ICTNET at Session Track TREC2014

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1 Introduction

In this paper, we describe our solutions of the Session Track at TREC 2014. Our main idea is to re-rank the documents the official supplies as RL1. In order to get good results of the re-ranked documents, we implement the learning to rank model which needs to extract some features. We use the relevance judgments of Session Track TREC 2013 as training set this year and also we use it as testing set by 5-fold cross-validation.

The rest of this paper is organized as follows. We detail our models in section 2. Section 3 describes our experiments, including our evaluation results. Conclusions are made in the last session.

2 Our Approach

In our work, we use some methods to utilizing the session information to improve the re-ranking results. We use the official's original RL1 as baseline and our goal is to re-rank the RL1 by using learning to rank model which needs to extract some features from the documents and the sessions.

2.1 Query Expansion(QE)

We use our method of query expansion in 2012[1]. A session may consist of several queries. The final expanded query consists of all the terms both in the historical queries and the current query. Let q_1 to q_{m-1} stand for previous queries and q_m stands for the current query. Then *Weight*(w, q) stands for the weight of word w in the final query q. We can calculate it as followed:

$$Weight(w,q) = \exp(d \cdot \max_{w \in q_i}\{i\}).$$

The later the word appears in the session, the more important it is. We set the parameter d as 0.05. The QE feature of the document is obtained by calculating the Weighted-BM25 score between the document and the expanded query.

2.2 Visual Document Model(VDM)

As we can get some documents in the session which may be relevant about the topic, then we can gather all the documents in the session and use the titles and contents of the documents to form a visual document. Then we use cosine similarity between the text formed by the current document's title and content and the visual document as VDM feature.

2.3 User's Attention Time(UAT)

User's attention time is very important in judging if the document is relevant[2]. We know that in the session some documents are clicked by the users while most of others are not. For each document d which is not clicked, we can estimate its UAT feature by using all the clicked documents d_j in the session as followed:

$$UTA(d) = \sum_j (UAT(d_j) \cdot CosSim(d, d_j)).$$

2.4 Learning to Rank

We use learning to rank model to incorporate the features extracted from documents and sessions. The SVMrank[3] is used to get a score for each candidate document and at last we re-ranking them depends on these scores.

2.5 RL2 and RL3

For RL2, we use only the current session while for RL3, we use all the sessions which have the same topic as the current session. All the methods that extract features have the flexibility. So for a document, if we can calculate its feature score according to one session, we can calculate its feature score according to all the sessions that have the same topic with the current session. All the features we used are shown in Table 1.

Table 1: Features used in SVMrank

Feature	Feature description
PageRank	The page rank score of the document.
QE	The query expansion score of the document.
SVD	The score of the session visual document model.
UAT	The score of user attention time model.
BM25QC	The BM25 score of the document's content and query.
CosSimQT	The cosine similarity score between the document's title and the query.
Clicked	If the document is clicked in the session, the score is 1. Otherwise it is 0.

3 Experiments

We use the relevance judgments of Session Track TREC 2013 as training set. As the material is not large, we use five-fold cross-validation to get the nDCG@10.

3.1 Experiment Setup

In the process of re-ranking the documents in RL1, we remove the stop words of each document and we do stemming as well.

3.2 Runs

There are three runs named ICTNET14SER1, ICTNET14SER2 and ICTNET14SER3. Each run's features are shown in Table 2.

Table 2: Used features of each RUN

	ICTNET14SER1	ICTNET14SER2	ICTNET14SER3
RL2	PageRank, QE, SVD, UAT, BM25QC, CosSimQT, Clicked	BM25QC, CosSimQT, SVD, QE	CosSimQT, SVD, QE, UAT
RL3	The same as above except that it use all the sessions that have the same topic with current session.	The same as above except that it use all the sessions that have the same topic with current session.	The same as above except that it use all the sessions that have the same topic with current session.

3.3 Results

Our finally results of nDCG@10 are shown in Table 3.

Table 3: Performance of Session track, TREC 2014

	ICTNET14SER1	ICTNET14SER2	ICTNET14SER3
RL1	**0.1890**	**0.1890**	**0.1890**
RL2	**0.2357**	**0.1976**	**0.2288**
RL3	**0.2431**	**0.2045**	**0.2356**

4 Conclusions

In this paper, we presented several approaches to verify whether a retrieve system can use increasing amounts of information prior to a query to improve effectiveness for that query. Firstly, we extract some features from the documents and the sessions. Then the learning to rank model is used to re-rank the candidate documents of the session.

For the future work, we would like to try to incorporate more features into the learning to rank model, e.g. the order of the clicked document in the page. Feature selection and parameter optimization would also choose to get better performance.

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6 References

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