The OntoNL Semantic Relatedness Measure for OWL Ontologies

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Abstract

An effect of the growing importance of the Semantic Web used for sharing knowledge over the Internet was the development and publishing of many ontologies in different domains. This led to the need of developing mechanisms for capturing the semantics of the ontologies. In this paper, we introduce the OntoNL Semantic Relatedness Measure, a fully automated way of measuring, in an asymmetric way, semantic relatedness between concepts of domain ontologies. We have developed metrics to guide the automation of the procedure by using feedback from an extensive evaluation with human subjects.

1. Introduction

The Semantic Web technologies have started to make a difference in making content machine processable and have begun to creep into use in some parts of the World Wide Web. This is accomplished by the use of ontologies that describe context in different domains.

An ontology describes a hierarchy of concepts usually related by subsumption relationships. In more sophisticated cases, suitable axioms are added in order to express other relationships between concepts and to constrain their intended interpretation [1]. A module dealing with ontologies can perform automated reasoning using the ontologies, and thus provide advanced services to intelligent applications such as: conceptual/semantic search and retrieval, software agents, decision support, speech and natural language understanding and knowledge management.

The need to determine semantic relatedness between two lexically expressed concepts is a problem that concerns especially natural language processing. Measures of relatedness or distance are used in applications of natural language processing as word sense disambiguation, determining the structure of texts, information extraction and retrieval and automatic indexing.

The methodology for calculating the semantic Relatedness of the concepts of a domain ontology is integrated in the OntoNL Framework [2], a natural language interface generator to knowledge repositories.

Given an OWL ontology, weights are assigned to links between concepts based on certain properties of the ontology, so that they measure the level of relatedness between concepts. In this way we can identify related concepts in the ontology that guide the semantic search procedure. An important property of the OntoNL Semantic Relatedness measure is that it is asymmetric (the relatedness between A and B does not imply the opposite) since relations that are described with natural language do not indicate mathematical rules.

The NLP literature provides the largest group of related work for measuring semantic relatedness that in most cases are based on lexical resources or WordNet [3] and other semantic networks or deal with computing taxonomic path length.

All the research results presented in the literature so far [4][5][6][8] were tested on specific ontologies like the WordNet and MeSH ontologies, they are not general and have not been tested in different domain ontologies that refer to different contexts. The WordNet and MeSH ontologies are well formed hierarchies of terms and the methodologies that have used them examined basically similarity between terms and not relatedness between concepts. Also, most of these approaches are focused on the comparison of nouns, limiting their generality to complex objects or even hierarchies of verbs.

In this paper we present the automation of the procedure for calculating the semantic relatedness between concepts of domain ontologies by using extensive experimentation with human subjects to fine tune the parameters of the system and to evaluate the performance of the OntoNL Semantic Relatedness Measure in different domains with different domain ontologies.

2. The OntoNL Semantic Relatedness Measure

The OntoNL Semantic Relatedness Measure depends on the semantic relations defined by OWL vocabulary. The methodology borrows and expands ideas from the research of Semantic Relatedness of concepts in semantic networks and can be found in details in [9].

The algorithm takes into account the semantic relation of OWL: EquivalentClass. The class that is OWL: EquivalentClass with a source class has a similarity (not relatedness) value 1. In our computations, the classes related to the source class of the ontology are also related with the same value to the equivalent class. We count the number of the common properties the two concepts share (numerator) and divide it with the number of the initial concept (denominator) and the number of the common properties the two concepts share that are **inverseOf** properties (numerator) and divide it with the number of the common properties the two concepts share (denominator):

$$\forall f_1 \geq f_2, f_2 > 0, f_1 + f_2 = 1:$$

$$rel_{prop}(c_1, c_2) = (f_1 \times \frac{\sum_{i=1}^{n} p_{ijk}}{\sum_{i=1}^{n} p_{ij}}) + (f_2 \times \frac{\sum_{i=1}^{n} p_{invijk}}{\sum_{i=1}^{n} p_{ijk}}), \quad (1)$$

In (1), the value p_{ij} represents the fact that concept c_j is related to concept c_i (value: 0 or 1 in general). The value p_{ijk} represents the fact that both concepts c_j and c_k are related to concept c_i. The p_{invijk} represents the fact that both concepts are inversely related. The factors f_1 and f_2 in general depend on the ontologies used, and we assume that they are experimentally determined for a given ontology.

The **conceptual distance** measure is based on three factors; the path distance, the specificity and the specialization. The path distance measures the relatedness of two concepts by counting the minimal path of edges between the two concepts through their structural relations (IS-A relations):

$$\forall d_{C1} \geq 1, d_{C2} \geq 1, d_{C1} + d_{C2} > 2:$$

$$pathDist(c_1, c_2) = \frac{d_{C1} + d_{C2}}{2 * D} \in (0,1] \quad \textbf{(2)}$$

where d_{C1} is the number of edges from concept 1 to the closer common subsumer and d_{C2} the number of edges from concept 2 to the closer common subsumer. D is the maximum depth of the ontology.

We claim that when the change of direction (from superClassing to subClassing and opposite) is close to the concept/subject of the language model ($d_{C1} << (d_{C1}+d_{C2})/2$), the two concepts are more related. When the direction of the path changes far from the reference concept then the semantics change as well (more specialization of the reference concept c_1 in comparison with the subsumer concept).

We count the specificity of the concepts inside the ontology by the following normalized weight value:

$$d_{C1} < \frac{d_{C1} + d_{C2}}{2} : w\_1_{specC1} = -\ln \frac{2 \times d_{C1}}{d_{C1} + d_{C2}} \in (0,1]$$

$$\text{then } d_{C1} \geq \frac{d_{C1} + d_{C2}}{2} : w\_1_{specC1} = 0 \quad (3)$$

We, also propose a method of counting the specialization of the concept - C1 based on the object properties of the subsumer, by the factor:

$$\forall \#ObjP_{C1} \leq 10 \times \#ObjP_S :$$

$$w\_2_{spec_{C1}} = 1 - \log \frac{\#ObjP_{C1}}{\#ObjP_S} \in [0,1] \quad (4)$$

where $ObjP_{C1}$ is the number of Object Properties of the concept C_1 and $ObjP_S$ is the number of ObjectProperties of the subsumer concept.

The conceptual distance measure then becomes:

$$rel_{CD} = \frac{w\_1_{specC1} + w\_2_{specC1} + 1 - pathDist(c_1, c_2)}{3} \quad (5)$$

The **related senses** measure counts the common senses of two concepts by counting the common nouns and synonyms extracted from the descriptions of the concepts in the ontology (owl:label, owl:comment) or from the descriptive part of the term meaning in the WordNet. Let S_1 be the description set of nouns for c_1 and S_2 the description set of nouns for c_2. The related senses measure is:

$$rel_{RS}(c_1, c_2) = \frac{|S_1 \cap S_2|}{|S_1 \cap S_2| + |S_1 \setminus S_2|} \quad (6)$$

The overall relatedness measure is the following:

$$\forall w_1 + w_2 + w_3 = 1, (w_1, w_2, w_3) > 0,$$

$$rel_{PROP}(c_1, c_2), rel_{CD}(c_1, c_2), rel_{RS}(c_1, c_2) \in [0,1]:$$

$$rel_{OntoNL} = w_1 \times rel_{PROP} + w_2 \times rel_{CD} + w_3 \times rel_{RS} \quad (7)$$

The three factors w_1, w_2 and w_3, help of balancing among the parameters depending on the application ontology.

3. Experimental Evaluation

We have focused our attention to the performance experimentation in a generic way utilizing readily available ontologies in the web, not carefully constructed by hand ontologies. As we discussed in the previous section the three factors w_1, w_2 and w_3 of the overall OntoNL measure help of balancing among the three sub-measure depending on the application ontology. We need to bound their values and provide the complete measurement that will show good results regardless of the OWL ontology used.

In order to assess the impact of each of the sub-measures we needed to evaluate it against a "gold standard" of object relatedness. To that end we designed a detailed experiment in which human subjects, selected from the Liberal Arts field and Computer Science field, were asked to assess the relatedness between pairs of objects (the results and discussion over the results can be found in [9]). The object pairs were selected from a number of ontologies freely available in the web[1]. The selection of the ontologies was based on the public availability of the ontologies and by the subjects' ability to relate to the ontology content (domain).

Our first objective was to investigate what are the values of the parameters f_1, f_2, w_1, w_2, w_3 for each ontology, and overall. We observed that the best computed manually values of these parameters strongly depend on the ontology. Their "optimal" experimental values are shown in Table 1.

Ontology	rel_{PROP}		rel_{OntoNL}		
	f_1	f_2	w_1	w_2	w_3
Soccer Ontology	0,5	0,5	0,7	0,2	0,1
Wine Ontology	0,65	0,35	0,5	0,25	0,25
People Ontology	0,1	0,9	0,45	0,2	0,35
Pizza Ontology	0,65	0,35	0,5	0,27	0,23
Koala Ontology	0,99	0,01	0,25	0,65	0,1
Images Ontology	0,33	0,67	0,45	0,5	0,05
Travel Ontology	0,9	0,1	0,7	0,1	0,2

Table 1: The values of the relative weights f_1 and f_2 of (1) and w_1 (for rel_{PROP}), w_2 (for rel_{CD}) and w_3 (for rel_{RS}) of (8) for the test set of ontologies

Using the best computed manually values for the parameters we studied how the computed relatedness measure among two concepts was correlated with the relatedness perceived by the human subjects.

Human Subjects Ratings				
Measure	rel_{PROP}	rel_{CD}	rel_{RS}	rel_{OntoNL}
Soccer Ontology	0,910	0,594	0,329	0,943
Wine Ontology	0,832	0,644	0,830	0,976
People Ontology	0,906	0,937	0,949	0,984
Pizza Ontology	0,657	0,77	-	0,863
Koala Ontology	0,492	0,846	0,285	0,857
Images Ontology	0,964	0,953	0,273	0,997
Travel Ontology	0,946	0,891	0,612	0,973

Table 2: The values of the coefficients of correlation between human ratings of relatedness and the OntoNL Semantic Relatedness sub-measures and overall measure

Table 2 shows the computed correlation coefficients with relative weights of Table 1 between the system computed relatedness measure and the human subjects evaluated relatedness.

4. The OntoNL Semantic Relatedness Measure's Weight Value Calculation

An observation mentioned above was the relatively large variability of the optimal weights for each ontology. Our scope was to develop an automatic method for determining the weights for any given ontology. We first determine the features of the OWL Ontology structure that we essentially can state their impact in the OntoNL Semantic Relatedness Measure:

Feature 1: Let C be a set whose elements are called concepts or classes. Let $|C| \in N$ were $N := \{1,2,3,...\}$, be the number of all Classes of the OWL Domain Ontology.

Feature 2: Let P be a set whose elements are called Object Properties. Let $|P| \in N$ were $N := \{1,2,3,...\}$, be the number of all Object Properties of the OWL Domain Ontology.

Feature 3: Let H^C be a class hierarchy, a set of classes. H^C is a directed, transitive relation $H^C \subseteq C \times C$ which is also called class taxonomy. $H^C(C_s, C_i)$ is the set where Cs is a sub-class of Ci. The number of subclasses (Cs) for a class Ci is defined as $|H^C(C_s, C_i)|$

Feature 4: A specific kind of relations is attributes A. The function $att : A \rightarrow C$ with $range(A) := STRING$ relates concepts with literal values.

The values of these features can be computed univocally in each case of ontologies we used for the evaluation experiments. The metrics we are proposing are not 'gold standard' measures of ontologies. Instead, the metrics are intended to evaluate certain aspects of ontologies and their potential for knowledge representation. To define the metrics we used as a guideline, work on ontology quality analysis [10], [11]. The category of metrics we are interested in is the schema metrics that evaluates ontology design and its potential for rich knowledge representation.

Metric 1 (μ_1)-Object Property Richness: This metric (*PR*) is defined as the average number of object properties per class. It is computed as the number properties for all classes (P) divided by the number of classes (C).

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[1]Images:http://www.mindswap.org/glapizco/technical.owl
Koala:http://protege.stanford.edu/plugins/owl/owl-library/koala.owl
People:http://owl.man.ac.uk/2005/07/sssw/people.html
Pizza:http://www.co-ode.org/ontologies/pizza/2005/05/16/pizza.owl
Soccer:http://lamia.ced.tuc.gr/ontologies/AVMDS03/soccer
Travel:http://learn.tsinghua.edu.cn/home-page/2003214945/travelontology.owl
Wine:http://www.w3.org/TR/owl-guide/wine.rdf

$$PR = \frac{|P|}{|C|} \quad (9)$$

Metric 2 (μ_2)-Inverse Object Property Richness: This metric (PR_{inv}) is defined as the average number of inverse object properties per class. It is computed as the number properties for all classes (P_{inv}) divided by the number of classes (C).

$$PR_{inv} = \frac{|P_{inv}|}{|C|} \quad (10)$$

Metric 3 (μ_3)-Specificity Richness: This metric (SR) is defined as the sum of all inner classes $\sum_{C_i \in C_{inner}}$ (all classes of the ontology except the leaf classes) of the number of properties of the subclass Cs of a class Ci ($P_{H^C(C_S,C_i)}$), minus the number of properties of the class Ci (P_{C_i}) divided by the number of properties of the subclass Cs ($P_{H^C(C_S,C_i)}$). This sum is divided by the number of the inner classes of the ontology.

$$SR = \frac{\sum_{C_i \in Cinner} \left(\left(\sum_{C_j \in H^C(C_S,C_i)} \frac{|P_{C_j}|}{|H^C(C_s,C_i)|} \right) - |P_{C_i}| \right)}{C_{inner}} \quad (11)$$

Metric 4 (μ_4)-Inheritance Richness: The inheritance richness of the schema (IR) is defined as the average number of subclasses per class.

$$IR = \frac{\sum_{C_i \in C} |H^C(C_S, C_i)|}{|C|} \quad (12)$$

Metric 5 (μ_5)-Readability: This metric indicates the existence of human readable descriptions in the ontology, such as comments, labels, or captions. Formally, the readability (R) of a class is defined as the sum of the number attributes that are comments and the number of attributes that are labels the class has.

$$R = |A, A = rdfs:comment| + |A, A = rdfs:label| \quad (13)$$

If the readability is equal to zero, then we define the readability as the average number of classes with one-word string names per all the classes of the ontology.

$$R = \frac{|A, A = rdfs:one\_word\_ID|}{|A, A = rdfs:ID|} \quad (14)$$

We are going to use methodologies from Linear Programming field [12] so to compute the impact of each metric to the weights of the OntoNL Semantic Relatedness Measure and the results that we have obtained empirically through experimentation as training data to determine the exact weight values of the metrics that we think that affect the parameters (f_1, f_2, w_1, w_2, w_3) of the OntoNL Semantic Relatedness Measurement. We observe that the best computed manually values of f_1, f_2, w_1, w_2, w_3 is affected by the characteristics of the ontology structure and description and the ontology metrics defined above.

We define:

$f_1 = f_1(\mu_1, \mu_3)$ (the influence parameter of the submeasure of the rel_{OP}) to indicate that f_1 depends on the ontology metrics μ_1 (object property richness) and μ_3 (specificity richness).

$f_2 = f_2(\mu_1, \mu_2, \mu_3)$ (the influence parameter of the submeasure of the rel_{OP}) is affected by the ontology metrics μ_1 (object property richness), μ_2 (inverse object property richness) and μ_3 (specificity richness).

$w_1 = w_1(\mu_1, \mu_2, \mu_3)$ (the influence parameter of rel_{OP}) is affected by the ontology metrics μ_1 (object property richness), (inverse object property richness) and μ_3 (specificity richness).

$w_2 = w_2(\mu_1, \mu_3, \mu_4)$ (the influence parameter of rel_{CD}) is affected by the ontology metrics μ_1 (object property richness), μ_3 (specificity richness) and μ_4 (specificity richness).

$w_3 = w_3(\mu_4, \mu_5)$ (the influence parameter of rel_{RS}) is affected by the ontology metrics μ_4 (specificity richness) and μ_5 (readability).

We want to determine the *how much* the metrics affect the influence parameters f_1, f_2, w_1, w_2, w_3 of the OntoNL Semantic Relatedness Measurement. To that purpose we have computed the ontology metrics for the 7 OWL domain ontologies that we have used for experimentation. Then we defined the objective functions to represent the problem as a linear programming problem. Since we assume a linear dependency of the parameters f_1, f_2, w_1, w_2, w_3 from the ontology metrics we can write:

$$f_1 \equiv f_1(\mu_1, \mu_3) := c_{11} \times \mu_1 + c_{13} \times \mu_3 - e_1$$
$$f_2 \equiv f_2(\mu_1, \mu_2, \mu_3) := c_{21} \times \mu_1 + c_{22} \times \mu_2 + c_{23} \times \mu_3 - e_2$$
$$w_1 \equiv w_1(\mu_1, \mu_2, \mu_3) := c_{31} \times \mu_1 + c_{32} \times \mu_2 + c_{33} \times \mu_3 - e_3$$
$$w_2 \equiv w_2(\mu_1, \mu_3, \mu_4) := c_{41} \times \mu_1 + c_{43} \times \mu_3 + c_{44} \times \mu_4 - e_4$$
$$w_3 \equiv w_3(\mu_4, \mu_5) := c_{54} \times \mu_4 + c_{55} \times \mu_5 - e_5$$

In these equations c_{ij} are constants and e_i's are error values. As training ontologies we will use the ones that we described above. For each one of these ontologies we have calculated the values of μ_1, μ_2, μ_3, μ_4 and μ_5. We also used as values for f_1, f_2, w_1, w_2, w_3 the values that gave the maximum correlations for the concept relatedness in the user experiments (table 1). The seven OWL Domain Ontologies that were used for experimentation were:

(1) Soccer Ontology, (2) Wine Ontology, (3) People Ontology, (4) Pizza Ontology, (5) Koala Ontology, (6) Images Ontology and (7) Travel Ontology.

We used a Linear Solver to compute the different *c* values and the deviations *e* from the values of Table 1. By calculating the values of the metrics and by multiplying them with the corresponding c values we will get the values of the influence parameters of the OntoNL Semantic Relatedness Measure automatically.

The results of the linear programming procedure are presented in Tables 3-7.

The weight values definition problem for f_1	
Name	**Final Value**
c1	**0,758196161**
c3	**0,435593623**
e11	0,05333553
e12	-0,074884789
e13	0,130046084
e14	-0,086183898
e15	-0,002707919
e16	-0,004941855
e17	-0,014663153

Table 3: The values of the constants of the metrics that influence the weight value f_1 of the OntoNL Sem. Rel. Measure and the deviations from the ontologies

In table 3 we find the values of c_1 and c_3 that we will use to multiply the computed ontology metrics μ_1 and μ_3 respectively in order to define the influence parameter f_1 of a domain ontology we want to process. The e11-e17 values are the deviations from the human judgments for each one of the seven ontologies used for experimentation.

The weight values definition problem for f_2	
Name	**Final Value**
c1	**0,049345079**
c2	**0,840100697**
c3	**0,047572988**
e21	0,136529522
e22	0,022606066
e23	-0,070313878
e24	0,022606066
e25	0,058533106
e26	-0,148934617
e27	-0,021026264

Table 4: The values of the constants of the metrics that influence the weight value f_2 of the OntoNL Sem. Rel. Measure and the deviations from the ontologies

In table 4 we find the values of c_1, c_2 and c_3 that we will use to multiple the computed ontology metrics μ_1, μ_2 and μ_3 respectively in order to define the influence parameter f_2 of a domain ontology we want to process. The e21-e27 values are the deviations from the human judgments for each one of the seven ontologies used for experimentation.

The weight values definition problem for w_1	
Name	**Final Value**
c1	**0,549347616**
c2	**0,310262499**
c3	**0,26487096**
e31	0,06518881
e32	-0,066029702
e33	-0,117953097
e34	-0,066029702
e35	0,021163584
e36	-0,267102916
e37	-0,061115641

Table 5: The values of the constants of the metrics that influence the weight value w_1 of the OntoNL Sem. Rel. Measure and the deviations from the ontologies

In table 5 we find the values of c_1, c_2 and c_3 that we will use to multiple the computed ontology metrics μ_1, μ_2 and μ_3 respectively in order to define the influence parameter w1 of a domain ontology we want to process. The e31-e37 values are the deviations from the human judgments for each one of the seven ontologies used for experimentation.

The weight values definition problem for w_2	
Name	**Final Value**
c1	**0,363197897**
c3	**0,046685606**
c4	**0,245670362**
e41	0,08867345
e42	0,016971459
e43	-0,043044046
e44	0,009254977
e45	-0,212717517
e46	-0,066789378
e47	0,207651054

Table 6: The values of the constants of the metrics that influence the weight value w_2 of the OntoNL Sem. Rel. Measure and the deviations from the ontologies

In table 6 we find the values of c_1, c_3 and c_4 that we will use to multiple the computed ontology metrics μ_1, μ_3 and μ_4 respectively in order to define the influence parameter w_2 of a domain ontology we want to process. The e41-e47 values are the deviations from the human judgments for each one of the seven ontologies used for experimentation.

The weight values definition problem for w_3	
Name	**Final Value**
c4	**0,278023071**
c5	**0,315776889**
e51	0,016872301
e52	-0,056071167
e53	-0,098853789
e54	-0,037958858
e55	0,064273687
e56	0,149284072
e57	-0,037546245

Table 7: The values of the constants of the metrics that influence the weight value w_{31} of the OntoNL Sem. Rel. Measure and the deviations from the ontologies

In table 7 we find the values of c_4 and c_5 values that we will use to multiple the computed ontology metrics metrics μ_4 and μ_5 respectively in order to define the influence parameter w_3 of a domain ontology we want to process. The e51-e57 values are the deviations from the human judgments for each one of the seven ontologies used for experimentation.

The largest deviation in Table 3 is for the ontology People since it is an ontology with a small number of Object Properties in comparison to the Classes that it has.

The largest deviations in Table 4 are for the ontologies Soccer and Images because of the small number of the inverse Object Properties for the Soccer Ontology and the lack of Specificity Richness as it was defined earlier in the Metrics for the Images ontology.

The largest deviations in Table 5 are for the ontologies People and Images because of the reasons that influence the bad performance in the calculation of the values of f_1 and f_2.

The largest deviations in Table 6 are for the ontologies Koala and Travel because they are quite flat as domain ontologies, they do not have a large Inheritance Richness as it was defined in the Metrics definition.

The largest deviation in Table 7 is for the ontology Images because it does not have descriptions, like comments and labels and because the names of the classes are mainly two word strings.

5. Conclusions

We have presented the methodology of the automatic calculation of the OntoNL Semantic Relatedness measure for OWL ontologies. The motivation of this work came from the absence of a general, domain-independent semantic relatedness measure. The measure was successfully used for natural language disambiguation and semantic ranking in the OntoNL Framework [13].

For the OntoNL Semantic Relatedness Measure evaluation, the framework takes into account a number of parameters regarding the characteristics of the ontologies involved and the types of users. We have focused our attention to the performance experimentation in a generic way utilizing readily available ontologies in the web, not carefully constructed by hand, ontologies.

We concluded to the parameters that affect the choice of the weight value for each one of the sub-measures developed to comprise the OntoNL measure and we used the evaluation empirical results and Linear Programming to define the values of these weights by defining ontology metrics that influence the weights of the OntoNL measure. The methodology showed that with the correct definition of ontology metrics we get realistic results for the relatedness of concepts of a domain ontology. The methodology was based on the feedback of the users we used for the experimentation. By using a more systematic way of extracting the knowledge and experience of the users we may get a more accurate definition of ontology metrics with even better results in comparison with human judgments.

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