A New Metric To Evaluate Ontology Modularization

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Abstract. As ontologies are the backbone of the Semantic Web, they attract much attention from researchers and engineers in many domains. This results in an increasing number of ontologies and semantic web applications. The number and complexity of such ontologies makes it hard for developers of ontologies and tools to decide which ontologies to use and reuse. To simplify the problem, a modularization algorithm can be used to partition ontologies into sets of modules. In order to evaluate the quality of modularization, we propose a new evaluation metric that quantifies the goodness of ontology modularization. In particular, we investigate the ontology module homogeneity, which assesses module cohesion, and the ontology module heterogeneity, which appraises module coupling. The experimental results demonstrate that the proposed metric is effective.

Keywords: Semantic Web, Ontology, Modularization, Evaluation metrics

1 Introduction

Ontologies represent the essential technology that enables and facilitates interoperability at the semantic level, providing a formal conceptualization of the data which can be shared, reused, and aligned. Therefore, ontologies have been attracting much attention of researchers and engineers in many fields such as knowledge management [11,12], semantic search [20], etc. As a result, there is a myriad of developed ontologies. For example, the National Center for Biomedical Ontology (NCBO) BioPortal [4] contains more than five hundred biomedical ontologies and controlled vocabularies [7].

With this large number of existing ontologies it becomes obvious that use/reuse of an existing ontology is preferable to building the ontology from scratch. However, large-scale ontologies are difficult to reuse [16]. Therefore, modularizing ontologies and reusing only part(s) of the ontologies appropriate for a given context are necessary approaches. Techniques for ontology modularization and

[4] http://bioportal.bioontology.org/

module integration are an effective way to build ontologies. Several tools for ontology modularization have been proposed and users employ these tools to prepare ontology-based systems [4,6,19,23].

The quality of an ontology (module) can be defined as the degree of conformance to functional and non-functional requirements [7]. This degree should be measurable. Current studies of the evaluation of modularization approaches focus on modularization algorithms and the evaluation of the taxonomical structure of a created module [16]. According to [8], ontology evaluation determines the quality and adequacy of an ontology for reuse in a specific context for a specific goal. The evaluation of ontology is crucial in many fields, however, we observe that the high cohesion and low coupling are the measures for the ontology evaluation, but they do not have a unique or specific definition.

Therefore, in this paper, we propose a new ontology modularization evaluation metric that can be used to assess the goodness of ontology modules. In particular, we propose the module homogeneity ($MOHO$) as a metric of the internal characteristics of module concepts, and the module heterogeneity ($MOHE$) as an assessment of interdependency between ontology modules. The $MOHO$ metric will exploit semantic and structural characteristics of module concepts, including concept names, the distances between concepts and the number of trees generated from modularization. On the other hand, the $MOHE$ metric will cover different aspects of relations between modules. According to our investigation, we discover that the proposed individual criteria accurately determine the cohesion of a module as well as the coupling between modules. Firstly, the size of module element is directly effected on cohesion, but we think it depends on individual classes, so we count the *lexical level* of each module to a measure for the module homogeneity. Secondly, the more connected concepts within the same module show how the high module homogeneity, therefore we count the number of connected concepts and namely the *number of trees*, since each tree shows one one connected component of concepts. Thirdly, the *depth of concepts* is an important aspect during the evaluation of the module homogeneity. The more the concepts within the same module are close to each other, the more module is cohesive. Lastly, one important issue when we partition one ontology is how many edges will be cut. Therefore, in the current development, we consider these individual and other evaluation metrics. We carried out a set of experiments to validate the proposed metric and the experimental results show that is valid and effective within the context of our partitioning tool [2].

Even if the main objective of the proposed metric is to evaluate the ontology modularization, it could be useful and can be used in many different scenarios. For example, it can be useful to ontology assessment to provide some insight to ontology developers to help them design ontologies, improve ontology quality, anticipate and reduce future maintenance requirements, as well as help ontology users choose the ontologies that best meet their needs.

The rest of the paper is organized as follows: we present a set of definitions and preliminaries used throughout the paper and a set of related work in Section

2. The proposed metric will be introduced in Section 3. Section 4 reports on the experimental results. Section 5 concludes the work.

2 Background

This section is devoted first to present basic definitions that will be used throughout the paper, and then to present related work.

2.1 Preliminaries

Let $\mathcal{O}$ be an *ontology* comprising of a set of axioms (classes, properties, relationships,) and $\sum(\mathcal{O})$ represent the signature of the ontology constituting a set of entity names occurring in the axioms of $\mathcal{O}$, i.e., its vocabulary [19]. In our implementation, each ontology is parsed and inferred by Apache Jena[5] and then the corresponding concept graph is drawn by mapping the inferred result. We define a *concept graph* $\mathcal{G} = (\mathcal{C}, \mathcal{R}, \mathcal{L})$ as a labeled directed graph, where $\mathcal{C} = \{c_1, c_2, ..., c_n\}$ is a finite set of nodes presenting the concepts of the ontology, i.e. its classes and data properties. $\mathcal{R} = \{r_1, r_2, ..., r_m\}$ stands for a finite set of directed edges showing various relationships between concepts in the ontology $\mathcal{O}$, such that $r_k \in \mathcal{R}$ represents a directed relation between two adjacent concepts $c_i, c_j \in \mathcal{C}$. $\mathcal{L}$ is a finite set of labels of graph nodes defining the properties of each concept, such as the names of concepts.

In general, ontology modularization covers the problem of identifying a fragment or a set of fragments of an ontology. The process of identifying a fragment of an ontology given a user input (request) is called *ontology module extraction* [10,21], while the process that partitions the ontology into a set of fragments is called *ontology partitioning* [2,3]. We define an *ontology module* $\mathcal{M}_i(\mathcal{O})$ of an ontology $\mathcal{O}$, with $\sum(\mathcal{M}_i) \subseteq \sum(\mathcal{O})$, such that $\mathcal{M}_i(\mathcal{O})$ contains the same information about the set of axioms of $\mathcal{M}_i$ as $\mathcal{O}$. In this paper, we consider the problem of evaluating the goodness of ontology partitioning techniques.

The ontology modularization process (partitioning) can be defined as follows: given an ontology $\mathcal{O}$ represented as a concept graph $\mathcal{G}$, the next step is to partition concepts, $\mathcal{C}$, of each graph into a set of modules $\mathcal{M}_1, \mathcal{M}_2, ..., \mathcal{M}_k$ such that the *cohesion* (module homogeneity) of concepts in one module should be high, while the *coupling* (module heterogeneity) between any two modules is low.

2.2 Related work

Ontology evaluation is a crucial task in different domains. Therefore, several approaches and metrics have been proposed and developed. Ma et.al [13] proposed a set of ontology metrics to measure ontology cohesion. These metrics are selected as the criteria of ontology measurement for ontology based systems. They include the number of ontology partitions, the number of minimally inconsistent subsets, the average impact of intra-module relationships, and the average depth

[5] https://jena.apache.org/

of maximum concept subsumption of leaf concept. These metrics have been integrated and implemented into an ontology measurement tool [14]. To evaluate the ontology modules, the approach in [17] introduces cohesion and coupling metrics based on the theory of software metrics.

Metrics to measure the complexity of ontologies, emphasising on the problem of increasing the complexity of maintenance and management as ontologies evolve have been proposed in [24]. The defined metrics are composed of primitive metrics and complexity metrics. Primitive metrics assess the basic level of information, including the total number of classes, relations, and paths. While, complex metrics quantify the average relations per concept, the average paths per concept, and the ratio of maximum path length to average path length of the ontology. These metrics examine the concept aggregation and coherence of an ontology. Orme et.al. [18] focused on the number of externally defined referenced concepts. They proposed a set of coupling metrics for ontology-based systems represented in OWL, such as the number of external classes, the reference to external classes, and referenced includes.

A formal definition of some helpful metrics is provided to analyze the coupling between classes in an ontology [9]. These metrics include coupling between entities (CBE) for ontologies with two possibilities. The CBE-out metric represents the coupling where the class belongs to the domain of the property, while CBE-in represents the coupling where the class belongs to the range of the property. Another evaluation framework has been proposed in [16], in which users can analyze and compare modularization tools. To design a new evaluation framework that enables the comparison of modularization tools, three perspectives of tool evaluation dimensions are proposed: modularization performance, data performance, and usability.

OntoQA [22] is a tool that implements a number of metrics such as richness, population, and cohesion. It proposes some schema metrics to measure the richness of schema relationships, attributes and schema inheritance. These metrics are focused on evaluating the ontology in general. Other proposed categories are class richness, average population, cohesion, the importance of a class, fullness of a class, class inheritance and class relationship richness, connectivity and readability. This work described two similar but not equal metrics. Class Relationship Richness is defined as the number of relationships that are being used by instances that belong to the class. On the other hand, the connectivity of a class is defined as the number of instances of other classes that are connected to instances of the selected class. The main differences are that these metrics take into account the instances belonging to the class instead of relations declared in the class.

3 Proposed Metric

To assess the goodness of the ontology modularization process, we introduce a new evaluation metric. To decide on the goodness of an ontology modularization approach, we need a set of metrics (evaluation criteria) that can be used to evaluate the cohesion and the coupling of the partitioning result. To this end,

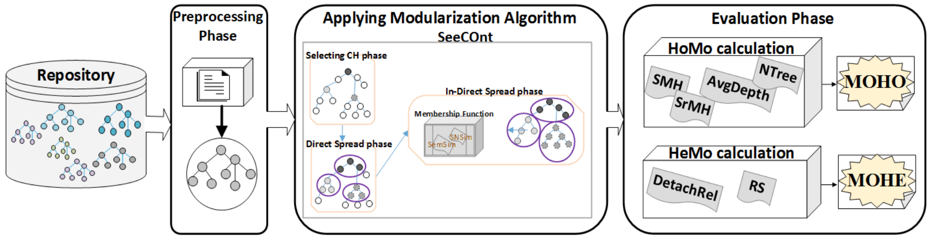

Fig. 1: OAPT partitioning framework.

we propose the module homogeneity ($MOHO$)metric as a criterion for the modularization coherence, and the module heterogeneity ($MOHE$) metric as a criterion for the modularization coupling. In the following, we first describe how to prepare ontology modules using our ontology partitioning tool [2] and then how to assess the goodness of ontology modularization using the proposed evaluation metrics.

3.1 Ontology modularization

There have been two major ways of modularizing ontologies: ontology partitioning and ontology module extraction. In partitioning-based approaches, the original ontology is usually divided into a number of modules, which are not necessarily disjointed. To cope with the ontology partitioning problem, we proposed and developed an ontology analysis and partitioning tool, called $OAPT$ [2], as shown in Fig.1. First, the input ontology is investigated and a set of ontology features is collected in order to guide the user if this ontology is worth to be modularized or not. After that the analyzed ontology will be partitioned using the specified modularization algorithm, called *SeeCOnt* [1]. To make this paper self-contained, we present a short description of the *SeeCOnt* approach. The approach has three main components: *preprocessing, ranking*, and *clustering*.

Each input/analyzed ontology is parsed and the corresponding concept graph is derived. After that, the approach starts to determine which nodes of the concept graph shall be selected as cluster (module) heads ($\mathcal{CH}s$). To this end, we propose a ranking function that quantifies the importance of nodes inside the concept graph. The next step is to select which concepts represent the cluster heads, $\mathcal{CH}$. If simply the nodes with the highest score are selected as the cluster heads, the distribution of these nodes within the concept graph would be disregarded. To avoid this problem, the distance between two cluster heads is measured, and among the highest score nodes, those with a specified distance from each other are selected as the cluster heads.

The final component of the *SeeCOnt* approach is to finalize the partitioning process. Once having decided upon the set of cluster heads ($\mathcal{CH}s$), the *SeeCOnt* approach creates one cluster for each cluster head. Then, it places direct children in the corresponding cluster and finally, for remaining nodes, a membership function is used to determine the appropriate cluster of each node.

Similar to *SeeCont*, various modularization methods have been developed and used. Because they are based on different assumptions and techniques, modules created by these methods are different. Consequently, it is difficult to compare them. Thus, useful measurements to evaluate modules are required.

3.2 Modularization Evaluation

In software engineering, there are many metrics that evaluate software modules. The most common two are coupling and cohesion, where cohesion represents the functionality of module and coupling represents the interdependency between pairs of modules [5,17]. Similar to software module metrics, ontology module metrics are designed to quantify ontology modules' properties. To this end, we propose module homogeneity ($MOHO$) to represent the module functionality and module heterogeneity ($MOHE$) to represent the module interdependency.

Module Homogeneity. To quantify the module homogeneity we pursue to evaluate semantic and structural characteristics of module concepts. Therefore, we propose the $MOHO$ metric to quantify the ontology modules homogeneity, which include the following individual metrics:

- **SMH metric.** A module comprises a set of concepts that represents a specific part of the domain. This means that the module should have a high cohesion. Semantic similarity measures can be used for different tasks such as term disambiguation and checking ontology for consistency and coherence [15]. Various lexical databases and dictionaries have been used to enhance the quality of these semantic metrics. We also make use of a semantic measure to evaluate the semantic consistency of concepts within a module. Given a module $\mathcal{M}_i = \{\mathcal{CH}, c_2, c_3, .., c_m\}$, with m concepts, where $\mathcal{CH}$ is the cluster head of the module, we use the following formula to compute the semantic module homogeneity (SMH):

$$SMH(\mathcal{M}_i) = \frac{1}{m-1} \sum_{j=2}^{m} SemSim(\mathcal{CH}, c_j) \tag{1}$$

  where $SemSim$ is the semantic similarity between the cluster head and the other concepts of the module, assuming that the cluster head represents the central of the module. Since the name of concepts are always represented by nouns, in this implementation, we consider the semantic relations between nouns. In general, we use the four common semantic relations: hyponym/hypernym (is-a), part meronym/part holonym (part-of), member meronym/member holonym (member-of) and substance meronym/substance holonym (substance-of) between module concepts.
- **SrMH metric.** We also evaluate the structural module homogeneity ($SrMH$) by measuring the distance between the cluster head and the other concepts within the module. It should be noted that this distance should be small

and ideally should be 0. For that, we use the following formula to compute $SrMH$

$$SrMH(\mathcal{M}_i) = \frac{1}{m-1}\sum_{j=2}^{m}\frac{1}{dist(\mathcal{CH}, c_j)} \tag{2}$$

where $dist(\mathcal{CH}, C_i)$ is the minimal path between $\mathcal{CH}$ and c_j.

- **AvgDepth.** It is also important to know what is the level of concepts in each module; checking how well module concepts are distributed. It can be used to measure the degree to which the semantic knowledge of an ontology to be measured is organized. Therefore, we propose the average depth of all concepts namely, **AvgDepth** which it shows in the following formula.

$$AvgDepth(\mathcal{M}_i) = \frac{\sum_{j=1}^{m} depth(c_j)}{m} \tag{3}$$

where $depth(C_j)$ is the path length of the concept c_j to the root of the concept graph.

- One more metric that can be used to validate the homogeneity of a module is the number of trees in each module, called **NTree**. It is a key issue that how many concepts are related to each other, or, are they separate from each other. So, we define one criterion to measure how many connected concepts exist in each module. If it is low, it shows the more cohesion. To compute this metric, we propose the following formula:

$$NTree(\mathcal{M}_i) = \frac{num\_of\_root\_concepts}{|\mathcal{M}_i|} \tag{4}$$

where $|\mathcal{M}_i|$ is the total number of concepts in a module $\mathcal{M}_i$.

By defining the individual metrics, we can define the combined module homogeneity metric ($MOHO$) as follows:

$$\begin{aligned} MOHO(\mathcal{M}_i) = w_1 \times SMH(\mathcal{M}_i) + w_2 \times SrMH(\mathcal{M}_i) \\ + w_3 \times AvgDepth(\mathcal{M}_i) + w_4 \times NTree(\mathcal{M}_i) \end{aligned} \tag{5}$$

where w_is are the weights to quantify each individual metric and $\sum_{i=1}^{4} w_i = 1$. Once computing the module homogeneity for each module, we can evaluate the homogeneity for the modularization process by defining the homogeneity of a modularization technique as follows:

$$\mathcal{MOHO}(\mathcal{M}) = \frac{1}{|\mathcal{O}|}\sum_{i=1}^{k} |\mathcal{M}_i| \times \mathcal{MOHO}(\mathcal{M}_i) \tag{6}$$

where k is the number of modules, $|\mathcal{M}_i|$ is the number of concepts in module i, and $|\mathcal{O}|$ is the total number of concepts in the original ontology.

Module Heterogeneity. To assess the module heterogeneity ($MOHE$), we quantify the interdependency between different modules. Therefore, we consider the following metrics:

– **Relative size (RS).** The heterogeneity metric evaluates the coupling between ontology modules. The higher the coupling between modules the higher the relatedness between them. It is a desirable property to keep ontology modules loosely coupled in order to be independently used. Given an ontology $\mathcal{O}$ modularized into a set of modules $\{\mathcal{M}_1, \mathcal{M}_2, \mathcal{M}_3, .., \mathcal{M}_k\}$. The first metric can be used to constitute $MOHE$ metric is the relative size. By the relative size, we ensure that the ontology concepts are "normally" distributed among the modules. To determine the relative size of modularization, we use the following formula:

$$RS(\mathcal{M}) = \frac{1}{k \times |\mathcal{O}|} \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} ||\mathcal{M}_i| - |\mathcal{M}_j|| \tag{7}$$

where $|\mathcal{M}_i|$ and $|\mathcal{O}|$ are the module and ontology sizes, respectively.

– **DetachRel.** Even if the relative size of concepts within ontology modules can be consider as a good indicator of how these concepts are distributed among the modules, however, we need another metric that quantifies the relationships between modules. If there is a concept $c_j \in \mathcal{M}_i$ such that all the properties (relations) of the concepts are belonging to the same module, then the module has a high cohesion and low coupling. However, in the contrast, if concept $c_l \in \mathcal{M}_j$ has some connected concepts in the other modules, i.e. $property(c_l) \in c_i \in \mathcal{M}_g$, $g \neq j$, it shows high coupling for $c_l \in \mathcal{M}_j$. Therefore, we propose the deployment of the number of detached relations between concepts (properties) as one of the coupling measure [17]. To compute such a metric, we define **DetachRel** as given in the following formula:

$$DetachRel(\mathcal{M}) = \frac{1}{k} \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} \frac{|r_{\mathcal{M}_i} \cap r_{\mathcal{M}_j}|}{|r_{\mathcal{M}_i} \cup r_{\mathcal{M}_j}|} \tag{8}$$

where $|r_{\mathcal{M}_i} \cap r_{\mathcal{M}_j}|$ is the number of relations exist in both modules $\mathcal{M}_i$ and $\mathcal{M}_j$.

4 Experimental Evaluation

We conducted a set of experiments to demonstrate that the proposed evaluation metrics are valid and effective within the context of our partitioning tool. To perform such evaluation, we collected a set of ontologies from the BioPortal repository[6] and the ontology search using some generic keywords. The collected ontologies represent different domains and have different characteristics, as shown in Table 1.

[6] http://bioportal.bioontology.org/

Table 1: Data set specification.

Ontology	*Domain*	*No. of class*	*No. of properties*	*No. of modules*
GFO	general	44	41	4
BCO	biological	126	203	4
mouse_anatomy	anatomy	2746	1	12
nci_anatomy	anatomy	3304	2	25
ENVO	environment	2159	4	16
OBOOE	Observation	630	32	8
PW	Pathway	2067	1	22
Delegation	Grip_computing	17	23	1
Koala	human	19	6	1
Dolce_lite	Dolce	36	71	1
HarryPotter	book	16	6	1
Conference	conference	58	65	1
Monetary	economic	38	28	4
Philosurfical	philosophy	376	314	10

4.1 Experimental Results

To prepare ontology modules for evaluation, we apply our modularization approach to partition the ontologies listed in Table 1. The module homogeneity ($MOHO$) as well as the module heterogeneity ($MOHE$) have been recorded and reported.

Module Homogeneity. We carried out this set of experiments to evaluate the quality of module homogeneity metrics. We applied our modularization approach to the set of ontologies listed in Table 1. The optimal number of modules for each ontology generated using our partitioning tool has been identified and listed into the table, too. First, we get the results for each individual $MOHO$ metric, such as SMH and the average module homogeneity has been computed using Eq.5. Results are reported in Figs. 2& 3. The results show, in general, that most of the tested ontologies have module homogeneity values greater than 0.2, which can be considered as a high value due to the involvement of several aspects to compute the module homogeneity. Secondly, ontologies partitioned only to one module have the higher $MOHO$ values. Furthermore, we observe that ontologies belonging to the bio-domain have zero value for SMH, since we are currently using the WordNet dictionary, which is more generic dictionary and it fails semantics relationships between concepts from the bio-domain.

Module Heterogeneity. In this set of experiments, we validate the module heterogeneity metric. We applied our modularization approach to the set of ontologies in Table 1 and computed both module heterogeneity metrics: relative size (RS) and DetachRel (Dat). Results are reported in Fig. 4. In general and as expected, ontologies partitioned only to one module have $MOHE$ values of 0 for both metrics. The figure also shows that RS indicates that the ontology concepts are nearly equally distributed between ontology modules, except BCO,

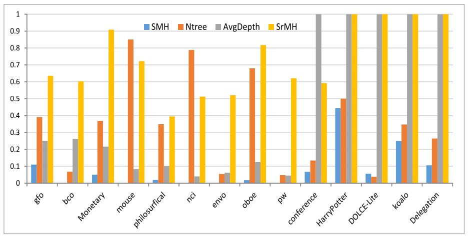

Fig. 2: Individual MOHO metrics.

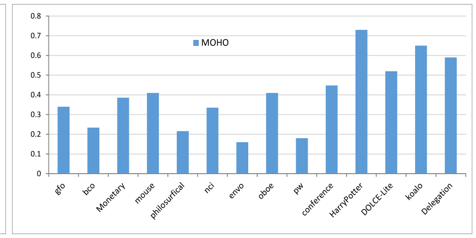

Fig. 3: Combined MOHO.

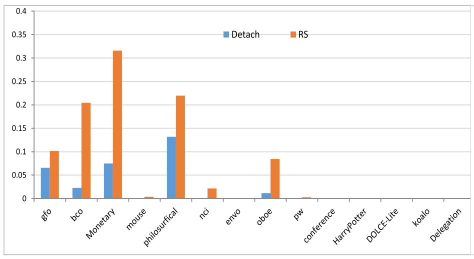

Fig. 4: DataechRel and RS.

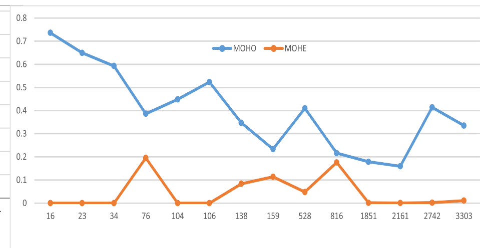

Fig. 5: Comparing MOHO and MOHE.

Monetary, and Philosurfical ontologies. It also indicates that this modularization approach produces the minimum overlap ($Detch$) between ontology modules, i.e. less coupling, except the Philosurfical ontology.

Furthermore, we study the relationships between $MOHO$ and $MOHE$ metrics and the size of ontology (listed in Table 1). Results are reported in Fig. 5. In general, for small size ontologies, the modularization has higher $MOHO$ (more coherent modules) and lower $MOHE$ (less coupled modules) except for the Monetary ontology. As the ontology size increases the $MOHO$ and $MOHE$ values decrease and are nearly constant, respectively.

5 Conclusion

In this paper, we introduced a new ontology modularization evaluation metric. We offer the module homogeneity metric to assess the module cohesion, while we propose the module heterogeneity metric to quantify the coupling between modules. To validate, the proposed metrics, we carried out a set of experiments utilizing ontologies from different domains. The experimental results demonstrate that the metric is effective. In the future, we plan to exploit different and domain specific dictionaries during the evaluation of the semantic module homogeneity. Furthermore, we plan to investigate relationships between the evaluation metrics and different parameters of the modularization approach.

Acknowledgments

This work is partly funded by DFG in the INFRA1 project of CRC AquaDiva.

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