

The Evaluation of Ontology Matching versus Text

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Lately, the ontologies have become more and more complex, and they are used in different domains. Some of the ontologies are domain independent; some are specific to a domain. In the case of text processing and information retrieval, it is important to identify the corresponding ontology to a specific text. If the ontology is of a great scale, only a part of it may be reflected in the natural language text. This article presents metrics which evaluate the degree in which an ontology matches a natural language text, from word counting metrics to text entailment based metrics.

Keywords: *Ontology, Natural Language Processing, Metric*

1 Introduction

The ontologies importance has increased in the last years, mostly because ontologies represent a computer understandable form to represent information [1], and so, the computer is able to answer rapidly to the user's questions. The main applications of the ontologies are in the field of semantic web and question answering [2].

This is the main reason for the developing ontologies, in various domains, such as the biomedical domain [3], and in various forms, from manual way, the work of different specialists or volunteers [4], to semi-automatic [5] and automatic ways [6].

Their usage will increase, since there are a lot of high quality [7] ontologies. Usually, an ontology is specific to a given domain. In some recent papers [8], [9], the problem of enriching an ontology was discussed. But, by continuously enriching an ontology, it can become very large, and it can contain parts which are not relevant for a specific task, such as the processing of a natural language text. This is why the following question has to be answered: which ontology corresponds to a specific text, in which amount, or which parts of it. For this problem I propose in this article a set of metrics, some with natural language processing roots.

2 Ontology

An ontology is a rigorous and exhaustive organization of some knowledge domain that is

usually hierarchical and contains all the relevant entities and their relations [10], or, "An explicit specification of a conceptualization." [11]. There are different kinds of ontologies, from the simplest ones, close to a natural language description, to the formal ones. But the most formal ones have the most applicability [12] [13].

After Alexander Maedche and Steffen Staab, the ontology learning approaches focus on the type of input: ontology learning from text, from dictionary, from knowledge base, from semi-structured schemata and from relational schemata [14].

Ontologies also differ in respect to the scope and purpose of their content. The most prominent distinction is between the domain ontologies describing specific fields of endeavor, like economics, and upper level ontologies describing the basic concepts and relationships invoked when information about any domain is expressed in natural language [15]. Usually the domain ontology is subordinated to the upper level ontology [16] (see Figure 1).

From the representation point of view, one type of ontology is the taxonomy. A taxonomy is a hierarchical classification of terms. The relation between two terms, a parent and a child, is usually an "is a" relation. The terms can also be characterized by a set of properties.

But the most general way to define an ontology is by using triplets [17]. A triplet is com-

posed from a subject or the concept, the predicate, which is a directional relation and the object, which is a characteristic. The relation and the characteristic can also be in their turn concepts. Any type of ontology can be represented in the triplet form, even if the ontology is a taxonomy or it has an integrate graph type structure.

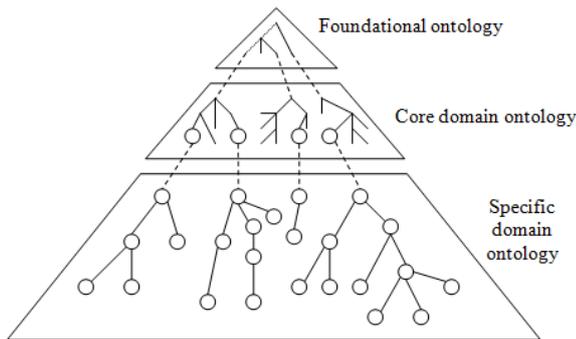


Fig. 1. The tree levels of generality in a domain ontology [16]

3 Ontology Evaluation

Considering the different types of learned ontologies and the way in which they were obtained, a quality assurance mean must be enforced. In this field a lot of work was done, for instance in [18], where the ontology quality assurance metrics are classified in three types:

- *structural measures*, which focus on the syntax of the ontology graph and the formal semantics (depth, breadth, tangledness, leaf cardinality, density, modularity, and others),
- *functional measures*, focusing on the relations holding between the ontology graph and its intended meaning (precision, recall, accuracy all in regard with the intended meaning, which differ from case to case: agreement assessment, topic assessment, modularity assessment, and so on), and
- *usability-profiling measures*, focusing on the ontology profile, which typically addresses the communication context of an ontology (lexical annotation of the ontology elements, compatibility, ...)

In [19], the ontology evaluation metrics are classified as:

- *size metrics* (number of classes, of properties, ...)
- *structural metrics* (number of roots, number of leafs, maximum depth of a sub-tree,...)
- *summarization metrics* (relative to an element: the depth where it's located, number of children, number of parents, and so on)

Regarding the ontology alignment, this problem is solved usually by similarity measures, mostly string similarities measures [20], [21]. The ontology matching versus text belongs to the second category, so the following proposed metrics will be precision and recall of the proposed matching criteria.

4 Related Work

The need to identify the proper ontology for a given task was discussed in different articles. In [22] the ontologies are searched and evaluated regarding a set of keywords. In [23], is proposed a framework for selecting the appropriate ontology for a particular biomedical text mining application. Another similar paper is [24], which uses some similarities metrics and machine learning techniques, based on the names, context, constraints and labels.

5 Metrics for the Evaluation of Ontology Matching versus a Natural Language Text

So, there are a lot of ontologies, many of which being continuously enriched. But, from the point of view of natural language processing, the following question has to be answered: Which ontology is the best ontology to be used for a particular text, and, which part of the ontology. In order to find this answer, I propose the usage of the some ontology evaluation metrics.

Whatever is the type of an ontology, even if it is only a simple taxonomy, the ontology contains a set of concepts. So, the first proposed metrics in this article will evaluate how many of the existing concepts can be found in the natural language text.

Because all kind of ontologies can be represented in the triplet form, the ontology is considered to be in the triplet form.

The recognition of textual entailment is one of the most complex tasks in natural language processing (NLP) and the progress on this task is the key to many applications such as Question Answering, Information Extraction, Information Retrieval, Text Summarization, and others [25]. In the following I propose the use of the text entailment relation to evaluate the degree in which an ontology matches a text, because the elements which compose an ontology are words, which belongs to a natural language, and the triplets can be seen as very simple sentences.

5.1 Quantitative Metrics

The simplest ontology matching to the text technique is to search the concepts in the text. So, the first proposed metric, similar to an ontology quality metric and to an ontologies matching technique is the *number of concepts found in the text*. Because the concepts can appear in the text both in singular as in plural form, I consider that the concept was found in the text if is found at least one word which starts with the same letters.

Some derived metrics can be evaluated in a similar manner: *the number of roots found in the text*, *the number of leafs found in the text*, and the list can continue.

All this metrics evaluates the number of distinct concepts, roots, leafs. Because the ontologies are in the triple format, the concepts appear more than one time. The roots are those concepts which appear only in the left parts of the triplets, and the leafs are the concepts which appear only in the right parts of the triplets.

This metric doesn't take into account the relations between the concepts. But the next metric use also the relations in the evaluation process.

To exemplify the proposed metrics, let's suppose that we have two triplets: "business is a kind of enterprise", "business has particulars house" [26] and the natural language sentence: "A guest house represents a small business". From those two triplets, three concepts are identified: "business" (the root), "enterprise" and "house" (the leafs). In the text, only business and house are found, so,

number of concepts found in the text is 2, *the number of roots found in the text* is 1, and *the number of leafs found in the text* is also 1.

5.2 Text Entailment Base Metrics

In the last period of time, the text entailment evaluation techniques have improved. An important encouraging role in this improvement is hold by the Recognizing Textual Entailment Challenges [27], which have supplied a set of training data, and reward the best obtained result.

So, the logical consequence relation, or the entailment relation can be used as a viable evaluation technique for other processes. This is the reason for which I propose the use of text entailment in order to evaluate the ontology matching with a text. And the reason is simple, as the most simple and popular way to represent an ontology is by using a triplet. A triplet is composed from a concept, a predicate and an object, so is similar with a simple sentence, which is usually composed from a subject, a predicate and an object.

But, a simple question is arisen: how can be used the text entailment relation in order to check if the ontology matches the natural language text? By checking if the text implies the ontology (ontology triple), or by checking if the ontology (ontology triple) implies the text? The answer must be searched in the definition of the text entailment relation, and in its directionality. Between two natural language texts, T respectively H , exists a text entailment relation, $T \rightarrow H$, if the meaning of H can be inferred from the meaning of T [25]. If the goal is to search if an ontology matches a text, then the second answer is the searched one. The use of text entailment relation in the ontology versus text matching process is by checking if the ontology, or bits of the ontology entails the natural language text.

So, the text entailment can be used to compare the entire ontology, seen as a big text with the target text, or only a part of it, searching if the relation holds between a triplet seen as a sentence and the target text. I named the two metrics: *entailment* (the ontology entails the text), respectively *number*

of entailments (how many triplets from the ontology entails the text). In the same time, it is interesting to see how many sentences are entailed by an ontology triplet, and so, I propose a third measure, *the number of entailed sentences* (every sentence entailed by a different triplet is numbered), and *the number of distinct entailed sentences* (only distinct sentences are numbered).

For the text entailment check, I used the best method identified in the [25], the cosine based method. A cosine measure evaluates the distance between two vectors. In the [25], the vectors considered represents the projection of a text to another, it has n components, as the number of distinct words found in the base text, and has as components 1 if the word from the base text exist in the projected text, and 0 otherwise. For instance, for the $\text{cos}_T(T,H)$, the base text is T , and the projected texts are T , respectively H . In [25], the text entailment relation $T \rightarrow H$ holds, if and only if $(|\text{cos}_{H \cup T}(T,H) - \text{cos}_T(T,H)| \leq 0.095 \vee |\text{cos}_H(T,H) - \text{cos}_{H \cup T}(T,H)| \leq 0.15) \wedge \max\{\text{cos}_T(T,H), \text{cos}_H(T,H), \text{cos}_{H \cup T}(T,H)\} \geq 0.7$.

For instance, considering from the previous example, the triplet “business has particulars house” as T and the same text natural language text as H , then $\text{cos}_T(T,H) = 0.70$ and is the cosine between the vectors (1,1,1,1) and (1,0,0,1) (only the words “business” and “house” are in the text. The verb “to have” and the adverb “particulars” are missing from the text H .)

5.3 Precision and Recall

All but one of the proposed metrics can be evaluated in a quantitative manner “the number of”, but, in a qualitative measure may be more important, because, usually, not all the ontologies have the same size, and sometimes is more important to find not if there are or aren't some matches, but, how many matches are recognized from the existing matches (the Precision), or, how many matches are recognized from the total number of tested elements (the Recall).

6 Evaluation

In order to evaluate the proposed metrics, I used a set of nine ontologies taken from the [26]. All the ontologies have as core the

business term, and they are composed from 1 to 37 triplets. In fact, all the nine ontologies are relatively close, they having as root senses of the word business: business concern, business enterprise, business sector, business activity, worry, job, aim, stage business and clientele. So, the stake is higher, to select from different ontologies, all with the same root, business, the most appropriate for a particular text. The triplets can be seen in the Table 1. All the relationships from the triplets differ from the “is a” relationship.

The nine ontologies were compared to a part of an article from Wikipedia about small business.

A small business is a business that is privately owned and operated, with a small number of employees and relatively low volume of sales. Small businesses are normally privately owned corporations, partnerships, or sole proprietorships. The legal definition of “small” varies by country and by industry. In the United States the Small Business Administration establishes small business size standards on an industry-by-industry basis, but generally specifies a small business as having fewer than 500 employees for manufacturing businesses and less than \$7 million in annual receipts for most nonmanufacturing businesses. In the European Union, a small business generally has under 50 employees. However, in Australia, a small business is defined by the Fair Work Act 2009 as one with fewer than 15 employees. By comparison, a medium sized business or mid-sized business has under 500 employees in the US, 250 in the European Union and fewer than 200 in Australia.

In addition to number of employees, other methods used to classify small companies include annual sales (turnover), value of assets and net profit (balance sheet), alone or in a mixed definition. These criteria are followed by the European Union, for instance (headcount, turnover and balance sheet totals). Small businesses are usually not dominant in their field of operation.

Small businesses are common in many countries, depending on the economic system in operation. Typical examples include: conven-

tailment was evaluated using the java application described in [25].

Unfortunately, the entailment measures aren't accurate enough, because of the difference of the complexity of the text or the text sentences in regard to the ontologies and the ontologies triplets. The obtained results are in the Tables 2 and 3. The results are inconclu-

sive because in every triplet the concept "business" is found as a word in the text, and because the size of the triplet is small, close to the number of words common in the triplet and in the text, these two cosine measures will be close, and as defined in the [25], this conduct to the "true" evaluation of the entailment relation.

Table 2. The evaluation of the entailment based metrics

Ontology number	1	2	3	4	5	6	7	8
entailment	TRUE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
number of entailments	19	37	2	5	4	31	5	8
number of entailed sentences	44	86	7	13	20	63	22	28
number of distinct entailed sentences	19	37	2	5	4	31	5	8

Table 3. The Recall measures for the entailment based metrics

Ontology number	1	2	3	4	5	6	7	8
entailment	TRUE	FALS E	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
number of entailments	100	100	100	100	100	100	100	100
number of entailed sentences	13.62	13.67	20.59	15.29	29.41	11.95	25.88	20.588
number of distinct entailed sentences	100	100	100	100	100	100	100	100

The first "quantitative" metrics proposed confirmed the supposition that only the first four ontologies and the sixth one match the text. Although in all ontologies the concept and the root business is found, only from the ontologies 1, 2, 4 and 6 can be founded leaves:

- from the ontology 1 are found 2 words: "house" and "manufacturing business" (Recall of 10.5%)
- from the ontology 2 are found 3 words: "industry", "field" and "field of operation" (Recall of 8.1%)
- from the ontology 4 is found a word: "trade" (Recall of 20%)
- from the ontology 6 are found 2 words: "trade" and "medium" (Recall of 6.5%)

Because I haven't the evaluation of an expert, I wasn't able to evaluate the precision of the proposed measures, and because of this, I offered only the Recall measure. The evalua-

tion for the sixth ontology is partially correct, because the concept "medium" from the ontology refers to a person's job, and the same word from the test text "a medium size business" refer to a measure. In fact, for the same reason, the lack of disambiguation, the concept business, different in those nine ontologies is found as the word "business" in the text.

From the number of founded words point of view, the ontology with the root business as business activity correspond the best to the text about small business. From the recall point of view, the ontology with the root business as business activity the best match to the text about small business. These two results are the ones expected.

7 Conclusion and Further Work

In this paper were proposed two types of me-

trics for the evaluation of the ontology matching versus a natural language text. The first ones are based on the statistical measure of the ontology concepts finding in the text, and the second one on the text entailment relation.

Although in the tests the text entailment measures were inconclusive, because of the big difference between the size of the tested ontologies and the size of tested text respective the tested sentences from the text, the first set of measures delivered the supposed results.

In the future I wish to improve the ontology matching technique by using other natural processing techniques, as the disambiguation and dictionary based word similarity.

Acknowledgements

This work was supported by ANCS-CNMP, project number PNII – 91037/2007.

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