publications cited within papers about compression".

Note that for example queries such as

```
//article[about(.,'neural networks')]//fm//au
```

which says something like "give me authors of articles about neural networks" are not considered interesting. From an IR perspective this query is equivalent to the query "give me articles about neural networks". The problem of extracting the authors is trivial. Therefore author names is not considered here as a natural target.

The above list is based on discussion in the working group and it is not necessary complete. If topic authors find other natural target elements they are encouraged to use them.

2.2 Structural conditions

The working group distinguished three natural types of structural conditions.

Co-occurrences

We want certain concepts to be covered in the same unit. Say, for example we would like to retrieve documents that discuss the use of handheld computers in health care. We would like to minimize the change of getting documents that discuss handheld computers and health care separately. We could try to express this in a query that asks for articles were handheld computers and health care are discussed in the same section.

```
//article[about(.//sec,'handheld computers health
care')]
```

Note that since we are doing IR, we do not enforce term occurrence restrictions. By co-occurrences we are referring to the co-occurrence of concepts but not terms.

Data-types

Data-types are interesting for retrieval in structured documents. For this particular collection they are of limited use. They should however be considered in retrieval from semantically richer collections which contain not only layout semantics. Examples are markup for chemical processes, financial market developments and geographical locations.

Roles

We want to restrict our attention to XML elements that represent a certain role; such as article author, author affiliation, etc. For example if we want articles authored by Bruce Croft:

```
//article[about(.//fm//au,'Bruce Croft')]
```

Similarly if we want articles that cite Bruce Croft:

```
//article[about(.//bb//au,'Bruce Croft')]
```

We could also restrict our attention to articles where an author is affiliated in California:

```
//article[about(.//fm//au//aff,'California')]
```

This list of natural constraints must be viewed in the context of the current collection. Different collections have different information needs. For collections that have a larger variety in tag-names it is probably easier to formulate natural structural queries.

2.3 Separation of constraints and targets

It was discussed whether the structural constraints and targets needed to be expressed in the same expression. More precisely the question was whether we should go back to the INEX 2002 notation. The main reason behind abandoning the INEX 2002 notation, was that the semantics of that notation was unclear.

Consider for example the query

```
//sec[about(.,'solar powered robots')
and about(.//fig,'robot on mars')]
```

Where we want the retrieved sections to contain figures. Note however, that this is perhaps not a good example for the current LaTeX–originated collection, since authors often use tricks to include figures.

3. QUERY LANGUAGE FOR INEX 2004

This section will report on the discussion within the working group about requirements for a query language. We will then outline the syntax and semantics of a query language that is currently being constructed as a future language for INEX.

3.1 Requirements

The existing syntax of CO proved adequate. Any changes must maintain compatibility with the existing CO topics.

As a query language for CAS titles, the group considered an extension of a subset of XPath. The idea is to take the current syntax extension of XPath, used at INEX 2003, but restrict the usage to an "IR minimum" as described in [4]. This restriction in functionality supports all the important features used in previous workshops. Some queries are known to contain deprecated features and are excluded from this compatibility requirement.

There already exist two data types, numeric and string. This is anticipated to expand in the future to include names, units of measure, and even geographic locations. The language must be extensible to include these at a future date.

Tag instancing is to be deprecated. Restricting a search to a first paragraph (p[1]) was considered unnecessary and unlikely to be used. Query 13 already uses this feature, but this query was considered contrived. Furthermore no relevance assessments are available for this query.

The use of XPath axis, the plethora of XPath syntax for discussing paths, is to be limited to the descendant axis. In particular, the child axis is to be outlawed. None of the queries used so-far, relied on the usage of the child axis. The child axis can be added at any time if a future collection calls for such information need. Path filtering is to remain. Application of multiple filters is to remain.

Use of the (not)-equal operator is to be deprecated for the string data-type. All textual queries are to be expressed in terms of the about predicate. For arithmetic qualification the operators are to be limited to >, <, =, >=, <=.

The semantics must be interpretable vaguely. The XPath semantics are clearly defined making it a database language. For INEX, an IR language is needed, one in which the semantics can be determined by the retrieval engine. In particular, the meaning of the Boolean operators "AND" and "OR" is to become loose and vague.

Multiple target elements is to be deprecated. Queries can specify only one target element. Queries with unspecified target elements are to be added. In these queries the retrieval engine is to choose the most appropriate target element.

Equivalence tags are to remain, but are beyond the scope of the query language.

3.2 Syntax and Semantics

Work is going on to create a detailed description of a query language for INEX 2004. We will mention the most important features here but the full details are beyond the scope of this paper and should be covered in the topic development guidelines.

For the CO topics there is no change from last year.

For the CAS topics we will only discuss the topic title. Other fields do not change between years. The CAS title queries can take two forms

```
//A[B]
//A[B]//C[D]
```

where A and C are path specifications but B and D are filters. To provide backward compatibility we should also consider the form

```
//A[B]//C
```

but as mentioned in a previous section, the added value of this type of topics for an IR test collection is none. The projection `//C` is trivial.

Paths

A path through the XML tree is specified as a sequence of nodes. The only relationship between nodes in a path is descendant. Child relationships are not supported. The wildcard '*' can be used as to refer to a unspecified type of target element. There is a question whether there is a need for including attributes for this collection. There is no (yet assessed) topic that uses attributes.

Strict interpretation: "//A" means any A tag in the tree. "//A//B" means any B descendant of an A tag in the tree. "//@C" means the C attribute of any tag. "//A//@C" means any C attribute anywhere in the tree beneath an A tag in the tree. "//A//*" is any descendant of A. "//*" is any descendant of the root, which also means any tag in the tree.

Loose interpretation: There is likely to be relevant information in the document in places not specified in a user query. The path specifications should therefore be considered hints as to where to look.

Filters

We support one string predicate and several numerical comparisons within the filters.

We use the `about(path,text)` string predicate used in INEX 2003. The textual part of this predicate should always be interpreted in a vague fashion. That is, the validity of the predicate will always need to be done by a human assessor. For example, the query

```
//article[about(.//p, '"information retrieval"')]
```

is strictly interpreted as "Return article tags for only those documents that contain a p tag whose content is about information retrieval". It is loosely interpreted as "What I want is most likely a whole article that discusses information retrieval in a p tag. Relevant results are not limited to this, but I'm pretty sure it'll help you find what I want."

For numeric values we support the operator <,>,=,>= and <=. As with string qualification, this is specified with a relative path. As an example. To "strictly" retrieve article tags from documents published during 2001 we write

```
//article[.//pdt//yr = 2001]
```

this query could equally be specified using string qualification as

```
//article[about(.//pdt//yr, '2001')]
```

In this example, a loose interpretation could be to ignore the qualification or to say that the article should be published around 2001-ish.

The above search predicates and comparison operators can be combined by the Boolean operators AND and OR. Also brackets can be used. Strict interpretation would be that the Boolean operators are strictly interpreted. Loose interpretation: AND is interpreted as ANDish, OR as ORish. The query contains the Boolean operators as hints on how to resolve the information need.

Examples

Examples of some CAS queries are given here along with strict interpretations. Loose interpretation of each is the same "I'm sure this'll help find what I want".

```
//sec[about(., 'mobile electronic payment system')]
```

Return sec tags where the sec tag mentions mobile electronic payment systems.

```
//*[about(., 'singular value decomposition')]
```

Return elements about singular value decomposition. This is a combination CAS-CO query where the retrieval engine must deduce the most appropriate element to return.

```
//article[.//fm//yr >= 1998]//sec[about(.,
'"virtual reality"')]
```

Return sec elements of documents where the yr tag under the fm tag under the article tag is numerically greater than or equal to 1998, and where a sec tag discusses 'virtual reality'.

```
//article[(.//fm//yr = 2000 OR .//fm//yr = 1999)
AND about(., '"intelligent transportation system"')]
//sec[about(., 'automation +vehicle')]
```

Return sec elements about vehicle automation from documents published in 1999 or 2000 that are about intelligent transportation systems.

We are currently working on a more detailed description of the syntax and semantics of the future INEX query language.

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Inex 2003 Working group report: Relevance

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In Inex 2003, relevance judgements were based on exhaustivity and specificity as dimensions of topical relevance. Both these dimensions were assessed on 4-point scale (i.e., not, marginally, fairly, highly specific / exhaustive; see [1]). This definition of relevance was chosen to suit the need to retrieve and rank elements of different granularity typical for structured document retrieval. The workshop, which attracted about 20 people, was not so much concerned with the concept or definition of relevance; rather the consequences of the chosen relevance definition on the assessment process were discussed. The practical experiences participants had on working with relevance assessments played a vital role in discussions. Four main themes came up during the sessions:

- How useful the dimensions of relevance are?
- What is the least meaningful unit to be assessed for relevance?
- Are the relevance assessments reliable?
- What is the validity of the assessment of VCAS and SCAS topics?

First, the issue of judging relevance along dimensions of exhaustivity and specificity was raised. The argument against these dimensions, and dimensions in general, was that it would be easier for the assessor to give only one relevance figure for each element to be assessed. This especially in case the used metric returns only one performance figure. Another opinion – which gained more support – was that the named dimensions help the assessor to become aware of the factors affecting the assessment, and thus help him to be more consistent. Should more dimensions of relevance be considered in assessment? Perhaps, but the question is how many balls the assessor can play with? This ballgame is still in the area of topicality.

Second, many of the participants were frustrated when assessing relevance of some minor elements that cannot really carry relevant meaning alone (e.g. article number or references). This was due to the assessment system forcing to judge all ascendant / descendant elements of any relevant element. This procedure is in accordance with relevance assessment rules which try to ascertain that *all* relevant elements are identified. However, the general opinion was strongly for making a list of elements that should neither be retrieved alone nor judged for relevance. Another argument in this discussion was that some elements could not be judged alone because 'a whole can be more than its parts'. Here the solution seemed to be that an element should be assessed on the basis of its relevance as an alone standing unit. This debate also touched upon the rules for assessment consistency in the online assessment tool.

Third, the consistency and reliability of relevance assessments were considered. Some participants thought that elements, which should be relevant, were judged non-relevant, i.e. they were not missed in assessment process but they were consciously assessed non-relevant. In the discussion it was obvious that people with different background had different understanding about the relevance that should be used. Those active in information retrieval were for topicality, but those working with DBMS were for system relevance (for manifestations of relevance, see [2]). This issue could not be agreed upon, yet the workshop made a suggestion for getting multiple relevant assessments for some topics in order to check the consistency of assessments. Later on it turned out that there already are multiple assessments for some topics, only the analysis of consistency is lacking.

Fourth, what is the role of 'vagueness' and 'strictness' in relevance assessment of content and structure (CAS) queries? This question seemed to divide opinions and practices: others had tried to assess the relevance according to whether the structural conditions were met or not; others had ignored the structural conditions because they were difficult to check. The relevance assessment guide gives support to both interpretations (see [1]). The whole matter is even more complicated because it is not quite clear how to implement 'vagueness' in retrieval and evaluation. The organizers investigate this matter.

The workshop made some suggestions for the INEX projects to come:

- It could be useful to re-use the old topics later on – with new / elaborated systems – to see whether any progress is made.
- The number of topics should be raised for better reliability of data. This, however, should be achieved without increasing the assessment load for individual groups. Two obvious possibilities were suggested: the number of participants could be higher, and the evaluation task could

be made easier (for example, by the list of elements not to retrieve / assess).

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Working Group Report: the Assessment Tool

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ABSTRACT

This paper is the report of the working group on the evaluation assessment interface that was used in INEX'03. This paper describes the changes that are planned for INEX'04 and the different issues that were raised during the working group session.

1. INTRODUCTION

A description of the INEX'03 interface can be found in [1].

This year, the assessment tool was completely redesigned. The first change was the user interface: a single document view was used both to read the document and to assess its components. This change was appreciated by almost every participant. Some enhancements have been suggested (section 2) to ease the assessment process through more user assistance.

The changes were not only cosmetic, as rules ensuring *consistency* and *exhaustivity* of assessments were a main component of the interface. The consistency check (section 3.1) ensures that assessments within the same document are consistent with respect to the definition of the INEX scale. For example, a non relevant element cannot contain relevant elements. The exhaustivity check (section 3.2) ensures that most (if not all) of the highly specific elements are found within assessed documents. Finding highly specific elements is an important point since finding those elements is the goal of an XML information retrieval system. Obtaining consistent and exhaustive relevance assessment is thus crucial for the appropriate comparison of retrieval approaches.

Notations

In this report, an assessment value in the INEX'03 scale is denoted by ExSy (exhaustivity is x, specificity is y), Ex (exhaustivity is x, specificity is unknown) or Sy (specificity is y, exhaustivity is unknown).

2. ENHANCEMENTS

In this section, enhancements that were proposed for the next INEX campaign are described. Every point will be considered when the current interface is extended, but time constraints will possibly postpone some enhancements.

Efficiency

After each assessment, the server (which is actually in Paris) is contacted in order to check the different constraints; its answer updates the document view. This solution was chosen as it was the easiest, but for assessors from distant countries – like e.g. USA, Australia, New Zealand – there was a noticeable delay. Two solutions to this problem are possible:

1. Set up local mirrors;
2. Perform the constraint check on the host (e.g. with javascript) and send the assessments for validation only when leaving the document view.

The first solution is the easiest as it does not involve new development. The second is the best because it allows to centralise all the assessments, but it involves new developments.

Interface

Some participants proposed interface enhancements that would help to speed up or ease the assessment process:

rules When assessing sets of elements, the interface sometimes fail to predict the set of values that those elements can take together. This clearly should not happen.

tree-view An XML tree view of the current document could give a quicker access to distant parts of the structure.

bookmarks When assessing a document, it is often useful to go and look around the element to assess and then come back to this element: bookmarks should allow to do this quicker.

keyword highlighting New highlighting modes like e.g. background, border, font colour in order to distinguish more easily different group of keywords.

New icon set

G. Kazai proposed a new icon set (figure 2) that is more closely related to the INEX'03 scale. Hopefully, the scale will not change next year so we can use them. An empty disc is used to symbolise the "irrelevant" part of the component; a plain disc (shades of blue, from highly to marginally exhaustive) symbolises the "relevant" part of the component.

Exhaustivity \ Specificity	0	1	2	3
0	○			
1		■○	■◑	●
2		■○	■◑	●
3		■○	■◑	●

Figure 1: The new icon set for INEX'04

3. CONSISTENCY AND EXHAUSTIVITY

In this section, consistency and exhaustivity rules are described. In each subsection, rules used for INEX'03 are first exposed. To ensure even more consistency and exhaustivity[1] in INEX'04 assessments, new rules are then proposed. Some of the latter are still to be debated.

In the following, an element is one XML tag while its children includes XML tags *and XML text nodes*. For example, a paragraph with some text within a `<it>` tag will have three children: a text node (before the `<it>`), the `<it>` node and then another text node (after the `</it>`). Even if text nodes cannot be assessed (this is an open issue), they are taken into account while applying the consistency and exhaustivity rules.

3.1 Consistency

The consistency rules ensure a set of assessments within the same document are consistent with respect to the definition of exhaustivity and specificity. They are both used to check an assessment is valid and to infer automatically some assessments. In INEX'03, 7 % of assessments were automatic. An element is automatically assessed when the rules reduces the set of possible assessments to one element: defining new rules not only ensures assessments are more consistent, it is also useful to speed up the assessment process. An element can also be inconsistent when this set is empty. This occurs when some rules change or are added, or when the interface fails to predict the possible choices. The latter can happen when one is assessing a set of elements.

INEX'03

1. The exhaustivity of an element is always superior or equal to the maximum of children exhaustivity. This rule ensure no more relevant information is found in an element than within each of its children.

2. The specificity of an element is inferior or equal to the specificity of any of its child. That rule states that the ratio of relevant information in the element cannot be superior to the ratio of relevant information in its children. For instance, we cannot assess the element S3 if all its children are S2.

New rules

The following rules were not added in INEX'03 due to time constraints, but can be somehow derived from the definition of exhaustivity and specificity, except the third one.

[1]exhaustivity is not related to the one of the INEX scale dimension, but to the extent with which all the S3 elements are found

1. The first is the symmetric case of the INEX'03 rule 1. It states that there cannot be more relevant information in an element than in its children: the exhaustivity of an element is inferior or equal to the sum of its children exhaustivity.

2. The ratio of relevant information in an element cannot be inferior to the ratio of relevant information in all its children: the element specificity is superior or equal to the minimum specificity of its children.

3. The last rule is (and was!) heavily discussed. Its role its to ensure that a highly specific element does not have any descendant with the same exhaustivity since it would imply that one of its descendants is as good as the element for an XML information retrieval system to retrieve. This rule is also an extension of the rule 1 in INEX'03: when the element is S3, the exhaustivity is always superior (and not anymore equal) to the maximum of children exhaustivity. The main critic of this rule is that the exhaustivity scale has only three values: the maximum number of elements between the root of the document and any leaf in the XML tree which can be highly specific is thus 3. Furthermore, descendants of an E1S3 element are not relevant with this rule. It should be debated whether this is a too restrictive hypothesis. Another solution would be to restrict the application of this rule to elements assessed E2S3 or E3S3 (and not anymore to elements assessed E1S3).

3.2 Exhaustivity

Exhaustivity rules were much more discussed than consistency rules. The main reason is that consistency rules are somehow *implied* by the definition of exhaustivity and specificity, while exhaustivity is not yet fully understood. The second one is that exhaustivity rules are applied after each assessment and add new elements in the set of assessments to be done. Adding too many elements increase the task burden while adding too few elements does not ensure anymore that we find all S3 elements. The balance between those two extrema is difficult to find.

But the importance of those rules is fully illustrated by this statistic: in INEX'03, 68 % of the S3 elements were not initially in the pools – which implies that adding elements *is* necessary to ensure the exhaustivity of the test collection.

INEX'03

1. When the element is not relevant, nothing is added. This rule is useful since we do want non relevant documents to be assessed as fast as possible – as assessor should concentrate on documents that contains relevant parts.

2. When the element is S3, do not add children but do add ancestors: when a highly specific element is found, there is no need to assess its descendants as this is the only kind of elements we are searching for. This is especially true if we consider the third new consistency rule.

3. Otherwise, add all the children and all the ancestors of the assessed element. This rule is applied when the

element is neither not relevant, neither highly specific: there is some more specific elements within it that have to be found.

New rules

Only one new rule is planned in order to reduce the number of elements to be added. This rule was obviously one of the most discussed one. The main idea is to prevent any "loss" of relevance between an element and its children, that is to only add the children of a marginally or fairly specific assessed element when there is no children that contain as much relevant information as the assessed element. More precisely, when the sum of the children exhaustivity is superior or equal to the element exhaustivity, no children are added. For example, if an element is assessed E3S2 and that all the relevance of the element is found in one child (that is, one child is E3), there is no need to ask for the assessors to find other relevant parts within the other children of the assessed element – though he can always assess them. Other children are thus removed from the list of elements that have to be assessed.

4. CONCLUSION

Some points that were discussed during this working group were fully debated; this proves the assessment tool is not only a graphical interface, it is also closely related to (1) the assessor effort (2) the quality of the INEX collection (3) the definition of what is relevance. This led to the "I don't wish to assess that" problem which is related to points (1), (2) and (3). What if I really don't want to assess an element? This debate, if I recall well, ended up (or almost) in the definition of a possible new value in INEX scale, namely the "not meaningful" value – the element cannot be judged by itself as it is too small (which implies descendants are also not meaningful?).

The new interface used in INEX'03 will be extended next year to include some of the changes described in this report. Some issues, especially those related to exhaustivity, were much debated in the working group and there is no full agreement upon participants. The new rules will thus be discussed in a forum which is available on the web (http://inex.lip6.fr), along with the possible proposition of new ones.

Eventually, I would like to thank every participant of this working group, feedback being an important part of the development of a good interface for assessments.

5. REFERENCES

[1] G. Kazai, M. Lalmas, and B. Piwowarski. Relevance assessment guide. In *Proceedings of the Second Annual Workshop of the Initiative for the Evaluation of XML retrieval (INEX)*, DELOS workshop, Dagstuhl, Germany, Dec. 2003. ERCIM.

Report of the INEX 2003 Metrics working group

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1 INTRODUCTION

This paper summarises the discussions of the metrics working group at the INEX 2003 Workshop, Dagstuhl, Dec 15-17 2003. Members of the group were Djoerd Hiemstra (U. of Twente), Jaap Kamps (ILLC, U. of Amsterdam), Gabriella Kazai (Queen Mary U. of London), Yosi Mass (IBM Haifa), Vojkan Mihajlovic (U. of Twente), Paul Ogilvie (Carnegie Mellon U.), Jovan Pehcevski (RMIT U.), Arjen de Vries (CWI) and Huyen-Trang Vu (LIP 6).

The aim of this workshop was to review the current INEX metrics, collect issues and concerns regarding the suitability of these metrics for the evaluation of content-oriented XML retrieval approaches, and to propose alternative solutions.

The discussions started with a summary of the evaluation objectives and the evaluation considerations to be taken into account (section 2). This was followed by an overview of the current INEX metrics (section 3) and the presentation of proposed new metrics (section 5). The results of the discussions are summarised in sections organised by the topic of the discussion: section 4 summarises the issues, opinions and suggestions with respect to the current metrics, section 6 reflects the comments the proposed metrics received and finally section 7 summarises any other voiced issues.

2 EVALUATION SETUP

2.1 What to evaluate?

INEX'03 defines three tasks: the CO (content-only), SCAS (strict content-and-structure) and VCAS (vague content-and-structure) ad-hoc retrieval of XML documents. Given the different retrieval paradigms these tasks are based on, it is necessary to define the objective of the evaluation separately for all three tasks.

Within the CO task, the aim of an XML retrieval system is to point users to the specific relevant portions of documents, where the user's query contains no structural hints regarding what the most appropriate granularity of relevant XML elements should be. Here the evaluation of a system's effectiveness should hence provide a measure with respect to the system's ability to retrieve components that are both exhaustive and specific to the user's request, where highly exhaustive and highly specific components should be ranked first.

Within the SCAS task, the aim of a retrieval system is to retrieve relevant nodes that strictly match the structural conditions specified within the query. The evaluation criterion should hence only consider a match between a result and a reference element if these conditions have been met.

In the VCAS task, the goal of a system is to retrieve relevant nodes that may not exactly conform to the structural conditions expressed within the user's query, but are structurally similar. The evaluation criteria employed here must therefore allow for a more flexible match between result and reference elements.

Within the workshop, only the evaluation of the CO task was considered in detail.

2.2 What to consider?

The evaluation considerations mentioned here are detailed in [4]. These were mostly just summarised and agreed upon in the workshop, but not discussed in detail.

The first consideration is that a measure of effectiveness within the framework of the INEX initiative must be able to integrate the two dimensions of relevance: exhaustivity and specificity. Second, it was acknowledged that the independence assumption of classical IR, according to which the relevance of a document is independent of the relevance of any other document, does not hold in INEX. This issue was then discussed in more detail when trying to address the problem of overlapping result elements (section 4.1). Another important factor that the group members agreed should be taken into consideration is the varying user effort associated with result elements due to the varying size (length) of returned components. This is already addressed by one of the current INEX metrics (inex-2003), and some of the new proposals have also integrated this parameter within their model (section 5). The final aspect listed was that of linear vs. non-linear output rankings. It was agreed to only concentrate on linear ordering.

3 OVERVIEW OF CURRENT INEX METRICS

This section gives a brief summary of the inex-2002 (aka. inex_eval) and inex-2003 (aka. inex_eval_ng) metrics in order to provide the necessary background information for their discussion in section 4. For a more detailed description of the metrics please refer to [3, 4].

3.1 The inex-2002 metric

The inex-2002 metric applies the measure of *precall* [10] to document components and computes the probability $P(rel|retr)$ that a component viewed by the user is relevant:

$$P(rel|retr)(x) := \frac{x \cdot n}{x \cdot n + esl_{x \cdot n}} \tag{1}$$

where $esl_{x \cdot n}$ denotes the *expected search length* [1], i.e. the expected number of non-relevant elements retrieved until an arbitrary recall point x is reached, and n is the total number of relevant components with respect to a given topic.

To apply the above metric, the two relevance dimensions were first mapped to a single relevance scale by employing a quantisation function, $\mathbf{f}_{quant}(e,s)\colon ES \rightarrow [0,1]$, where ES denotes the set of possible assessment pairs (e,s):

$$\begin{aligned} ES = \{&(0,0),(1,1),(1,2),(1,3),\\ &(2,1),(2,2),(2,3),(3,1),(3,2),(3,3)\}\end{aligned}$$

Two quantisation functions were used: $\mathbf{f}_{strict}$ (Equation 2) and $\mathbf{f}_{gen}$ (Equation 3). The former is used to evaluate retrieval methods with respect to their capability of retrieving highly exhaustive and highly specific document components. The generalised function credits document components according to their *degree of* relevance.

$$\mathbf{f}_{strict}(e,s) := \begin{cases} 1 & \text{if } e = 3 \text{ and } s = 3, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

$$\mathbf{f}_{gen}(e,s) := \begin{cases} 1 & \text{if } (e,s) = (3,3), \\ 0.75 & \text{if } (e,s) \in \{(2,3),(3,\{2,1\})\}, \\ 0.5 & \text{if } (e,s) \in \{(1,3),(2,\{2,1\})\}, \\ 0.25 & \text{if } (e,s) \in \{(1,2),(1,1)\}, \\ 0 & \text{if } (e,s) = (0,0). \end{cases} \tag{3}$$

3.2 The inex-2003 metric

A problem with the inex-2002 metric is that it ignores possible overlaps between result elements and rewards the retrieval of a relevant component regardless if it has already been seen by the user either fully or in part.

The inex-2003 metric aims to provide a solution to this problem by incorporating component size and overlap within the definition of recall and precision (Equations 4 and 5). (For the derivation of the formulae based on an interpretation of the relevance dimensions within an ideal concept space [12] refer to [4].) Instead of measuring, e.g., precision or recall after a certain number of document components retrieved, the total size of the retrieved document components is used as the basic parameter, while overlap is accounted by considering only the increment to the parts of the components already seen. The calculations here assume that relevant information is distributed uniformly throughout a component.

$$\text{recall}_o = \frac{\sum_{i=1}^{k} e(c_i) \cdot \frac{|c_i'|}{|c_i|}}{\sum_{i=1}^{N} e(c_i)} \tag{4}$$

$$\text{precision}_o = \frac{\sum_{i=1}^{k} s(c_i) \cdot |c_i'|}{\sum_{i=1}^{k} |c_i'|} \tag{5}$$

Components $c_1, \ldots, c_k$ in Equations 4 and 5 form a ranked result list, N is the total number of components in the collection, $e(c_i)$ and $s(c_i)$ denote the quantised assessment value of component c_i according to the exhaustivity and specificity dimensions, respectively, $|c_i|$ denotes the size of the component, while $|c_i'|$ is the size of the component that has not been seen by the user previously. Given a component representation such as a set of (term, position) pairs, $|c_i'|$ can be calculated as:

$$|c_i'| = |c_i - \bigcup_{c \in C[1,n-1]} (c)| \tag{6}$$

where n is the rank position of c_i in the output list, and $C[1, n-1]$ is the set of components retrieved between the ranks $[1, n-1]$.

Since the inex-2003 metric treats the two relevance dimensions separately, the quantisation functions were also redefined to provide a separate mapping for exhaustivity, $\mathbf{f'}_{quant}(e)\colon E \rightarrow [0,1]$ and specificity, $\mathbf{f'}_{quant}(s)\colon S \rightarrow [0,1]$, where $E = \{0,1,2,3\}$ and $S = \{0,1,2,3\}$. For the strict case, the result of the quantisation was 1 if $e = 3$ or $s = 3$, respectively, and 0 otherwise. For the generalised case, the quantisation function was defined as $\mathbf{f'}_{gen}(e) = e/3$ and $\mathbf{f'}_{gen}(s) = s/3$.

4 DISCUSSION OF CURRENT INEX METRICS

4.1 Overlapping result elements

A criticism of the inex-2002 metric was that it did not address the problem of overlapping result elements and hence produced better effectiveness results for systems that returned multiple nested components. Evidence to show this effect was given by Benjamin Piwowarski. Figure 1 shows the recall-precision graphs he obtained for different simulated runs, each representing possible retrieval approaches. The graph clearly illustrates that better effectiveness is achieved by systems that return not only the most desired components, but also their parent or ascendant elements. It was agreed that such a system behaviour should not be rewarded, but in fact should be penalised.

A number of suggestions were made as to how the problem of overlapping result elements should be addressed. One recommendation was to remove overlapping results from the submissions prior to the evaluation. This was later rejected as it was thought that such a method would be too lenient while it would also lack the ability to distinguish between systems that, correctly, do not return multiple nested components from those that do. This approach would also provide false effectiveness results given that it changes the actual result lists. An alternative solution is to penalise the retrieval of overlapping result elements. Here the question of how such a penalty-scheme should work was brought up. One suggestion was to only score the first result element that matches a given relevant reference component and regard any additional results that overlap with the same reference element as irrelevant. Two concerns were voiced regarding this proposal. One is that such a method may affect the recall base (i.e. leading to varying recall base), and, second, that it may also prove to be too unstable (i.e. too sensitive to retrieval order). For example, given a section element, $s1$, assessed as $(3,3)$, its article ascendant element, $a1$, assessed as $(3,1)$, and two rankings $r1 = [a1, s1]$ and $r2 = [s1, a1]$, we obtain the following precision values (using the generalised recall and precision calculations of [8] and the generalised quantisation function of Equation 3):

$$P_{r1} = (0.75 + 0)/2 = 0.375$$

$$P_{r2} = (1 + 0)/2 = 0.5$$

It was highlighted that the inex-2003 metric, which already implements a strategy to penalise overlapping results, may be more stable than the above method. This is because contrary to the above method, which only scores the first hit from a number of overlapping results, the inex-2003 metric provides a scoring mechanism that gives partial score to overlapping results, where the score is proportional to the not-yet-seen portion of the component. For example, for the above two rankings, we obtain the following precision values (using Equation 5):

$$P_{r1} = \frac{0.3 \cdot len(a1) + 0 \cdot len(s1 - a1)}{len(a1) + len(s1 - a1)} = 0.3$$

$$P_{r2} = \frac{1 \cdot len(s1) + 0.3 \cdot len(a1 - s1)}{len(s1) + len(a1 - s1)} = 1 \cdot 0.1 + 0.3 \cdot 0.9 = 0.37$$

Note that the above calculations assume that the section forms $1/10$-th of the length of the article.

However, a criticism of the inex-2003 metric was that it had separated the two dimensions of relevance while according to the definitions both are required in order to identify the most appropriate units of retrieval. Members of the working group expressed concern regarding the exact meaning of such a measure of recall or precision, which are solely based on the exhaustivity or specificity dimension, respectively. It was agreed that further investigation of this issue would be beneficial.

In summary, preference was given to the inex-2002 metric, although it was agreed that suitable mechanisms should be developed to address the overlap of result elements. The main concerns regarding the inex-2003 metric concerned its separation of the two relevance dimensions and its stability (or sensitivity to small changes in the ranking).

4.2 Quantisation functions

Members of the working group expressed a clear preference towards the use of the strict quantisation functions since the problem of overlapping results presents

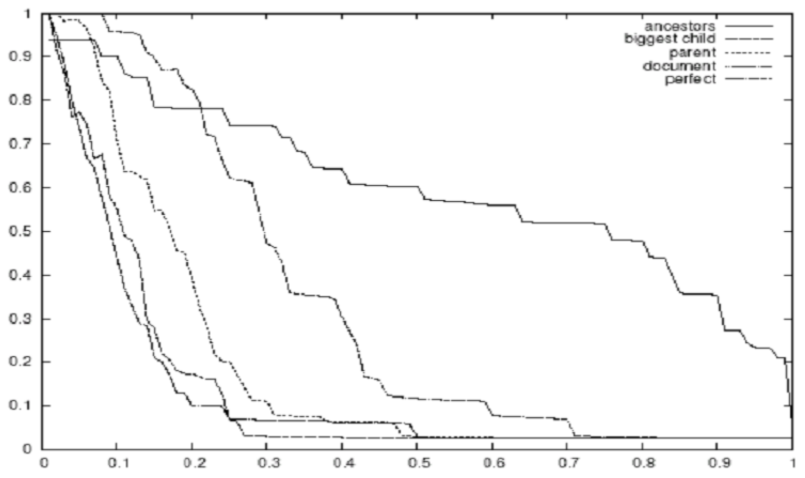

Figure 1: Generalised precision-recall for simulated runs

less of an issue in this case. It was also seen to provide more comprehensible results compared with the generalised quantisation functions. Some members have in fact suggested to base the evaluation solely on the strict assessment criteria.

This suggestion has lead to a discussion questioning the validity of the methodology employed for constructing the test collection. The argument was that if the evaluation only makes use of the components assessed as $(3, 3)$ then there should be no reason to justify the currently required effort in collecting such extensive assessments.

The main counter-argument against this proposal was that the definition of the ad-hoc XML retrieval task states that systems should find *all* relevant information, i.e. not just highly relevant information (but should rank highly relevant components first). Therefore, evaluation based on $(3, 3)$ elements only does not provide suitable evaluation criterion in INEX. It was pointed out that systems that do well on retrieving $(3, 3)$ components may not be appropriate for recall-oriented retrieval tasks (this was also the finding of [8]). In addition, it was emphasised that relevant elements assessed other than $(3, 3)$ are not simply a means for the evaluation of near misses, but these components contain relevant information to varying degree, which may be of interest to the user. At this point, Birger Larsen was also invited into the discussion. He further detailed the benefits of graded relevance assessments (see [8, 5, 11]), adding that "Future metrics can make use of the rich data even if we do not yet know how".

Additional arguments against the use of only $(3, 3)$ assessments included points that the recall-base may be too small for reliable evaluation, that assessors would label more elements as $(3, 3)$ due to the lack of alternative relevance degrees, and that no automatic mechanisms could be used to reliably infer the relevance degree of ascendant or descendant relevant components (unless binary relevance is adopted).

As a result of the discussion, it was agreed that it is necessary to consider all levels of relevant components within the evaluation. It was also agreed that due to the overlap problem this criterion is currently not evaluated sufficiently in INEX (which is also believed to be the primary reason why so much emphasis has been attributed so far to the results of the strict evaluation measures).

This has then lead to the agreement that the generalised quantisation functions must also be employed within the evaluation. As mentioned earlier, the aim of the generalised quantisation is to allow the scoring of result elements proportional to their degree of relevance. This viewpoint makes the generalised functions more suitable for the evaluation of content-oriented XML retrieval systems as it closer reflects the evaluation criterion compared with the strict quantisation functions. However, the problem of overlapping result components, which remains so far largely unsolved, does present an issue regarding the output of such an evaluation.

Aiming towards an intermediate solution to the problem, a number of new quantisation functions were defined to be used with the inex-2002 metric. The originating idea here was to find a solution, which like the strict quantisation functions minimises the overlap problem, while at the same time, like the generalised quantisation functions better reflects the evaluation criterion (i.e. finding all relevant elements). Two classes of quantisation functions were defined: specificity-oriented and exhaustivity-oriented functions. The specificity-oriented functions apply strict quantisation with respect to the specificity dimension only, while allow to consider different degrees of exhaustivity. They aim to evaluate systems according to their ability to retrieve the most specific relevant components, where the exhaustivity of the component may vary from marginally and fairly exhaustive to highly exhaustive (Equation 7) or only from fairly to highly exhaustive (Equation 8).

$$\mathbf{f}_{s3\_e321}(e,s) := \begin{cases} 1 & \text{if } e \in \{3,2,1\} \text{ and } s = 3, \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

$$\mathbf{f}_{s3\_e32}(e,s) := \begin{cases} 1 & \text{if } e \in \{3,2\} \text{ and } s = 3, \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

Similarly to the specificity-oriented functions, exhaustivity-oriented quantisation functions were also defined (Equations 9 and 10). Note, however, that these exhaustivity-oriented functions suffer from the same overlap problem as the generalised quantisation functions.

$$\mathbf{f}_{e3\_s321}(e,s) := \begin{cases} 1 & \text{if } e = 3 \text{ and } s \in \{3,2,1\}, \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

$$\mathbf{f}_{e3\_s32}(e,s) := \begin{cases} 1 & \text{if } e = 3 \quad \text{and } s \in \{3,2\}, \\ 0 & \text{otherwise.} \end{cases} \tag{10}$$

In summary, it was agreed that the strict quantisation functions, although are less effected by the overlap problem, are not sufficient alone for the evaluation of XML retrieval. They are useful and necessary, but they reflect a rather strict evaluation criterion according to which only highly exhaustive and highly specific elements are considered relevant for the user. On the other hand, although the generalised quantisations allow a more detailed evaluation, they suffer from the problem of overlapping result elements. As an intermediate solution new versions of the strict quantisation functions were proposed.

5 PROPOSED METRICS

Two proposals were presented in detail: the Expected Ratio of Relevant documents (ERR) and the Tolerance to Irrelevance (T_2I) metrics. An additional two proposals, both based on extensions of the Cumulated Gain based metrics [6], were only mentioned during the workshop. This section provides a brief summary of all these proposals.

5.1 Expected Ratio of Relevant

The Expected Ratio of Relevant documents (ERR) was proposed by Benjamin Piwowarski and Patrick Gallinary. This measure provides an estimate of the expectation of the number of relevant document elements (doxels) a user sees when consulting the list of the first k returned doxels, divided by the expectation of the number of relevant doxels a user would see when exploring all the doxels of the database (i.e. the total number of relevant elements for a given topic, denoted by E). The value of ERR for each k between 1 and the total number of retrieved doxels N is given as:

$$\text{ERR} = \frac{\mathbb{E}[N_R|N = k]}{\mathbb{E}[N_R|N = E]} \tag{11}$$

where $N_R|N = k$ represents the total number of relevant doxels the user has access to within the first k elements in the result list, and $N_R|N = E$ represents the total number of relevant doxels within the whole collection.

The actual calculation of this estimate is based on a hypothetical user behaviour, which extends the assumptions used in classical IR, e.g. users browse elements in the list in a linear order, etc., with two additional hypotheses. The first is that the user is assumed to browse through the retrieved document's structure (that is, he/she can ”jump” with a given probability from one element to another within the same document). It is however assumed that users cannot use hyperlinks (i.e. jump to another document). The second hypothesis is that this browsing is influenced by the specificity of the doxels. Based on these assumptions, the parameters within the model are estimated leading to a final estimate of the ERR value.

Further details on this metric are available in [9].

5.2 Tolerance to Irrelevance

Arjen de Vries, Gabriella Kazai and Mounia Lalmas proposed a measure, which is based on an alternative definition of correct results. The main idea is that a user merely needs an entry-point into the document that is ‘close’ to relevant information. Taking this view, a retrieval system produces a ranked list of entry points. The user starts reading the retrieved article from the suggested entry point, giving up when no relevant information is found for some number of words or sentences. So, the user processes the retrieved information until his or her *tolerance to irrelevance* (T_2I) has been reached, at which point the user proceeds to the next system result.

This discourages systems from returning fragments that are too large, since if the entry-point is too far away from the relevant reference component, the user's tolerance to irrelevance will have been exhausted before the relevant information has been reached. The problem with multiple system results intersecting the same reference component is eliminated by extending the definition of irrelevance, according to which a previously seen reference fragment is no longer considered relevant.

T_2I variants of three existing evaluation metrics for system performance are given in [2]. Their common underlying principle is that retrieval systems are ranked on their ability to maximise the number of relevant fragments shown to the user while minimising the amount of user effort wasted on irrelevant information. The tolerance to irrelevance is expressed by a single parameter, τ_{NR}, that represents the maximum amount of non-relevant text the user is expected to read before giving up. The length of retrieved relevant components is ignored, assuming that each result has equal value to the user.

5.3 Cumulated Gain for XML

Two separate proposals were made for the extension of the Cumulated Gain (CG) based evaluation measures [6] for the evaluation of XML retrieval. One by Huyen-Trang Vu and another by Gabriella Kazai.

Huyen-Trang Vu is currently working on a variation of the discounted cumulated gain (DCG) measure, where the discount function employed makes use of a component-length normalisation function. This function is similar to the length normalisation of the inex-2003 metric and takes into account the size of the not-yet-seen part of the retrieved component, where uniform distribution of relevant information within a component is assumed. She is also working on an experimental analysis of the INEX evaluation results with the aim to reach some consensus about evaluation issues raised in INEX such as the overlap problem and the usage of graded assessments. A paper describing the approach is currently in preparation.

The approach taken by Gabriella Kazai is to extend the (D)CG based metrics by separating the model of user behaviour from the actual metric employed. This is achieved via the definition of a set of relevance value (RV) functions implementing scoring mechanisms based on parameters including the relevance degree of a retrieved component, the ratio of already viewed parts, etc. Each such RV function models different possible user behaviours. Within the (D)CG framework, an RV function is then used as a means to calculate the relevance score of a document component within the result list, hence, producing the gain vector G, which forms the basis of the (D)CG calculations. She also proposed different functions for the estimation of a component-part's relevance degree, which moves away from the uniform distribution assumption and is based on the assessment data of the component's child nodes. A paper describing the approach has since been submitted for publication [7].

6 DISCUSSION OF PROPOSED METRICS

All proposals were welcomed by the group. ERR was regarded as an encouraging measure although concerns were raised regarding the use of possibly too many parameters that needed to be estimated. T_2I was assessed as a promising, simple but potentially powerful framework, which however so far lacked implementation details. Both metrics were said to benefit from experiments and analysis of their working.

The CG based metrics were not discussed.

7 OTHER ISSUES

Additional issues raised during the workshop included general problems, such as problems experienced when trying to install the INEX evaluation software. Another criticism was the lack of documentation provided.

The point that systems could not be tuned due to fact that the metrics were not published prior to the task execution was also raised. A related issue concerned the understanding of the metrics and of their workings. A general recommendation was to publish metrics early on within the evaluation round. Another suggestion was to provide effectiveness results for P@5, P@10, P@20 as part of the official evaluation.

Concerns regarding the consistency of assessments due to the increased cognitive load were also expressed. The organisers offered to investigate this issue by providing an analysis of the collected assessments of topics from multiple assessors.

Other issues raised included concerns that article only retrieval was hard to beat. This has lead to questions regarding the quality of the topics used within the test collection and the problem of how to ensure that answer elements were components smaller than

Task	Metric
CO	inex-2002
	inex-2003
	ERR
	T_2I
SCAS	inex-2002
	ERR
	T_2I
VCAS	Extensions of the CO metrics to provide partial score based on structural similarity using distance measures.

Table 1: Tasks and metrics

article elements while maintaining realistic information needs. While no solution was identified, the issue was raised as a concern that should be considered during the topic development process.

The working group ended with a discussion on which metrics can be used for the evaluation of which tasks (i.e. CO, CAS and SCAS). This is summarised in Table 1.

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Appendix

INEX’03 Guidelines for Topic Development

The aim of the INEX initiative is to provide means, in the form of a large test collection and appropriate scoring methods, for the evaluation of content-oriented XML retrieval. Within the INEX initiative it is the task of the participating organisations to provide the topics and relevance assessments that will contribute to the test collection. Each participating organisation therefore plays a vital role in this collaborative effort.

1. Introduction

Test collections, as traditionally used in information retrieval (IR), consist of three parts: a set of documents, a set of information needs called topics, and a set of relevance assessments listing for each topic the set of relevant documents.

A test collection for XML retrieval differs from traditional IR test collections in many respects. Although it still consists of the same three parts, the nature of these parts is fundamentally different. In IR test collections, documents are considered as units of unstructured text, topic statements are generally treated as collections of terms and/or phrases, and relevance assessments provide judgements whether a document as a whole is relevant to a query or not. XML documents, on the other hand, organise their content into smaller, nested structural elements. Each of these elements in the document’s hierarchy, along with the document itself, is a retrievable unit. Regarding the topics, with the use of XML query languages, users of an XML retrieval system are able to combine both content and structural conditions within their information need and restrict their search to specific structural elements within an XML collection. Finally the relevance assessments for an XML collection must also consider the structural nature of the documents and provide assessments at different structural levels.

This guide deals only with the topics of the test collection and provides detailed guidelines for their creation for INEX 2003.

2. Topic creation criteria

Creating a set of topics for a test collection requires a balance between competing interests. It is a well-known fact that the performance of retrieval systems varies largely for different topics. This variation is usually greater than the performance variation of different retrieval methods on the same topic. Thus, to judge whether one retrieval strategy is in general more effective than another strategy, the retrieval performance must be averaged over a large, diverse set of topics. In addition, to be a useful diagnostic tool, the average performance of the retrieval systems on the topics can be neither too good nor too bad as little can be learned about retrieval strategies if systems retrieve no or only relevant documents.

When creating topics, a number of factors should be taken into account.

1. **The author of a topic should be either an expert or the very least be familiar with the subject area covered by the collection!** (Note that the author of a topic should also be the assessor of relevance!)
2. Topics should reflect what real users of operational systems might ask.
3. Topics should be representative of the type of service that operational systems might provide.
4. Topics should be diverse.
5. Topics may also differ in their coverage, e.g. broad or narrow topic queries.

3. Query types

As last year, in INEX 2003 we distinguish two types of query:

- *Content-only (CO) queries*: are requests that ignore the document structure and contain only content related conditions, e.g. only specify what a document/component should be about (without specifying what that component is). The need for this type of query for the evaluation of XML retrieval stems from the fact that users either do not care about the structure of the result components or are not familiar with the exact structure of the XML documents.

- *Content-and-structure (CAS) queries*: are topic statements, which contain explicit references to the XML structure, and restrict the context of interest and/or the context of certain search concepts.

4. Topic format

Both CO and CAS topics are made up of four parts:

- *Topic title*: a short version of the topic statement. It serves as a summary of both the content and structural requirements of the user's information need. The exact format of the topic title is discussed in more detail later in this section.
- *Topic description*: a one or two sentence natural language definition of an information need.
- *Narrative*: a detailed explanation of the topic statement and the description of what makes a document/component relevant or not.
- *Keywords*: a set of comma-separated scan terms that are used in the collection exploration phase of the topic development process (see Section 5.2) to retrieve relevant documents/components. Scan terms may be single words or phrases and may include synonyms, broader or narrower terms from those listed in the topic description or topic title.

The format of the topic title in 2003 is different to that used in INEX 2002. This year, the format is based on XPath, the proposed language for addressing parts of XML documents. The XPath notation is adopted in INEX 2003 to refer to the logical structure and the attributes of the XML documents. However, since XPath is a very rich and powerful language, we restrict ourselves to a subset of XPath, which has been identified by the INEX 2002 Topic Format working group as providing an "IR minimum". This subset corresponds (mainly) to the use of path expressions as described in Section 2 of the document XML Path Language (XPath) Version 1.0, W3C Working Draft 16 November 1999 (available at http://www.w3.org/TR/xpath). More precisely, the topic format will make use of Axes (Section 2.2), Predicates (Section 2.4), and will use the abbreviated syntax described in Section 2.5 of the aforementioned document.

Below are examples of path expressions (taken from Section 2.5 of the XPath 1.0 standard):

- `para` selects the `para` element children of the context node
- `*` selects all element children of the context node
- `@attr` selects the `attr` attribute of the context node
- `@*` selects all the attributes of the context node
- `para[1]` selects the first `para` child of the context node
- `*/para` selects all `para` grandchildren of the context node
- `/doc/chapter[5]/section[2]` selects the second `section` of the fifth `chapter` of `doc`
- `chapter//para` selects the `para` descendants element of the `chapter` element children of the context node
- `//para` selects all the `para` descendants of the document root and thus selects all `para` elements in the same document as the context node
- `//olist/item` selects all the `item` elements in the same document as the context node that have an `olist` parent
- `.` selects the context node
- `.//para` selects the `para` element descendants of the context node
- `..` selects the parent of the context node
- `../@lang` selects the `lang` attribute of the parent of the context node
- `para[@type='warning']` selects all `para` children of the context node that have a `type` attribute with value `warning`
- `para[@type='warning'][5]` selects the fifth `para` child of the context node that has a `type` attribute with value `warning`
- `para[5][@type='warning']` selects the fifth `para` child of the context node if that child has a `type` attribute with value `warning`
- `chapter[title='Introduction']` selects the `chapter` children of the context node that have one or more `title` children with string-value equal to `Introduction`

- `chapter[title]` selects the `chapter` children of the context node that have one or more `title` children
- `employee[@secretary and @assistant]` selects all the `employee` children of the context node that have both a `secretary` attribute and an `assistant` attribute

4.1. The *about()* function

In INEX, an "aboutness" concept, in the form of an *about(path, string)* function, has been added to the standard XPath syntax to deal with the content aspect of a user query. This concept was necessary in order to introduce the uncertainty inherent in IR into the world of the more exact-match XPath principle. The *about()* function should be used as the basis to provide a ranking of the retrieved elements with respect to content. Note that the *about(path,string)* clause is different from the *contains(path,string)* function of the XPath standard (see XPath 1.0, http://www.w3.org/TR/xpath). The latter returns true if the text value of the element defined by the path contains the string argument, and otherwise returns false. On the other hand, the *about()* function returns true if the element defined by the path argument is "about" the concept(s) defined by the string argument without having to actually contain the exact string value.

The *about()* function is usually applied to a context element, `CE`. This is described by the following syntax: `CE[about(path, string)]`. A context element is described using a standard XPath path expression (see the examples of path expressions in Section 4). It defines a "base node" against which relative paths, using the "." notation, can be defined within the *path* argument of the *about()* function. For example, `//article[about(.//sec,'"XML retrieval"')]` represents the request to retrieve articles that contain within them a section about "XML retrieval". Another example is `//article[about(.//sec, '"XML retrieval"') and about(.//sec,'evaluation')]`, which is a representation of the request to retrieve articles, which contain a section about "XML retrieval" and also a section on evaluation (where the two sections may be different or may be the same). We will look at more complex structures when we discuss the format of the CAS topic titles. The *string* parameter may contain a number of space-separated terms, where a term may be a single word or a phrase encapsulated in double-quotes. Furthermore, the symbols + and − may be used to express additional preferences for certain terms, where + is used to emphasise a concept and − is used to denote an unwanted concept. In summary, a *string* parameter may incorporate the following components:

- Terms (single words or phrases)
- "" (double-quotes to encapsulate phrases)
- + (expressing "must be about")
- − (denoting "must not be about")

The syntax of a *string* argument is:

```
String   ::=   term ' '
             | '+'term ' '
             | '−'term ' '
Term     ::=   single word
             | '"'phrase'"'
```

A *string* must be enclosed between single quotes. For example, `//article[about(.//sec, '"XML retrieval" +XML -"information retrieval"')]` would correspond to the request to retrieve articles that contain a section which is about XML retrieval but not about information retrieval, and where XML is characterised as an important concept.

Although at this point we are not talking about relevance assessment we would like to make a note here to emphasise that for relevance assessments the symbols + and − should be interpreted with a fuzzy "flavour" and not simply as must contain or must not contain conditions. Following on from the definition of the *about()* function above, a component may be considered relevant even if it does not contain the query term(s), but is "about" the concept(s) expressed by the query term(s). Similarly a component may be relevant even if it contains, for example, only one half of a phrase.

4.2 CO Topics

The topic title of a CO topic is a short, usually a 2-5 terms representation of the topic statement. Since CO topics ignore the document structure, their topic title will only consist of one *about()* clause applied to any context elements denoted by the path `//*`. The *path* argument of the *about()* function must be set to "." (dot) to refer to the context element. The *string* argument is made up of terms that best describe what the user is looking for. Take as an example the topic title `//*[about(., '"XML retrieval"')`, which is the representation of the request to retrieve any elements that are about "XML retrieval".

In order to simplify this syntax, we remove all components of the topic title that are the same for all CO topics (e.g. the context element, the *path* argument, etc.). As a result, we end up with just the *string* argument of the *about()* function, e.g. replacing `//*[about(path, string)]` with `string`, where we also ignore the single quotes.

The topic title of a CO topic is therefore defined as a set of space separated terms, optionally associated with the symbols + and −, where a term may be a single word or a phrase encapsulated in double-quotes. The syntax of the CO topic titles hence matches the syntax of the *string* argument specified above (Section 4.1).

Examples of CO topic titles

1. Retrieve documents/components about computer science degrees that are not master degrees:

```
<title>"computer science" +degree –master</title>
```

2. Retrieve document/components about summer holidays in England:

```
<title>"summer holiday" +England</title>
```

Example of a CO topic

```
<inex_topic topic_id="1" query_type="CO">
       <title>
              "summer holiday" "winter holiday" +"England"
       </title>
       <description>
              Winter or summer holidays in England.
       </description>
       <narrative>
              To be relevant, a document or component must contain
              information about winter or summer holidays in England.
       </narrative>
       <keywords>
              summer, winter, holiday, England, skiing, beach
       </keywords>
</inex_topic>
```

4.3 CAS Topic

The general structure of a CAS topic title is as follows:

```
CE [ filter ] CE [ filter ] … CE [filter] CE [filter]
```

`CE` refers to the context element. The series of context elements, where the first `CE` acts as the root node, describes a branch of an XML tree. Each context element is relative to the context element that precedes it in the sequence. This branch forms the path of the target element that is to be returned to the user. A filter is defined as a set of about clauses (e.g. *about(path, string)*) and other predicate clauses (e.g. `@yr = '2001'`), which are joined by Boolean expressions. The *path* argument of the *about()* function can be expressed relative to the context element by using the "." notation. For example, `//article[.//@yr = '2001']//sec[about(.,'+"XML retrieval"')`, is the expression of a request to retrieve sections about "XML retrieval" of articles written in 2001. This query has two context elements, namely `//article` and `//sec`, which together define the target element. `//article//sec`.

A filter may contain a set of *about()* functions and/or a set of standard XPath string operators: =, !=, >, <, >= and <=. The conditions expressed by these functions and operators can be combined using the Boolean operators: AND and OR, together with the use of parenthesis to group such conditions

together. For example, `//article[about(.//p,'+"holiday"') AND .//@yr='2002']`, retrieves articles that contain paragraphs about "holiday" and have a published date of 2002. Note that while the series of context elements must describe a branch of the XML tree, the filter components allow for the definition of content conditions on different branches of a tree within the context element. Take the earlier mentioned example (Section 4.1) of `//article[about(.//sec,'"XML retrieval"') and about(.//sec,'evaluation')]` requesting article elements, which contain a section about "XML retrieval" and also a section on "evaluation" (where the two sections may be different or may be the same). Here two independent branches of the tree rooted in `//article` are described.
`NOTE THAT FOR AN INEX CAS TOPIC, IT IS A REQUIREMENT THAT A FILTER CONTAINING AN ABOUT() FUNCTION MUST BE SPECIFIED FOR THE LAST CONTEXT ELEMENT!` Multiple target elements are not allowed in INEX 2003. Also note that specifying one context element only, and setting it to `//*`, while setting the *path* argument of the *about()* functions to ".", we arrive back at a CO topic title.

Examples of CAS topic titles[1]

1. Return section elements, which are about summer holidays, where the section element is a descendent of article element, and the article is from 2001 or 2002:

   ```
   <title>
       //article[.//@yr = '2001' OR .//@yr = '2002']//sec[about(.,
       '"summer holidays"')]
   </title>
   ```

   The above query has two context elements, `//article` and `//sec`, each with their own filters, one containing a standard Xpath predicate and the other containing an *about()* clause. The target element defined by the above query is `//article//sec`.

   Note that the following query is not a valid INEX query as it does not contain an *about()* function:

   ```
   <title>
       //article[.//@yr = '2001' OR .//@yr = '2002']
   </title>
   ```

   The following query is not valid because there is no filter applied to the last context element (e.g. //sec):

   ```
   <title>
       //article[.//@yr = '2001' OR about(., '"summer holiday"']//sec
    </title>
   ```

In the remainder of the examples for simplicity we ignore the `<title> </title>` tags.

2. Retrieve all articles that were published in 2001 and are about summer holidays:

   ```
   //article[.//@yr = '2001' AND about(./, '"summer holidays"')]
   ```

3. Return article elements published in 2001 that contain section elements about summer holidays:

   ```
   //article[.//@yr = '2001' AND about(.//sec, '"summer holidays"')]
   ```

4. Return articles from 2001, which contain section elements about summer holidays or section elements about winter holidays:

   ```
   //article[.//@yr = '2001'  AND (about(.//sec, '"summer holidays"')OR
   about (.//sec, '"winter holidays"'))]
   ```

   A query requesting articles from 2001 containing section elements about summer and winter holidays would be as follows:

   ```
   //article[.//@yr = '2001' AND (about(.//sec, '+"summer holidays"
   +"winter holidays"')]
   ```

5. Return section elements, which are about summer holidays and that are the grandchildren of article elements, where the article is from 2001 or 2002:

[1] Note that these examples do not conform to the structure or content of the INEX document collection

```
//article[.//@yr = '2001' or .//@yr = '2002']/*/sec[about(., '"summer
holidays"')]
```

6. Return articles on XML retrieval, where the article contains a section on evaluation:

```
//article[about(., '"XML retrieval"') AND about(.//sec, 'evaluation')]
```

7. Retrieve articles that were published in 2002 and contain a section about "XML retrieval":

```
//article[about(.//sec, '"XML retrieval"') AND .//@yr='2002']
```

8. Retrieve those sections of articles published in 2002 that are about "XML retrieval":

```
//article[.//@yr='2002']//sec[about(.//sec, '"XML retrieval"')]
```

9. Retrieve those sections of articles that contain both a figure about "CORBA" and a figure caption about "XML":

```
//article//sec[about(.//fig, 'CORBA') AND about(.//figc, 'XML')]
```

Example of a CAS topic

```
<inex_topic topic_id="2" query_type="CAS">
      <title>
            //article[.//@yr = '2001' OR .//@yr = '2002']//sec[about(.,
            '"summer holidays"')]
      </title>
      <description>
            Summer holidays either of 2001 or of 2002.
      </description>
      <narrative>
            Return section elements, which are about summer holidays, where
            the sections is descendent of article element, and the article
            is from 2001 or 2002.
      </narrative>
      <keywords>
            summer, holiday, 2001,2002
      </keywords>
</inex_topic>
```

4.4. Equivalent tags

This section lists the defined set of "equivalent" tags (alias/role/metedata) in the INEX test collection. We are proposing aliases for the following classes of nodes (identified directly from the DTD):

Paragraph-like nodes: ilrj|ip1|ip2|ip3|ip4|ip5|item-none|p|p1|p2|p3
Section nodes: sec|ss1|ss2|ss3
List environments: dl|l1|l2|l3|l4|l5|l6|l7|l8|l9|la|lb|lc|ld|le|list|numeric-list|numeric-rbrace|bullet-list
Headings: h|h1|h1a|h2|h2a|h3|h4

4.5. Topics DTD

The overall structure of the INEX topics is given in the DTD below (Note that additional attributes may be added at a later stage).

```
<?xml version="1.0" encoding="ISO-8859-1" ?>
<!ELEMENT inex_topic (title, description, narrative, keywords)>
<!ELEMENT title (#PCDATA)>
<!ELEMENT description (#PCDATA)>
<!ELEMENT narrative (#PCDATA)>
<!ELEMENT keywords (#PCDATA)>
<!ATTLIST inex_topic
  topic_id   CDATA  #REQUIRED
  query_type CDATA  #REQUIRED
>
```

5. Procedure for topic development

Each participating group will have to submit **3 CO and 3 CAS** queries by the **30 May 2003** by filling in the Candidate Topic Form (one per topic) at

http://inex.is.informatik.uni-duisburg.de:2003/internal/TopicSubmission.html

This section outlines the procedures involved in the development of candidate topics. There are four steps in creating topics for a test collection: 1) creating the initial topic statements, 2) exploring the collection, 3) selecting final set of topics, and 4) refining the topic statements.

5.1. Initial topic statements

In this step, you should create a one or two sentence description of the information you are seeking. This should be a simple description of the information need without regard to retrieval system capabilities or document collection peculiarities. This should be recorded in the topic description field.

Use either a printout or directly the on-line version of the Candidate Topic Form to record all information on a topic you are creating.

5.2. Collection exploration

In this step the initial topic statements are used to explore the document collection in order to obtain an estimate of the number of relevant documents/elements in the collection and to evaluate whether this topic can be judged consistently in the assessment phase. You may use any retrieval engine for this task, including your own or HyRex (HyRex can be accessed via http://inex.is.informatik.uni-duisburg.de:2003/internal/#topics).

Using the Candidate Topic Form record the set of keywords that you use for retrieval (make sure to record all the keywords from all iteration of your search or if you use query expansion strategies the query terms generated by the process). You should try and make your search queries (e.g. set of keywords) as expressive as possible for the kind of documents you wish to retrieve: think of the words that would make good scan words when assessing, and use those as your query keywords.

Next, judge the top 25 documents/components of your retrieval result. Using the Candidate Topic Form record the number of found relevant components and the XPath path representing each relevant element. If you have found less than 2 or more than 20 relevant components within the top 25 results, you should abandon the topic and start with a new one! If you have found at least 2 relevant components and no more than 20, perform a feedback search (don't forget to record the terms (if any) that you decide to add to your query keywords). Judge the top 100 (some of them you will have judged already), and record the number of relevant documents/components in Candidate Topic Form.

Finally write your detailed explanation on what makes a document/component relevant and record this in the narrative field of the topic. Make sure your description is as exhaustive as possible as there will be a couple of months gap before you will return to the topic for relevance assessments. The expectation is that by judging 100 documents/components you will have determined how you will judge the topic in the assessment phase. The narrative of the topic should reflect this.

To assess the relevance of a retrieved document/component use the following working definition: mark a document/component relevant if it would be useful if you were writing a report on the subject of the topic, or if it contributes towards satisfying your information need. Each document/component should be judged on it own merits. That is, a document/component is still relevant even if it is the thirtieth document/component you have seen with the same information. It is crucial to obtain exhaustive relevance judgements. It is also very important that your judgement of relevance is consistent throughout this task.

5.3. Refining topic statements

Refining the topic statement means finalising the topic title, description, keywords and narrative. Note that it should be possible to use each of the four parts of a topic in a stand-alone fashion (e.g. using only the title for retrieval, or only the description for filtering etc.).

Once you finished, submit the on-line Candidate Topic Form at

http://inex.is.informatik.uni-duisburg.de:2003/internal/TopicSubmission.html.

Make sure you submit all **6** candidate topics no later than the 30 May 2003.

5.4. Topic selection

From the received candidate topics, we (the clearinghouse) will then decide which topics to use such that a wide range of likely number of relevant documents is included. The data obtained from the collection exploration phase will be used as input to the topic selection process. We will then distribute final set of topics back to you to be used for the retrieval and evaluation.

We would like to thank you for your contribution.

Acknowledgements

The topic format proposed in this document is based on the outcome of a working group set up during the INEX 2002 workshop in Dagstuhl and the intense discussions on the INEX 2003 mailing list. We are very grateful for their contribution.

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06 May, 2003
Updated 12 May 2003

INEX'03 Retrieval Task and Result Submission Format Specification

Retrieval Task

The retrieval task to be performed by the participating groups of INEX'03 is defined as the ad-hoc retrieval of XML documents. In information retrieval literature, ad-hoc retrieval is described as a simulation of how a library might be used, and it involves the searching of a static set of documents using a new set of topics. While the principle is the same, the difference for INEX is that the library consists of XML documents, the queries may contain both content and structural conditions and, in response to a query, arbitrary XML elements may be retrieved from the library. Within the ad-hoc retrieval task we define the following three sub-tasks:

CO: Content-oriented XML retrieval using content-only (CO) queries. As described in the INEX'03 Topic Development Guide, CO queries are requests that ignore the document structure and contain only content related conditions, e.g. only specify what a document/component should be about (without specifying what that component is). The need for this type of query for the evaluation of XML retrieval stems from the fact that users may not care about the structure of the result components or may not be familiar with the exact structure of the XML documents. In this task, it is left to the retrieval system to identify the most appropriate XML elements to return to the user. These elements are components that are most specific and most exhaustive with respect to the topic of request. Most specific here means that the component is highly focused on the topic, while exhaustive reflects that the topic is exhaustively discussed within the component.

SCAS: Content-oriented XML retrieval based on content-and-structure (CAS) queries, where the structural constraints of a query must be <u>strictly</u> matched. CAS queries are topic statements, which contain explicit references to the XML structure, and explicitly specify the contexts of the user's interest (e.g. target elements) and/or the contexts of certain search concepts (e.g. containment conditions). In this task, the user's query is considered as an exact formulation of his/her information need, where the structural conditions specified within the query must be satisfied exactly by the retrieved components.

VCAS: Content-oriented XML retrieval based on content-and-structure (CAS) queries, where the structural constraints of a query can be treated as <u>vague</u> conditions. This task deviates from the previous one in that XML elements 'structurally similar' to those specified in the query may be considered correct answers. The idea behind this sub-task is to allow the evaluation of XML retrieval systems that aim to implement a more fuzzy approach to XML retrieval, where not only the content conditions within a user query are treated with uncertainty but also the expressed structural conditions. These systems aim to return components that contain the information sought after by the user even if the result elements do not exactly meet the structural conditions expressed in the query.

The actual search queries put to the retrieval engines (e.g. used to search the document collection) may be generated either manually or automatically from any part of the topics, with the exception of the narrative. Please note that <u>at least one submitted run for each sub-task must be with the use of automatic queries</u>.

Result Submission

For each sub-task up to 3 runs may be submitted. The results of one run must be contained in one submission file (e.g. up to 9 files can be submitted in total). A submission may contain up to **1500** retrieval results for each of the INEX topics included within that sub-task (e.g. for the CO sub-task only submit the search results obtained for the CO topics).

Submission format

For relevance assessments and the evaluation of the results we require submission files to be in the format described in this section. The overall submission format is defined in the following DTD:

```
<!ELEMENT inex-submission          (description, topic+)>
<!ATTLIST inex-submission
     participant-id          CDATA         #REQUIRED
     run-id                  CDATA         #REQUIRED
     task     ( CO | SCAS | VCAS )         #REQUIRED
     query    (automatic | manual)         #REQUIRED
     topic-part  (T | D | K | TD | TK | DK | TDK)  #REQUIRED
>
<!ELEMENT description        (#PCDATA)>
<!ELEMENT topic              (result*)>
<!ATTLIST topic
     topic-id                CDATA         #REQUIRED
>
<!ELEMENT result             (file, path, rank?, rsv?)>
<!ELEMENT file               (#PCDATA)>
<!ELEMENT path               (#PCDATA)>
<!ELEMENT rank               (#PCDATA)>
<!ELEMENT rsv                (#PCDATA)>
```

Each submission must specify the following information:

- `participant-id`: the participant ID of the submitting institute (available at http://inex.is.informatik.uni-duisburg.de:2003/inex03/servlet/ShowParticipants),
- `run-id`: a run ID (which must be unique for the submissions sent from one organisation – also please use meaningful names as much as possible),
- `task`: the identification of the task (e.g. `CO`, `SCAS` or `VCAS`),
- `query`: the identification of whether the query was constructed automatically or manually from the topic,
- `topic-part`: the specification of whether the automatic or manual query was generated from the topic title only (`T`), the topic description only (`D`), the keywords only (`K`), the combination of the topic title and the topic description (`TD`), the combination of the topic title and the keywords (`TK`), the combination of the topic description and keywords (`DK`), or the combination of the topic title, topic description and keywords (`TDK`).

Furthermore each submitted run must contain a (brief) `description` of the retrieval approach applied to generate the search results.

A submission should then contain a number of `topic`s, each identified by its topic ID (as provided with the topics). For each topic a maximum of **1500** `result` elements may be included. A result element is described by a `file` name and an element `path` and it may include `rank` and/or retrieval status value (`rsv`) information.

Before detailing these elements, below is a sample submission file:

```
<inex-submission participant-id="12" run-id="VSM_Aggr_06" task="CO"
query="automatic" topic-part="TK">
    <description>Using VSM to compute RSV at leaf level combined with
          aggregation at retrieval time, assuming independence and using
          acc=0.6.
    </description>
    <topic topic-id="01">
        <result>
            <file>tc/2001/t0111</file>
             <path>/article[1]/bm[1]/ack[1]</path>
            <rsv>0.67</rsv>
        </result>
        <result>
            <file>an/1995/a1004</file>
            <path>/article[1]/bdy[1]/sec[1]/p[3]</path>
            <rsv>0.1</rsv>
        </result>
        [ ... ]
    </topic>
    <topic topic-id="02">
        [ ... ]
    </topic>
    [ ... ]
</inex-submission>
```

Rank and RSV
The `rank` and `rsv` elements are provided for submissions based on a retrieval approach producing ranked output. The ranking of the result elements can be described in terms of

- Rank values, which are consecutive natural numbers, starting with 1. Note that there can be more than one element per rank.
- Retrieval status values (RSVs), which are positive real numbers. Note that there may be several elements having the same RSV value.

Either of these methods may be used to describe the ranking within a submission. If both rank and rsv are given, the rank value is used for evaluation. These elements may be omitted from a submission if a retrieval approach does not produce ranked output.

File and path
Since XML retrieval approaches may return arbitrary XML nodes from the documents of the INEX collection, we need a way to identify these nodes without ambiguity. Within INEX submissions, elements are identified by means of a `file` name and an element (node) `path` specification, which must be given in XPath syntax.

File names must be given relative to the INEX collection's "xml" directory (excluding the "xml" directory itself from the file path). The file path should use '/' for separating directories. Note that only article files (e.g. no "volume.xml" files) can be referenced here. The extension ".xml" must be left out. Example:

```
an/1995/a1004
```

Element paths are given in XPath syntax. To be more precise, only fully specified paths are allowed, as described by the following grammar:

```
Path            ::=  '/' ElementNode Path
                     | '/' ElementNode '/' AttributeNode
                     | '/' ElementNode

ElementNode     ::=  ElementName Index

AttributeNode   ::=  '@' AttributeName

Index           ::=  '[' integer ']'
```

Example:

```
/article[1]/bdy[1]/sec[4]/p[3]
```

This path identifies the element which can be found if we start at the document root, select the first "article" element, then within that, select the first "bdy" element, within which we select the fourth "sec" element, and finally within that element we select the third "p" element. Note that XPath counts elements starting with 1 and takes into account the element type, e.g. if a section had a title and two paragraphs then their paths would be given as: `../title[1]`, `../p[1]` and `../p[2]`.

When producing the XPath expressions of result elements, the equivalent-tags rules (see INEX'03 Guidelines for Topic Development) must be ignored, e.g. result elements must be identified in line with the original structure of the XML documents! For example, given the structure: `<sec><p>..</p><ip5>..</ip5><p>..</p></sec>)` the following XPaths should be generated: `/sec[1]`, `/sec[1]/p[1]`, `/sec[1]/ip5[1]`, and `/sec[1]/p[2]`. Note that the same structure, taking into account the equivalent-tags rules, would result in the XPaths: `/sec[1]`, `/sec[1]/p[1]`, `/sec[1]/p[2]`, and `/sec[1]/p[3]`. However, result elements identified by the latter XPaths will lead to incorrect evaluations of the submitted runs.

A result element is identified unambiguously using the combination of its file name and element path. Example:

```
<result>
    <file>an/1995/a1004</file>
    <path>/article[1]/bdy[1]/sec[1]/p[3]</path>
</result>
```

An application that can be used to check the correctness of a given path specification is available at
http://inex.is.informatik.uni-duisburg.de:2003/browse.html
Note that this application requires the input of a file name and element path. If these are correctly given, the specified XML element within its container article element will be displayed.

Result Submission Procedure

An online submission tool will be provided. Details on how to submit will be circulated as part of a separate document in the near future.

July 23, 2003
Gabriella Kazai, Mounia Lalmas, Norbert Goevert and Saadia Malik

INEX'03 Relevance Assessment Guide

1. Introduction

During the retrieval runs, participating organisations evaluated the 66 INEX'03 topics (36 content-only and 30 content-and-structure queries) against the IEEE Computer Society document collection and produced a list (or set) of document components (XML elements[1]) as their retrieval results for each topic. The top 1500 components in a topic's retrieval results were then submitted to INEX. The submissions received from the different participating groups have now been pooled and redistributed to the participating groups (to the topic authors whenever possible) for relevance assessment. Note that the assessment of a given topic should not be regarded as a group task, but should be provided by one person only (e.g. by the topic author or the assigned assessor).

The aim of this guide is to outline the process of providing relevance assessments for the INEX'03 test collection. This requires first a definition of relevance for XML retrieval (Section 2), followed by details of what (Sections 3) and how (Section 4) to assess. Finally, we describe the on-line relevance assessment system that should be used to record your assessments (Section 5).

2. Relevance dimensions: exhaustivity and specificity

Relevance in INEX is defined according to the following two dimensions:

- ***Exhaustivity (e-value for short),*** *which describes the extent to which the document component discusses the topic of request.*
- ***Specificity (s-value for short),*** *which describes the extent to which the document component focuses on the topic of request.*

To assess exhaustivity, we adopt the following 4-point scale:

> **0: Not exhaustive,** the document component does not discuss the topic of request at all.
> **1: Marginally exhaustive**, the document component discusses only few aspects of the topic of request.
> **2: Fairly exhaustive**, the document component discusses many aspects of the topic of request.
> **3: Highly exhaustive**, the document component discusses most or all aspects of the topic of request.

To assess specificity, we adopt the following 4-point scale:

> **0: Not specific**, the topic of request is not a theme of the document component.
> **1: Marginally specific**, the topic of request is a minor theme of the document component
> **2: Fairly specific**, the topic of request is a major theme of the document component.
> **3: Highly specific**, the topic of request is the only theme of the document component.

A document component can be assessed as highly exhaustive (e-value 3) even if it is not specific to the topic of request – that is, the topic of request can be a major theme (s-value 2) or a minor theme (s-value 1) of the component – as long as all or most aspects of the topic is discussed (e.g. a component may be highly exhaustive to the topic regardless of how much additional, irrelevant information it contains). Similarly, a document component can be assessed as highly specific (s-value 3) even if it discusses many (e-value 2) or only a few (e-value 1) aspects of the topic - as long as the topic of request is the only theme of the component. However, a document component that does not discuss the topic of request at all (e-value 0) must have an s-value of 0, and vice versa.

[1] The terms document component and XML element are used interchangeably.

3. What to judge

Depending on the topic, a pooled result set may contain initially between 500 and 1,500 document components of 500 - 510 articles, where a component may be a title, paragraph, section, or whole article etc.

Traditionally, in evaluation initiatives for information retrieval, like TREC, relevance is judged on document level, which is treated as the atomic unit of retrieval. In XML retrieval, the retrieval results may contain document components of varying granularity, e.g. paragraphs, subsections, sections, articles etc. Therefore, to provide comprehensive relevance assessment for an XML test collection, *it is necessary to obtain assessment for the different levels of granularity.*

This means that if you find, say, a section of an article relevant to the topic of the request, you will then need to provide assessment - both with regards to exhaustivity and specificity - for the found relevant component, for all its ascendant elements until you reach the article component, and for all its descendant elements until you have identified all relevant sub-components.

Such comprehensive assessments are necessary as it is demonstrated by the following example. Consider the XML structure in Figure 1. Let us say that you judged Section C, the document component that encapsulates all text fragments relevant to the topic, as highly exhaustive (e-value 3) and fairly specific (s-value 2). Given only this single assessment it would not be possible to deduce the exhaustivity and specificity levels of the ascending or descending elements. For example, Body D and Article E may be judged fairly or marginally specific depending on the volume of additional, irrelevant information contained within the sections other than Section C. Looking at the sub-components of Section C, it is clear that no conclusions can be drawn from Section C's assessment regarding the exhaustivity or specificity levels of its sub-components. For instance, both Sub-Sections A and B may be marginally, fairly or highly exhaustive, and smaller components, such as Paragraph 3, could even be irrelevant.

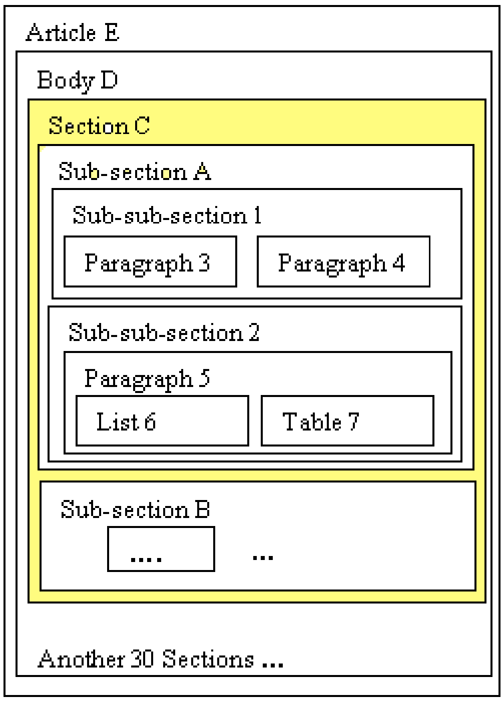


Figure 1. Example XML structure and result element

As a general rule it can be said that the exhaustivity level of a parent element is always equal to or greater than the exhaustivity level of its children elements. This is due to the cumulative characteristics of exhaustiveness. For example, the parent of a highly exhaustive element will always be highly exhaustive since the child element already discusses all or most aspects of the topic. Another rule for the exhaustivity dimension is that the parent of non-exhaustive child elements (i.e. all with e-value 0) will also be not exhaustive (e-value 0). A rule regarding specificity is that an element has an s-value that is greater than 0 if one of its child elements has an s-value different from 0, and less or equal to the maximum s-value of all its child elements. For instance, suppose that a parent element has tiny child element with s-value 1 and a large child element with s-value 2, then the s-value of that parent element will be 1 or 2. However, besides these general rules, no specific rules exist that would automate all the assessment of ascendant and descendant elements of relevant components. Therefore, you will need to explicitly judge all elements that contain relevant information. This is the only way to ensure both exhaustive and consistent relevance assessments.

4. How to judge

To assess the exhaustivity and specificity of document components, we recommend a three-pass approach.

- During the first pass, you should skim-read the whole article (that a result element is a part of - even if the result element itself is not relevant!) and identify any relevant information as you go along. The on-line system will assist you in this task by highlighting keywords within the article (see Section 5).
- In the second pass, you should assess the exhaustivity and specificity of the relevant components (i.e. identified in the first phase), and that of their ascendant and descendant XML elements.
- To ensure exhaustive assessments, in the third phase, you should assess the exhaustivity and specificity of the descendant XML elements of all elements that have been assessed as relevant during the second phase.

The on-line assessment system (see Section 5) will identify for you all elements that have to be assessed for phases 2 and 3.

During the relevance assessment of a given topic, all parts of the topic specification should be consulted in the following order of priority: narrative, topic description, topic title and keywords. The narrative should be treated as the most authoritative description of the user's information need, and hence it serves as the main point of reference against which relevance should be assessed. In case there is conflicting information between the narrative and other parts of a topic, the information contained in the narrative is decisive. The keywords should be used strictly as a source of possibly relevant cue words and hence only as a means of aiding your assessment. You should not rely only on the presence or absence of these keywords in document components to judge their relevance. It may be that a component contains some or maybe all the keywords, but is irrelevant to the topic of the request. Also, there may be components that contain none of the keywords yet are relevant to the topic. The same applies to the terms listed within the topic title!

In the case of content-and-structure (CAS) topics, the topic titles contain structural constraints in the form of XPath expressions. Although the structural conditions are there to impose a constraint on the structure, you are asked as an assessor to assess the elements returned for a CAS topic as whether they satisfy your information need (as specified by the topic) mainly with respect to the content criterion. Therefore, you should not assess an element as “not relevant” because the structural condition is not satisfied. In fact, your assessment of CAS topic should be very similar to that of content-only (CO) topics, although in the former the structural conditions may influence your assessment (to a small extent).

Note that some result elements are related to each other (ascendant/descendant), e.g. an article and some sections or paragraphs within the article. This should not influence your assessment. For example if the pooled result contains Chapter 1 and then Section 1.3, you should not assume that Section 1.3 is more relevant than Sections 1.1, 1.2, and 1.4, or that Chapter 1 is more relevant than Section 1.3 or vice versa. Remember that the pooled results are the product of different retrieval engines, which warrants no assumptions about the level of relevance based on the number of retrieved related components!

You should judge each document component on its own merits! That is, a document component is still relevant even if it the twentieth you have seen with the same information! It is imperative that you maintain consistency in your judgement during assessment. Referring to the topic text from time to time will help you maintain judgement consistency.

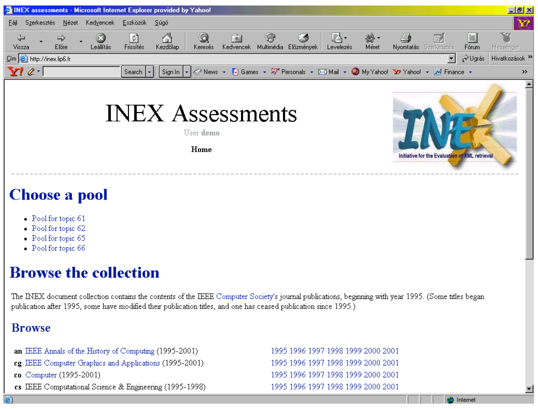
5. Using the on-line assessment system

There is an on-line relevance assessment system provided at:

http://inex.lip6.fr

which allows you to view the pooled result set of the topics assigned to you for assessment, to browse the IEEE-CS document collection and to record your assessments. Use your username and password to access this system.

After logging in, you will be presented with the Home page (see Figure 2) enlisting the topic ID numbers of the topics assigned to you for assessment (under the title "Choose a pool"). This page can always be reached by clicking on the **Home** link on any subsequent pages.


INEX assessments - Microsoft Internet Explorer provided by Yahoo!
Fájl Szerkesztés Nézet Kedvencek Eszközök Súgó
Vissza Előre Leállítás Frissítés Kezdőlap Keresés Kedvencek Multimédia Előzmények Levelezés Méret Nyomtatás Szerkesztés Fórum Messenger
Cím http://inex.lip6.fr
Ugrás Hivatkozások
Search Sign In News Games Personals Mail My Yahoo! Yahoo! Finance
Initiative for the Evaluation of XML retrieval
Internet

INEX Assessments

User demo

Home

Choose a pool

- Pool for topic 61
- Pool for topic 62
- Pool for topic 65
- Pool for topic 66

Browse the collection

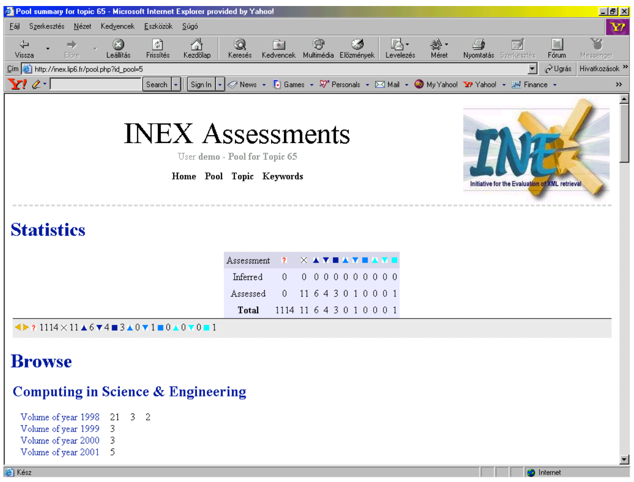
The INEX document collection contains the contents of the IEEE Computer Society's journal publications, beginning with year 1995. (Some titles began publication after 1995, some have modified their publication titles, and one has ceased publication since 1995.)

Browse

an	IEEE Annals of the History of Computing (1995-2001)	1995 1996 1997 1998 1999 2000 2001
cg	IEEE Computer Graphics and Applications (1995-2001)	1995 1996 1997 1998 1999 2000 2001
co	Computer (1995-2001)	1995 1996 1997 1998 1999 2000 2001
cs	IEEE Computational Science & Engineering (1995-1998)	1995 1996 1997 1998 1999 2000 2001

Figure 2. Home page of the assessment system

Clicking on a topic ID will display the pool main page for that topic (see Figure 3).


Pool summary for topic 65 - Microsoft Internet Explorer provided by Yahoo!
Fájl Szerkesztés Nézet Kedvencek Eszközök Súgó
Vissza Előre Leállítás Frissítés Kezdőlap Keresés Kedvencek Multimédia Előzmények Levelezés Méret Nyomtatás Szerkesztés Fórum Messenger
Cím http://inex.lip6.fr/pool.php?id_pool=5
Ugrás Hivatkozások
Search Sign In News Games Personals Mail My Yahoo! Yahoo! Finance
Initiative for the Evaluation of XML retrieval
Kész
Internet

INEX Assessments

User demo - Pool for Topic 65

Home Pool Topic Keywords

Statistics

Assessment	?	×	▲	▼	■	▲	▼	■	▲	▼	■
Inferred	0	0	0	0	0	0	0	0	0	0	0
Assessed	0	11	6	4	3	0	1	0	0	0	1
Total	1114	11	6	4	3	0	1	0	0	0	1

◀ ▶ ? 1114 × 11 ▲ 6 ▼ 4 ■ 3 ▲ 0 ▼ 1 ■ 0 ▲ 0 ▼ 0 ■ 1

Browse

Computing in Science & Engineering

Volume of year 1998	21	3	2
Volume of year 1999	3		
Volume of year 2000	3		
Volume of year 2001	5		

Figure 3. Pool main page

At the top of the pool main page the following links are shown: **Home**, **Pool**, **Topic** and **Keywords**. By clicking on the **Pool** link you can always return to this starting main pool page during your work. By selecting the **Topic** link you can display the topic text in a popup window. This is useful as it allows you to refer to the topic at any time during your assessment. The **Keywords** link allows you to edit a list of *coloured keywords* (cue words or phrases). This feature allows you to specify a list of words or phrases to be highlighted when viewing the contents of an article during assessment. These cue words or phrases can help you in locating potentially relevant texts within an article and will aid you in speeding up your assessment (so add as many relevant cue words as you can think of)! You may edit, add to or delete your list of keywords at any time during your assessment (remember, however, to reload the currently assessed document to reflect the changes). You may also specify the preferred highlighting colour for each and every keyword. After selecting the Keywords link, a popup window will appear showing a table of coloured cells. A border surrounding a cell signifies a colour that is already used for highlighting some keywords. You can move the mouse cursor over this cell to display the list of keywords that will be highlighted in that colour. To edit the list of words or phrases for a given colour, click on the cell of your choice. You will be prompted to enter a list of words or phrases (one per line) to highlight. Note that the words or phrases you specify will be matched against the text in the assessed documents in their exact form, i.e. no stemming is performed.

In the on-line assessment system, the following scheme is used:

1. *Exhaustivity level* is displayed in different shades of blue.
2. Geometric shapes are used for *specificity level*.

The tables below show the different icons used to indicate the relevance value of an XML element.

?	Element to assess
✗	Element is not relevant

Exhaustivity	Highly exhaustive	Fairly exhaustive	Marginally exhaustive
Specificity			
Highly specific	■	■	■
Fairly specific	▼	▼	▼
Marginally specific	▲	▲	▲

Table 1: Icons used to indicate relevance values

Note that all icons except the ? icon can be used by assessors to specify the relevance value (the exhaustivity and specificity level) of an element. The ? icon is used by the on-line assessment system only to mark components that need to be assessed.

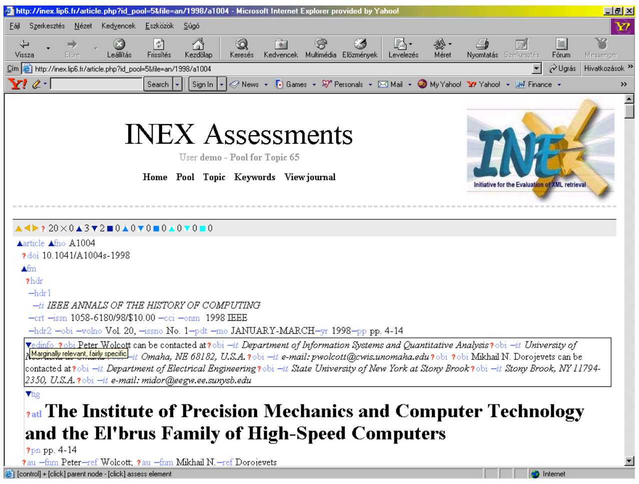
This year, the assessment system makes use of two types of inference mechanisms to ensure exhaustive and consistent assessments: we refer to these as passive and active inferences. The passive type simply identifies new elements to be assessed based on those already assessed. For example, for any relevant element (e.g. any component assessed other than "not relevant"), the relevance of its child elements must be assessed, even if these were not part of the original assessment pool (i.e. have not been retrieved). With the application of the passive inference rules, these need-to-be-assessed components will be marked with the ? icon. Unlike the passive rules, the active inference rules are able to derive the relevance value of some elements. These inferred relevance values will be marked using a red border. For example, ⊠ denotes "inferred as not relevant", which is assigned to a component if all its child elements have been assessed as "not relevant".

The on-line assessment system provides three main views:

1. The pool view
2. The volume view
3. The article view

In each of these views, a *status bar* appears at the bottom of the window and shows statistics on the current view: how many elements have been assessed as highly exhaustive and highly specific, as highly exhaustive and fairly specific, etc; how many elements have been assessed as not relevant (□); and how many elements remain to be assessed (?). Only when no more elements remain to be assessed is the assessment for that view (pool / volume / article) complete.

In the status bar, three arrows may be used to navigate quickly between the elements to be assessed. The *up arrow* enables you to move from the article view to the volume view or from the volume view to the pool view (you move in the opposite direction by selecting a volume and then an article from the displayed lists). The *left arrow* can be used to go to the previous element to be assessed, while the *right arrow* to go to the next element to be assessed.


http://inex.lip6.fr/article.php?id_pool=5&file=an/1998/a1004 - Microsoft Internet Explorer provided by Yahoo!
Fájl Szerkesztés Nézet Kedvencek Eszközök Súgó
Vissza Előre Leállítás Frissítés Kezdőlap Keresés Kedvencek Multimédia Előzmények Levelezés Méret Nyomtatás Szerkesztés Fórum Messenger
Cím http://inex.lip6.fr/article.php?id_pool=5&file=an/1998/a1004
Ugrás Hivatkozások
Search Sign In News Games Personals Mail My Yahoo! Yahoo! Finance
Initiative for the Evaluation of XML retrieval
Internet

INEX Assessments

User demo - Pool for Topic 65

Home Pool Topic Keywords View journal

▲◀▶? 20 × 0 ▲ 3 ▼ 2 ■ 0 ▲ 0 ▼ 0 ■ 0 ▲ 0 ▼ 0 ■ 0

▲article ▲fno A1004
?doi 10.1041/A1004s-1998
▲fm
?hdr
–hdr1
–ti *IEEE ANNALS OF THE HISTORY OF COMPUTING*
–crt –issn 1058-6180/98/$10.00 –cci –onm 1998 IEEE
–hdr2 –obi –volno Vol. 20, –issno No. 1–pdt –mo JANUARY-MARCH–yr 1998–pp pp. 4-14
▼edinfo ?obi Peter Wolcott can be contacted at ?obi –it *Department of Information Systems and Quantitative Analysis* ?obi –it *University of* Marginally relevant, fairly specific –it *Omaha, NE 68182, U.S.A.* ?obi –it *e-mail: pwolcott@cwis.unomaha.edu* ?obi ?obi Mikhail N. Dorojevets can be contacted at ?obi –it *Department of Electrical Engineering* ?obi –it *State University of New York at Stony Brook* ?obi –it *Stony Brook, NY 11794-2350, U.S.A.* ?obi –it *e-mail: midor@eegw.ee.sunysb.edu*
▼tig
?atl **The Institute of Precision Mechanics and Computer Technology and the El'brus Family of High-Speed Computers**
?pn pp. 4-14
?au –fnm Peter–ref Wolcott; ?au –fnm Mikhail N.–ref Dorojevets

[control] + [click] parent node - [click] assess element

Figure 4. Article view

It is in the article view that elements can be assessed. The article view displays all the elements that form an article, whether these elements are to be assessed or not. In addition, the article view (see Figure 4) shows every XML tag in the article but tries to keep an eye-friendly view of the article. XML tags are displayed between brackets, in light blue, and according to their given (or inferred) assessments when applicable. For instance, an <abs> tag that has been assessed as "highly exhaustive and fairly specific" is displayed as follows:

[▼abs]

The mouse cursor becomes a cross when it is held over an XML tag name. You can then:

- Control-click to scroll to the parent element. The parent element will be highlighted in less than a second (in red).
- Click to display the assessment panel for the element. The assessment panel has three components: the path (first line), the current assessment (second line), and the set of 11 icons (reflecting all possible assignments shown in Table 1). Forbidden assessments (e.g. assessing a parent element as not relevant where one of its child elements is relevant) are displayed in a grey box. To assess the current element, click on the icon with the corresponding relevance value. To hide the panel, click anywhere else in the panel.

Note that you do not need to save your relevance assessments, as the on-line assessment system will automatically do this.

Acknowledgements

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