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A method for ontology-based semantic relatedness measurement

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Abstract: There are many methods having different approaches for assessing similarity and relatedness and they are used in many application areas, including web service discovery, invocation and composition, word sense disambiguation, information retrieval, ontology alignment and merging, document clustering, and short answer grading. These methods can be categorized as path-based, information content-based, feature-based, geometric model-based, and hybrid approaches. These approaches use resources such as concept hierarchy, conceptual graph, and corpus for computing similarity and relatedness. With the rise of the semantic web, ontologies have attracted the attention of several researchers. Ontologies represented in the Web Ontology Language (OWL) are also valuable resources for similarity and relatedness measurement. The method proposed in this paper interprets some OWL constructs to assess semantic relatedness. The motivation behind this is to benefit from the rich expressive power of OWL to obtain better semantic relatedness measurement results. The success of the method has been validated against human judgments. The correlation between human judgments and automatically computed semantic relatedness values was calculated as 0.685 and was significant at the 0.01 level.

Key words: Semantic relatedness, semantic similarity, ontology, OWL, semantic relatedness measurement

1. Introduction

As the volume of information in electronic environment increases, expectations from computers for performing more intelligent tasks are becoming unavoidable needs. One of the intelligent actions computers can perform is assessing similarity and relatedness between 2 entities, such as documents, concepts, or words. Some examples for application areas for similarity and relatedness measurement include web service discovery, invocation and composition [1], word sense disambiguation [2], information retrieval [3], ontology alignment and merging [4], document clustering [5], and short answer grading [6].

In order to be able to assess semantic similarity or relatedness between 2 entities, a reference that provides the necessary basis for automatic judgment is essential. A concept hierarchy, a conceptual graph, or a corpus can be used for this purpose, as well as ontologies, which can also be represented as a conceptual graph. With the rise of the semantic web, ontologies are more widely used. Ontology representation languages are being proposed and standardized by well-known organizations such as the World Wide Web Consortium (W3C). The Web Ontology Language (OWL) is a language that was developed and promoted for ontology representation. The objective of our study is interpreting the constructs provided by OWL for assessing semantic relatedness.

Section 2 provides an introduction to semantic similarity and semantic relatedness, their differences and application areas, and the spreading activation theory that forms the basis for the ontology-based semantic

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relatedness measurement method proposed in this paper. Section 3 summarizes related work in the literature and the motivation behind our study. Section 4 explains the method developed within the scope of our study. The "ontological path" concept, which is present in the literature, was reinterpreted from a metamodeling perspective and used for semantic similarity measurement. Based on this concept, the development process of the method is explained. In Section 5, the results are discussed. Finally, Section 6 concludes the paper.

2. Background knowledge

Similarity and relatedness are 2 important and interrelated subjects in computer science and psychology. Since the automatic measurements of similarity and relatedness have many applications in diverse areas, this problem has attracted the interest of many researchers. These research efforts have ended up with many measurement methods proposed. The first subsection explains semantic similarity and semantic relatedness and provides examples of usage areas for the similarity and relatedness measurement methods.

Similarity and relatedness measurement methods need resources in order to be able to compute a value for similarity and relatedness. In our study, ontologies are used as resources for measuring semantic relatedness. The reason for this is the resemblance between how ontologies represent domain knowledge and how concepts are stored in the memories of humans. According to Anderson [7], information is encoded in memory as cognitive units and these units form an interconnected network. Information retrieval is performed by spreading activation throughout the network. On the other hand, an ontology is an explicit specification of entities that are assumed to exist in a domain of interest. The second subsection introduces the spreading activation theory that forms the cognitive basis for the measurement method developed in our study.

2.1. Similarity and relatedness

Similarity and relatedness are 2 important concepts for computer science and psychology, to which many research efforts have been allocated. Similarity plays an important role in knowledge and behavior theories in psychology. Similarity provides the fundamentals for humans to classify objects, form concepts, and make generalizations [8]. Relatedness means being related or having a relationship. On the other hand, similarity defines the state of being similar, e.g., having characteristics in common or alike in substance or essentials. Similarity is a special case of relatedness [9]. Similar concepts are related to each other through their common characteristics. Relatedness covers more types of relationships among concepts than similarity does. For instance, "car" and "wheel" are related to each other through a part-of relationship, whereas "hot" and "cold" are related through an antonym relationship [10]. In both cases, the concepts are related, but not similar.

Similarity and relatedness measurement can be applied to solve many problems in different areas. Depending on the problem, similarity and relatedness can be measured among many types of entities, such as words, sentences, texts, concepts, or ontologies.

OWL-S, an ontology for semantic annotation of web services, enables web services to be discovered, invocated, and composed intelligently [1]. With semantic annotation of web service descriptions using ontological terms, web service discovery, invocation, and composition problems have been turned into semantic similarity or relatedness measurement problems to some extent. Leacock and Chodorow [2] computed semantic similarities between words using semantic relationships in WordNet [11] and used these similarity measurement results for word sense disambiguation. Mao and Chu used Unified Medical Language System (UMLS) for computing similarities between words and used these similarity measurement results for improving recall and precision ratios [12] in information retrieval [3].

2.2. Spreading activation theory

Humans organize and store acquired information in various ways in their memories. Knowledge is a form of information that is organized, integrated, and stored in the memory. There are theories that explain how knowledge is represented in the memory, such as the clustering model, set-theory model, network model [13], and Object-Attribute-Relation model [14]. The main idea behind these theories is that concepts are stored in the memory on a network whose edges are associations among concepts.

According to the spreading activation theory [15], when a concept is mentally processed, its node is activated. Activation spreads from a concept to other concepts through links. Each node representing a concept has an activation level. A concept is activated if this level is exceeded. The strength of the activation decreases as the activation spreads along the links and moves away from the starting concept. At a point, the spreading of the activation fades away.

3. Related work and motivation

Since similarity and relatedness measurement methods have many applications in many different areas, many methods have been proposed in the literature. These methods can be grouped in many ways. Within the scope of this study, the existing methods have been grouped into 5 clusters, namely the path-based, information content-based, feature-based, geometric model-based, and hybrid methods. Path-based methods measure similarity based on the number of nodes and/or edges on a conceptual hierarchy or graph. Information content-based methods consider the frequencies of concepts in a corpus for similarity measurement. Feature-based methods define concepts by their features and compute a similarity value based on the similarity between the feature sets of the concepts. Geometric model-based methods represent concepts as a point in n-dimensional space and similarity is determined based on the distance between these points. Hybrid methods combine some of the aforementioned methods.

In order to be able to measure similarity or relatedness between 2 entities, one or more references should be used. These references can be structured, such as a concept hierarchy, conceptual graph, or lexical database, or unstructured, such as a corpus. The expressive power of a reference determines the variety of computations that can be done on this reference. More diverse computations can be done on a conceptual graph that includes IS-A, antonymy, and distinctness relationship types than a concept hierarchy that only includes IS-A type relationships.

Assigning coefficients to constructs that represent relationships between concepts has been proposed by some researchers [16,17]. A coefficient assignment for relationships is a way of interpreting the path between 2 concepts in order to assess their similarity or relatedness. Wang et al. [16] assigned a coefficient of 0.8 to IS-A relationships and 0.6 to part-of relationships. Mazuel and Sabouret [17] assigned a coefficient of 0.4 to part-of relationships. These coefficients were determined by maximizing the consistency of the similarity or relatedness measurement results with some other benchmarks. One of these benchmarks is the correlation with human judgments for similarities between concepts.

The objective of our study is to simulate human relatedness judgment using ontologies. As illustrated in Figure 1, the ontology-based relatedness measurement method substitutes the procedural knowledge of a human that defines how relatedness judgment is made. Ontologies replace declarative knowledge that is stored as concept networks in the memory. Consequently, the ontology-based semantic relatedness measurement method uses ontologies as a reference in order to assess the relatedness between 2 concepts automatically.

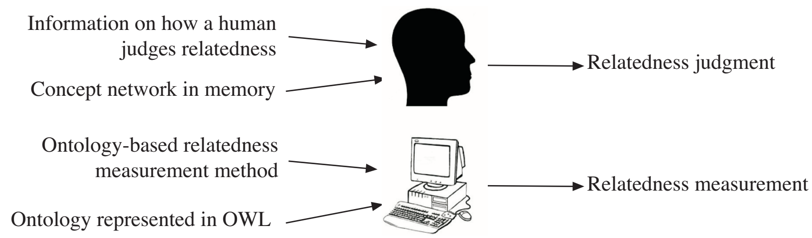


Figure 1. Relatedness judgment of the human and automatic relatedness measurement.

The existing similarity and relatedness measurement methods do not consider many types of relationships in conceptual models. The most considered relationship type is IS-A type relationships. OWL provides a rich set of constructs for modeling. The motivation behind this study is interpreting the semantics of the OWL constructs for assessing relatedness. The contribution of each OWL construct (that can be on ontological paths) to semantic relatedness was defined by analyzing the ratings given by humans to evaluate the semantic relatedness between concept pairs.

4. Ontology-based semantic relatedness measurement

The spreading activation theory, which explains how humans recall information from memory, has been employed for measuring the semantic relatedness between 2 terms in an ontology developed with OWL. According to this theory, the degree of relatedness between 2 concepts depends on how closely these concepts are stored in the memory. This approach forms the basis for the path-based similarity and relatedness measurement methods. Rada et al. [18] stated that the distance between 2 concepts can be expressed in terms of the length of the shortest path between these concepts. They considered IS-A relationships among concepts when calculating distance, as did most other researchers [2,12,19–23]. Some researchers, such as Wang et al. [16], took part-of as well as IS-A relationships into account. As a starting point of this study, it is proposed that rich OWL constructs shall be used for semantic relatedness measurement.

4.1. Ontological path

The basic idea of interpreting the path between 2 concepts, as path-based similarity and relatedness measurement methods suggest, forms the fundamental basis of the method developed within the scope of our study. This approach is also consistent with the spreading activation theory. Therefore, the semantic relatedness between 2 concepts in an ontology developed with OWL will be computed by interpreting the paths between these concepts. However, it is important to define which paths are considered when measuring semantic relatedness. In our study, the paths that will be considered for semantic relatedness measurement are defined from a metamodeling perspective.

Metamodel is defined as a model of models [24]. A metamodel represents the abstract syntax of a language [25] and makes statements about what can be expressed in the valid models of a certain modeling language [26]. The W3C's OWL language specification written in English defines the abstract syntax for OWL and determines valid models (ontologies) that can be expressed with OWL.

Atkinson et al. make an important distinction between linguistic and ontological classification. Linguistic classification is defined as the basic type/instance relationship that exists between an element of a model and an element of the abstract syntax of the language used to express the model [27]. Ontological classification can be defined as the type/instance relationship between the elements of a model.

Figure 2 illustrates the orthogonal classification architecture (OCA) by Atkinson and Kühne [28]. The OCA applies the conventional UML metamodeling hierarchy in 2 orthogonal dimensions [27]. As illustrated in Figure 2, the L_2 level contains the linguistic classifiers (abstract and concrete syntax elements) of elements of models at the L_1 level. Following this principle, the OWL specification is a model of the OWL modeling language and it is a linguistic metamodel residing at the L_2 level [29]. According to the model in Figure 2, the concepts "WineColor" and "Rose" are residing at the same linguistic level, L_1, whereas they are at different ontological levels, O_1 and O_0, respectively.

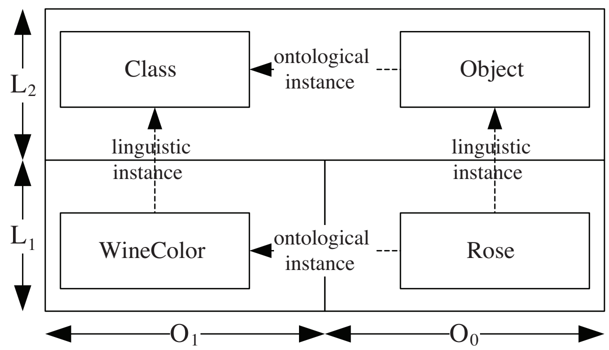


Figure 2. A sample knowledge model fraction illustrating "ontological instance" and "linguistic instance".

According to the example illustrated in Figure 2, "Rose" is an "Object" from a linguistic perspective, whereas it is a type of "WineColor" from an ontological perspective. When a semantic relatedness judgment is made by a human, the state of being a "WineColor", which may make sense from humans' domain knowledge point of view in the real world, will be considered; on the other hand, the state of being an "Object", which makes sense from a knowledge modeling point of view, will be ignored.

Inspired by the study of Atkinson and Kühne [28], an ontological path is defined as a path on which only concepts residing on the L_1 level are present. In other words, an ontological path consists of concepts that are also present in the domain of interest and excludes concepts that belong to the L_2 level. Atkinson and Kühne concentrate on type/instance relationships resulting in orthogonal linguistic and ontological levels, and this distinction has some implications on domain-specific modeling. In our study, we concentrate on how ontologies can represent a concept network that is in the memory of humans. Therefore, based on the distinction between linguistic and ontological instance relationships, we argue that the part of an ontology that resides on the L_1 level can represent a concept network that is stored in the memory of a human. Elements residing on the L_2 level, relationships among concepts at the L_2 level, and relationships crossing the metalevel boundary between the L_1 and L_2 levels should be left out when representing a concept network that is stored in the memory of a human and hence should not be considered when computing semantic relatedness. All of the concepts and relationships residing at the L_1 level should be considered for semantic relatedness measurement. This means that all of the ontological levels in an ontology at the L_1 level are in the scope of the semantic relatedness measurement. Therefore, ontological levels will not be emphasized in the Figures through the rest of the paper and these levels will be treated as one level, named O_n.

According to the ontology fraction illustrated in Figure 3, the semantic relatedness between "EarlyHarvest" and "LateHarvest" concepts can be computed by interpreting rdfs:subClassOf language constructs, which form a path between these concepts. On the other hand, the semantic relatedness between the concepts "Winery" and "Wine" cannot be computed by interpreting the path composed of 2 rdf:type language constructs.

The difference between the latter and the former is that the owl:Class node, which is not a concept in the wine domain, is on the path between the concepts "Winery" and "Wine". Therefore, stating that "Winery" and "Wine" are both an owl:Class does not make sense from a human semantic relatedness judgment point of view.

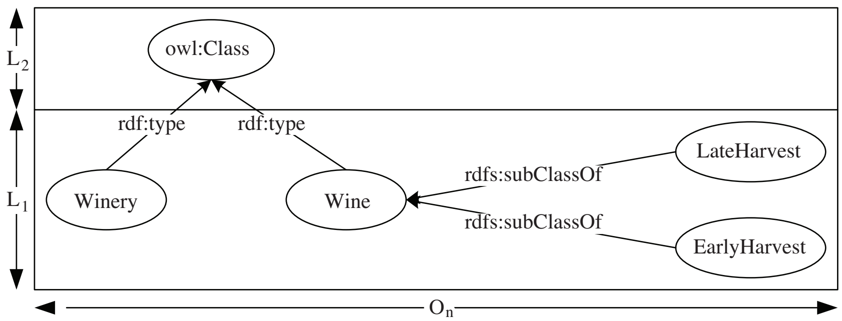


Figure 3. A fraction of "Wine" ontology (www.w3.org/TR/owl-guide/wine.rdf).

Consequently, each statement present in ontologies must not be considered when computing semantic relatedness. Concepts residing at the L_2 level are nonsense when simulating humans' relatedness judgment, since these relationships are not present in the domain of interest and hence are not part of the knowledge stored in humans' memory. Starting from this assumption, an "ontological path" should be composed of concepts that are also present in the domain of interest.

The concept of "ontological path" can be found in some publications in the literature. For instance, OntoSearch finds the best ontological path between 2 concepts in an ontology. The relationship between these 2 concepts depends on the length of the path and the types of the edges on the path [30]. In our study, the paths between concepts have been interpreted like those in the study by Onyshkevych [30]. However, in our study, the ontological path is defined from a metamodeling perspective and the concepts that are present in a domain of interest are considered when interpreting the paths between concepts.

4.2. Measuring semantic relatedness using an ontological path

Like all of the path-based methods in the literature, it is proposed to interpret the path between 2 concepts in order to compute the semantic relatedness. As illustrated in Figure 4, the concepts C_1 and C_3 are related to each other through the relationships lc_1 and lc_2 ("lc" has been used as an acronym for "language construct") via the concept C_2.

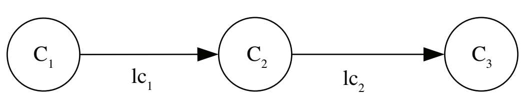


Figure 4. The path between concepts C_1 and C_3.

According to the sample illustrated in Figure 4, the semantic relatedness between concepts C_1 and C_3 is proposed to be computed by multiplying each "semantic relatedness coefficient" (src) of the language constructs forming the path between the concepts. Following this rule, the semantic relatedness between concepts C_1 and C_3 can be computed using the equation illustrated in Eq. (1). The semantic relatedness coefficient can be defined as a numerical value that represents the degree of contribution of a language construct to the semantic relatedness value computed for 2 concepts.

$$\text{Semantic Relatedness}(C_1, C_3) = src(lc_1) \times src(lc_2) \tag{1}$$

Figure 5 illustrates a fraction of an ontology from the "Wine" ontology. According to this ontology fraction, the "madeFromGrape" property has a domain from the "Wine" class and a range of the "WineGrape" class.

Figure 5. A fraction of the "Wine" ontology.

According to the sample illustrated in Figure 5, the semantic relatedness between the concepts "Wine" and "WineGrape" can be computed using the equation illustrated in Eq. (2).

$$\text{Semantic Relatedness(Wine, WineGrape)} = \text{src(rdfs:domain)} \times \text{src(rdfs:range)} \tag{2}$$

Assigning coefficients for different relationship types is applied in some semantic similarity and relatedness measurement methods [16,17]. The methods followed for determining these coefficients are mostly based on maximizing the correlation between human judgments and the results obtained by applying a semantic similarity or relatedness method. In our study, the coefficients are determined by conducting a survey and collecting data on the semantic relatedness judgments of humans.

4.3. Assessing OWL constructs from an ontological path perspective

An ontological path should be composed of concepts that are also present in the domain of interest. Starting from this point, all OWL constructs should be assessed, whether they can be present on an ontological path or not. An OWL construct can reside on an ontological path if it can associate 2 concepts that are residing at the L_1 level. After this assessment, a list of OWL constructs will be obtained whose semantic relatedness coefficients will be determined.

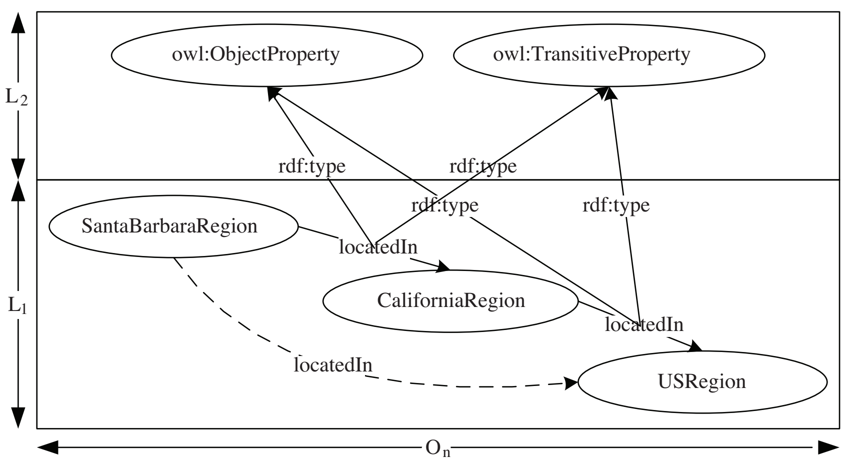
The owl:Class construct indicates that a resource in an ontology is a class. Similarly, the owl:ObjectProperty and owl:DatatypeProperty constructs indicate that a resource in an ontology is a property. All of these constructs reside at the L_2 level and do not have any correspondence in the domain of interest.

The rdfs:subClassOf and rdfs:subPropertyOf constructs enable us to define taxonomies made up of classes and properties, respectively. These constructs represent IS-A relationships between the concepts residing at the L_1 level, which are also present in the domain of interest and thus can be part of an ontological path.

The owl:equivalentClass and owl:equivalentProperty constructs define the fact that 2 classes and 2 properties have the same extension, respectively. Therefore, these constructs represent equivalence relationships between the concepts residing at the L_1 level, which are also present in the domain of interest. Similarly, owl:sameAs indicates that 2 individuals are the same, which is also a valid statement in the domain of interest. Consequently, the owl:equivalentClass, owl:equivalentProperty, and owl:sameAs constructs can be found on an ontological path.

owl:disjointWith defines the state of disjointedness between 2 classes. This entails that if an individual is a member of a class, this individual cannot be a member of another class that is in disjoint with the first class. The distinctness of 2 individuals is defined using the owl:differentFrom construct. The owl:AllDifferent and owl:distinctMembers constructs are used for defining the distinctness of more than 2 individuals. The disjointedness and distinctness relationships are defined between concepts on the L_1 level. Since statements formed with the owl:AllDifferent and owl:distinctMembers constructs can be redefined using the owl:differentFrom construct, the determination of semantic relatedness coefficients for only the owl:disjointWith and owl:differentFrom constructs will be sufficient.

The owl:TransitiveProperty, owl:SymmetricProperty, owl:FunctionalProperty, and owl:InverseFunctionalProperty constructs define the characteristics of the properties defined in an ontology. For a property, the information of being transitive, symmetric, functional, or inverse functional does not make any sense for the semantic relatedness measurement in the domain of interest. Therefore, these constructs cannot be present on an ontological path. However, statements inferred using these constructs can form a part of an ontological path. According to the ontology fraction illustrated in Figure 6, the "locatedIn" property is transitive, which is a fact that must not be considered for the relatedness judgment in the domain of interest. However, the statement defining the "locatedIn" relationship between "SantaBarbaraRegion" and "USRegion" should be considered for the semantic relatedness judgment. This statement is drawn from 3 statements, namely "SantaBarbaraRegion locatedIn CaliforniaRegion", "CaliforniaRegion locatedIn USRegion", and "locatedIn relationship is transitive". Consequently, semantic relatedness coefficients must not be computed for the owl:TransitiveProperty, owl:SymmetricProperty, owl:FunctionalProperty, and owl:InverseFunctionalProperty constructs and inferred statements through these constructs may be important for semantic relatedness measurement.



The statements in the knowledgebase:		
locatedIn	rdf:type	owl:ObjectProperty
locatedIn	rdf:type	owl:TransitiveProperty
SantaBarbaraRegion	locatedIn	CaliforniaRegion
CaliforniaRegion	locatedIn	USRegion
Inferred Statements:		
SantaBarbaraRegion	locatedIn	USRegion

Figure 6. A fraction of the "Wine" ontology.

The domain of a property defines which classes this property can belong to and the range of a property defines which values this property is allowed to take. OWL has 2 constructs for defining the domain and range of a property, namely rdfs:domain and rdfs:range, respectively. Since these constructs define the relationships between the concepts and their properties, which also exist in the domain of interest, semantic relatedness coefficients should be computed for these constructs. The owl:inverseof construct allows us to define the inverse of a property. For instance, the "hasMaker" property is the inverse of a property named "producesWine" in the "Wine" ontology. This construct defines an opposition relationship between 2 properties and these relationships are residing at the L_1 level. Therefore, the owl:inverseof construct is within the scope for semantic relatedness coefficient assessment.

The owl:DeprecatedClass and owl:DeprecatedProperty constructs are used for phasing out an old vocabulary and do not have any meaning in the domain of interest; hence, these constructs are out of the scope of the semantic relatedness coefficient assessment. The owl:Ontology, owl:imports, owl:versionInfo, owl:priorVersion, owl:backwardCompatibleWith, and owl:incompatibleWith constructs provide metadata for an ontology itself; thus, their semantic relatedness coefficients should not be assessed. The rdfs:label, rdfs:comment, rdfs:seeAlso, rdfs:isDefinedBy, and owl:AnnotationProperty constructs are used for annotating classes, properties, and individuals in ontologies and do not formally model any concept or relationship in the domain of interest. Consequently, semantic relatedness coefficients of these constructs do not need to be assessed.

Some constructs do not define relationships between named classes, properties, or individuals. As illustrated in Figure 7, the subject of the owl:onProperty predicate is an unnamed node having a type of owl:Restriction. Therefore, it is not possible to assess semantic relatedness coefficients via ratings obtained from humans. The owl:minCardinality, owl:maxCardinality, and owl:cardinality constructs restrict the number of values a property can have. Therefore, the ranges of these constructs are a number; for instance, having the same number as a cardinality value does not entail that 2 properties are semantically related in the domain of interest. For these reasons, the owl:unionOf, owl:complementOf, owl:intersectionOf, owl:oneof, owl:DataRange, owl:Restriction, owl:onProperty, owl:allValuesFrom, owl:someValuesFrom, owl:minCardinality, owl:maxCardinality, owl:cardinality, and owl:hasValue constructs are excluded from semantic relatedness coefficient assessment.

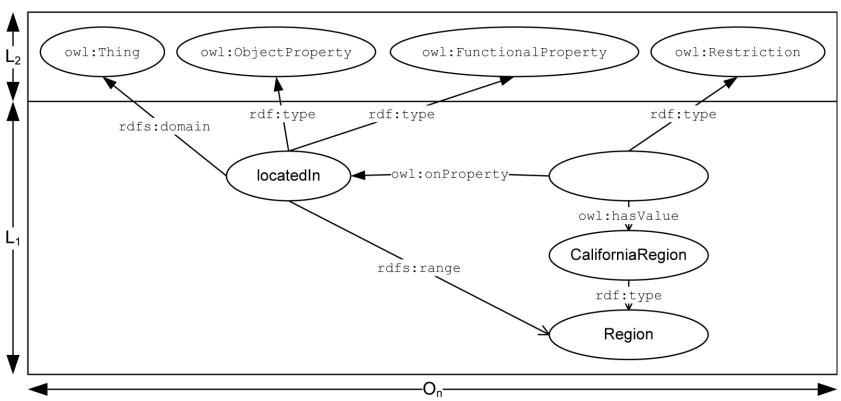


Figure 7. A fraction of the "Wine" ontology.

Some of the relationships defined by OWL constructs are symmetric, while some are not. A semantic similarity or relatedness measurement method that treats all of the relationships as symmetric will not be appropriate in some cases, such as, for instance, in query expansion [31].

Some of the constructs chosen for semantic relatedness coefficient assessment are not symmetric. The rdfs:subClassOf and rdfs:subPropertyOf constructs represent IS-A relationships between classes and properties, respectively. Since the IS-A relationship has a direction (namely, from general to specific or vice versa), semantic relatedness coefficients should be assessed for both directions. Similarly, since relationships defined by the rdfs:domain and rdfs:range constructs have a direction, their semantic relatedness coefficients should be assessed by taking the relationship direction into account. The owl:equivalentClass, owl:equivalentProperty, owl:inverseOf, owl:disjointWith, and owl:differentFrom constructs are symmetric by their definition. For instance, if a knowledge base contains a "A owl:equivalentClass B" statement, a "B owl:equivalentClass A" statement will be inferred by the reasoner. Therefore, the semantic relatedness coefficients of these 5 constructs should be assessed without taking the relationship direction into account.

4.4. Semantic relatedness coefficients of OWL constructs

A list of 143 concept pairs has been prepared for determining the semantic relatedness coefficients of OWL constructs (refer to Table A1 in the Appendix). In order to determine 143 concept pairs, 201 ontologies (from the Semantic Web for Earth and Environmental Terminology project of NASA, Protégé Ontology Repository, and Tones Ontology Repository) have been analyzed. The analysis was done with a program developed using the Java programming language and Jena library [32]. After the analysis, all of the statements in these ontologies were listed in Resource Description Framework (RDF) triples. Of those, 143 were selected for manually determining the semantic relatedness coefficients of OWL constructs and 143 concept pairs are related to 9 different OWL constructs, namely rdfs:subClassOf, rdfs:subPropertyOf, owl:equivalentClass, owl:equivalentProperty, rdfs:domain, rdfs:range, owl:disjointWith, owl:differentFrom, and owl:inverseOf. Concept pairs that are too specific for a domain have been excluded from the list. By doing so, participants were not required to have domain-specific knowledge for rating the semantic relatedness. All of the concept pairs were originally in English and these were translated into Turkish.

The data collection task was divided into 2 phases. In the preliminary phase, survey explanations and the comprehensibility of the concept pairs were evaluated by 3 psychologists and 3 computer/electrical electronics engineers. The reason for selecting these participant profiles for the preliminary study was the high number of research and applications in similarity and relatedness done in the psychology and computer science fields. After receiving feedback from 6 participants, the survey instructions were updated and some concept pairs were changed or rephrased.

In the primary phase, 66 participants gave a value representing the semantic relatedness between these 143 concept pairs. Values representing the semantic relatedness were allowed to be between 0 and 10. The value 0 means that 2 concepts are not related at all and the value 10 means that 2 concepts are the same or identical. The native language of 57 of the participants was Turkish and the native language of 9 of the participants was English. All of the participants took surveys prepared in their native language. This was done to assess whether translation errors took place while translating the concept pairs from English into Turkish.

The first analysis made of the collected data was by independent samples t-test. According to the results obtained from the independent samples t-test ($P = 0.067$), there was not a significant difference between the results of the Turkish native speakers ($avg = 6.55$) and the English native speakers ($avg = 6.15$). Therefore, all of the data collected were combined and analyzed together.

At the next step, outliers were identified and excluded from the result set. Z-transformation was applied and responses including z-values smaller than -3.29 and larger than $+3.29$ were excluded from the result set. Data collected from 7 participants were excluded from the result set and the final set included the responses from 59 participants.

The process for computing the semantic relatedness coefficients for each OWL construct is illustrated in Figure 8. An average relatedness value (RV_Avg) was computed by averaging all of the relatedness values collected from the participants for each concept pair. Afterwards, the concept pairs were grouped into clusters according to the OWL constructs to which they were related based on the 201 ontologies analyzed. At the last step, average relatedness values (RV_Avg) in each cluster were averaged and the semantic relatedness coefficients (src) for each OWL construct were computed. Semantic relatedness coefficients by OWL constructs are illustrated in the last table in Figure 8.

Based on Eq. (1) and the semantic relatedness coefficients illustrated in Figure 8, the semantic relatedness between the "EarlyHarvest" and "LateHarvest" concepts, illustrated in Figure 3, is computed as in Eq. (3).

$$\text{Semantic Relatedness(EarlyHarvest, LateHarvest)} = \text{src(rdfs:subClassOf)} \times \text{src(rdfs:subClassOf)}$$
$$= 0.72149 \times 0.69384 = 0.50060 \tag{3}$$

#	Concept1		Concept2		P1		P2		...		P59	
CP1	**C(1,1)**	Deficit	**C(1,2)**	Excess	**RV(1,1)**	10	**RV(1,2)**	9	**...**	...	**RV(1,59)**	8
CP2	**C(2,1)**	Physics	**C(2,2)**	Science	**RV(2,1)**	9	**RV(2,2)**	7	**...**	...	**RV(2,59)**	7
CP3	**C(3,1)**	Day	**C(3,2)**	Date	**RV(3,1)**	8	**RV(3,2)**	8	**...**	...	**RV(3,59)**	8
...	**...**	...	**...**	...	**...**	...	**...**	...	**...**	...	**...**	...
CP143	**C(143,1)**	North	**C(143,2)**	South	**RV(143,1)**	10	**RV(143,2)**	10	**...**	...	**RV(143,59)**	9

#	Concept1		Concept2		RV_Avg	
CP1	**C(1,1)**	Deficit	**C(1,2)**	Excess	**RV_Avg1 = Avg(RV(1,1),RV(1,2),…,RV(1,143))**	Avg(10,9,...,8) = 8.10169
CP2	**C(2,1)**	Physics	**C(2,2)**	Science	**RV_Avg2 = Avg(RV(2,1),RV(2,2),…,RV(2,143))**	Avg(9,7,...,7) = 7.84745
CP3	**C(3,1)**	Day	**C(3,2)**	Date	**RV_Avg3 = Avg(RV(3,1),RV(3,2),…,RV(3,143))**	Avg(8,8,...,8) = 7.40677
...	**...**	...	**...**	...	**...**	...
CP143	**C(143,1)**	North	**C(143,2)**	South	**RV_Avg143 = Avg(RV(143,1),RV(143,2),…,RV(143,59))**	Avg(10,10,...,9) = 8.89830

	#	Concept1		Concept2		RV_Avg	
`owl:disjointWith`	**CP1**	**C(1,1)**	Deficit	**C(1,2)**	Excess	**RV_Avg1**	8.10169
	CP19	**C(19,1)**	Internal	**C(19,2)**	External	**RV_Avg19**	8.57627
	CP35	**C(35,1)**	Base	**C(35,2)**	Acid	**RV_Avg35**	7.47457
	...	**...**	...	**...**	...	**...**	...
`rdfs:subClassOf (from specific to general)`	**CP2**	**C(2,1)**	Physics	**C(2,2)**	Science	**RV_Avg2**	7.84745
	CP5	**C(5,1)**	Fire	**C(5,2)**	Disaster	**RV_Avg5**	7.16949
	...	**...**	...	**...**	...	**...**	...
`rdfs:subClassOf (from general to specific)`	**CP9**	**C(9,1)**	Animal	**C(9,2)**	Cow	**RV_Avg9**	7.16949
	CP133	**C(133,1)**	City	**C(133,2)**	Capital	**RV_Avg133**	5.89830
	...	**...**	...	**...**	...	**...**	...
	...	**...**	...	**...**	...	**...**	...

OWL construct	Semantic relatedness coefficient (src)
`owl:inverseOf`	0.85254
`owl:equivalentClass`	0.80228
`rdfs:subClassOf (from specific to general)`	0.72149
`rdfs:subPropertyOf (from specific to general)`	0.70409
`rdfs:domain (from property to domain)`	0.69768
`rdfs:subClassOf (from general to specific)`	0.69384
`owl:equivalentProperty`	0.68156
`rdfs:subPropertyOf (from general to specific)`	0.66135
`owl:disjointWith`	0.65774
`rdfs:domain (from domain to property)`	0.58072
`rdfs:range (from property to range)`	0.50690
`rdfs:range (from range to property)`	0.30593
`owl:differentFrom`	0.19194

Figure 8. Computation process of semantic relatedness coefficients for OWL constructs.

The ontological path between "EarlyHarvest" and "LateHarvest" includes 2 IS-A relationships, 1 from specific to general and 1 from general to specific. Therefore, the semantic relatedness is computed by multiplying the coefficients of these 2 language constructs.

4.5. Experimental evaluation

The most common approach for evaluating the success of similarity and relatedness measurement methods is comparing the automatically computed similarity or relatedness values with human judgments. In order to be able to make this type of evaluation, researchers formed word pair lists and asked human participants to rate the similarity or relatedness of these word pairs.

Rubenstein and Goodenough [33] generated a word pair list consisting of 65 pairs and asked participants to rate the similarity of these word pairs. The word pair list of Miller and Charles [34] consisted of 30 word pairs and was rated by 38 undergraduate students. Finkelstein et al. [35] constituted a list of 353 word pairs, where 153 word pairs were rated by 13 participants and 200 were rated by 16 participants. The participants gave a score of 0 for completely dissimilar words and a score of 10 for completely similar or identical words.

In our study, 24 concept pairs (some concepts consisted of more than 1 word) were formed by analyzing 201 ontologies (refer to Table A2 in the Appendix). The selected concept pairs based on the ontologies analyzed had different types of relationships (such as IS-A, antonymy, or distinctness) and were translated into Turkish. The Turkish version of the concept pairs was rated by 57 participants whose native language was Turkish, and the English version was rated by 9 participants whose native language was English. The participants gave a score of 0 for completely unrelated concept pairs and 10 for completely related or identical concept pairs.

The first analysis made of the collected data was by independent samples t-test, in order to assess whether translation errors took place when translating the concept pairs present in English into Turkish. According to the results obtained from the independent samples t-test ($P = 0.99$), there was not a significant difference between the results of the Turkish native speakers ($avg = 5.97$) and the English native speakers ($avg = 5.98$). Therefore, all of the data collected were combined and analyzed together.

At the next step, outliers were identified and excluded from the result set. Z-transformation was applied and responses including z-values smaller than -3.29 and larger than $+3.29$ were excluded from the result set. The data collected from 3 participants were excluded from the result set and the final set included responses from 63 participants. After excluding the outliers, the final relatedness score for each concept pair was computed by averaging the participants' scores and dividing this average by 10.

For computing the semantic relatedness values for selected concept pairs, a program was developed using the Java programming language. The steps for computing the semantic relatedness values between concepts are illustrated in Figure 9. Jena [32] was used for ontologies to be read into and represented in memory. Pellet [36], which is an OWL DL reasoning engine, was used for inferring statements. The depth-first search algorithm was used for finding paths between the concepts.

In order to assess the success of the ontology-based relatedness measurement method, automatically calculated scores were analyzed with human judgments using the Pearson product–moment correlation technique. The correlation was significant and positive ($r = 0.685$, $P < 0.01$).

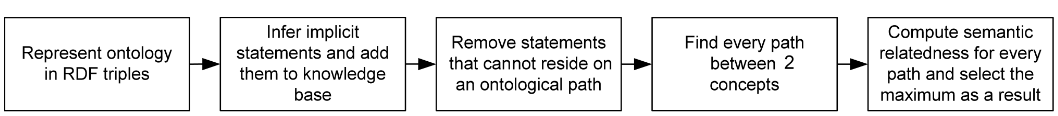


Figure 9. Steps for computing semantic relatedness values.

5. Discussion

There are many similarity and relatedness measurement methods proposed in the literature. Most of these methods have been evaluated against human judgments. The correlations between human judgments and automatically calculated scores by some similarity measurement methods are illustrated in the Table. The maximum correlation reported was 0.85. It can be observed from the Table that as the number of word pairs increases, the correlations decrease.

Table. Correlations between human judgments and automatically calculated scores by the similarity measurement methods.

	Rubenstein and Goodenough's 65 word pairs [33]	Miller and Charles' 30 word pairs [34]	Finkelstein et al.'s 353 word pairs [35]
Resnik [9]	0.78 [40]	0.77 [40]	0.37 [41]
Rada et al. [18]	-	0.64 [17]	0.25 [17]
Wu and Palmer [19]	-	0.80 [38]	-
Jiang and Conrath [37]	0.82 [40]	0.85 [40]	0.34 [41]
Lin [38]	0.82 [40]	0.83 [38]	0.36 [41]
Leacock and Chodorow [2]	0.84 [40]	0.82 [40]	0.36 [41]
Gabrilovich and Markovitch [39]	-	-	0.72 [39]

According to the correlations illustrated in the Table, the ontology-based relatedness measurement method could not achieve the best results. However, it should be emphasized that all of the methods whose successes were evaluated were similarity measurement methods. The relatedness concept has a broader scope than similarity. It incorporates more types of relationships, including similarity. In order to be able to assess more types of relationships between concepts, more expressive representation languages are needed. The IS-A relationship is commonly used for the assessment of similarity and relatedness. The IS-A relationship only implies a similarity between concepts, not any other kind of relationship that implies relatedness between concepts. On the other hand, some languages like OWL provide more types of constructs that enable users to define richer relationships. OWL provides constructs for defining IS-A (for concepts and properties), equality, distinctness, antonymy, property domain, and range relationships. Interpreting the semantics of these constructs for assessing relatedness seems to be logical to cope with the complexity of relatedness. As a result, it can be said that the relatedness method developed within the scope of this study is successful to some degree.

The graph of the human ratings and the automatically calculated relatedness values is illustrated in Figure 10. Based on the graph, it can be concluded that the automatic relatedness measurement method can simulate human judgments to some degree by keeping in mind that the relatedness values calculated are relative and not absolute.

The method developed within the scope of this study is inspired by spreading activation theory. The relatedness between 2 concepts depends on the constructs that connect these concepts. The contribution of each construct has been expressed by a coefficient between 0 and 1 and determined experimentally. The reason for choosing coefficients between 0 and 1 was to simulate the deflating behavior of the spreading activation as it moves further along a path. Since these coefficients are multiplied while moving along a path, the relatedness between the 2 concepts decreases as the length of the path increases and converges to 0 at some point in line with the spreading activation theory. All of the paths between the concepts are considered and the maximum relatedness value obtained determines the final result.

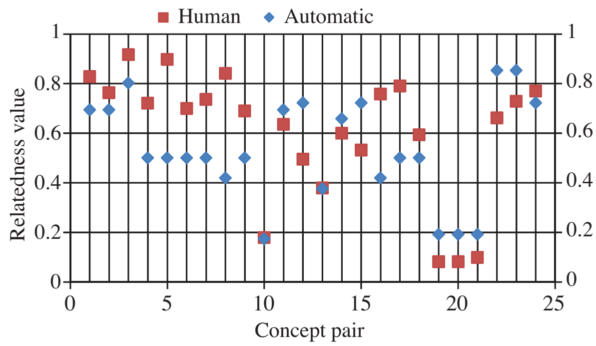


Figure 10. Graph of the human ratings versus the automatically calculated relatedness values.

6. Conclusion and future work

Automatic assessment of semantic similarity and relatedness is important for solving many problems. Better assessments lead to better results in solving such problems. With the rise of the semantic web, expressive ontology representation languages are being proposed. Using this expressive power for assessing semantic similarity and relatedness seems logical.

According to the results we obtained in our experiment, using the semantics of OWL constructs for assessing relatedness is promising. However, evaluating the success of a relatedness measurement method by comparing its results with human judgments is a common practice, but not sufficient to come to a reliable conclusion. Similarity and relatedness measurement methods are not beneficial themselves unless they are applied for solving one or more real world problems, such as web service discovery, invocation and composition, word sense disambiguation, information retrieval, ontology alignment and merging, document clustering, or short answer rating. Our objective is to use our method for assessing the coherence of texts written in natural language.

Semantic relatedness coefficients of 9 OWL constructs have been determined in this study. There are some constructs that can reside on an ontological path besides these 9 constructs. The semantic relatedness coefficient of the rdf:type construct should be determined for situations in which it defines the class of an individual.

In this study, 143 concept pairs were used to assess semantic relatedness coefficients. Increasing the number of concept pairs and the number of participants will lead to better results.

A criticism that can be expressed for semantic relatedness coefficients could be that they are the same for all ontologies and domains. Determining the ontology and/or domain specific semantic relatedness coefficients, based on coefficients presented in our study, may increase the success of the method.

Appendix

Table A1. List of 143 concept pairs used for determining the semantic relatedness coefficients of OWL constructs.

#	Concept 1	Concept 2	Average relatedness value	#	Concept 1	Concept 2	Average relatedness value
1	Sweet	Dry	2.38983	73	Greater than	Less than or equal	7.61017
2	Pizza	Banana	1.44068	74	Publications	Document	4.91525
3	Deficit	Excess	8.10169	75	Located in	Region	5.81356
4	Internal	External	8.57627	76	Made from fruit	Fruit	7.59322
5	Homogeneous	Heterogeneous	8.61017	77	Success in	Research	4.52542
6	Negative	Positive	8.86441	78	Opposite to	Direction	5.11864
7	Artificial	Natural	8.54237	79	Kills	Organism	2.64407
8	Oblique	Parallel	4.91525	80	Director	Person	4.83051
9	Condensed	Fluid	6.25424	81	Direction	opposite to	4.50847
10	Brine	Saline Water	8.30508	82	Organism	kills	1.96610
11	Asymmetry	Symmetry	8.50847	83	Person	Director	2.67797
12	Cooling	Heating	8.57627	84	Chemistry	Science	7.30508
13	Weathering	Erosion	7.50847	85	Kinetic energy	Energy	7.62712
14	Fast ice	Drift ice	6.54237	86	Sociology	Behavioral science	6.89831
15	Base	Acid	7.47458	87	Ratio	Division	7.18644
16	Military	Civil	8.35593	88	Physics	Science	7.84746
17	Landing	Takeoff	8.27119	89	Plain	Surface	6.37288
18	Manager	Assistant	6.72881	90	Local time	Time zone	7.44068
19	Son	Daughter	8.30508	91	Tornado	Storm	7.83051
20	Document	Project	5.03390	92	Sunny	Sky condition	6.88136
21	Project	Person	4.28814	93	Cloudy	Sky condition	7.55932
22	Person	Organization	4.84746	94	Cow	Animal	8.15254
23	Buyer	Seller	8.64407	95	Animal	Organism	5.18644
24	Visa	Passport	8.47458	96	Fish	Marine animal	8.28814
25	Ticket	Passport	5.16949	97	Human	Mammal	6.74576
26	Child	Retiree	2.33898	98	Fire	Disaster	7.16949
27	Sport	Relaxation	4.40678	99	Cultivation	Agriculture	6.81356
28	Meat	Pasta	3.94915	100	Signal	Communication	6.79661
29	Fruit	Dessert	6.23729	101	Wireless	Communication method	7.27119
30	Fruit	Seafood	1.25424	102	Mobile phone	Phone	7.89831
31	Seafood	Fowl	3.47458	103	Battery	Energy storage	7.11864
32	Capacity	Battery	5.57627	104	Electricity	Energy	8.16949
33	Postcode	Address	7.84746	105	Customer	Person	4.54237
34	Currency	Price	6.05085	106	Safari	Adventure	6.88136
35	Day	Date	7.40678	107	University	Educational institution	7.77966
36	City	Address	5.74576	108	Helicopter	Aircraft	8.10169
37	Hour	Time	8.40678	109	Yoga	Relaxation	7.49153
38	Seat number	Seat	7.74576	110	Energy	Electricity	8.03390
39	Minute	Time	8.16949	111	Vehicle	Ship	6.16949
40	has father	Person	5.05085	112	Aircraft	Jet	7.37288

Table A1. Continued.

#	Concept 1	Concept 2	Average relatedness value	#	Concept 1	Concept 2	Average relatedness value
41	Last name	Person	6.20339	113	Person	Customer	3.18644
42	Made from grape	Wine	8.45763	114	Personnel	Manager	6.91525
43	Date	Year	7.76271	115	City	Capital	5.89831
44	Person	Has father	3.49153	116	Adventure	Safari	7.01695
45	Group	Member	7.22034	117	Sweet fruit	Grape	6.37288
46	Document	Topic	5.10169	118	Meat	Red meat	8.06780
47	Person	Last name	4.66102	119	Politician	Senator	8.13559
48	Person	Know	4.47458	120	Educational institution	University	7.71186
49	Animal	Has habitat	4.30508	121	Mean of transportation	Automobile	7.93220
50	Ticket	Arrival date	5.94915	122	Athlete	Basketball player	6.22034
51	Tourist	Temporarily living in	5.66102	123	State of matter	Gas	8.00000
52	Wine	Made from grape	7.57627	124	Chemical state	Volatile	4.93220
53	Battery	Capacity	5.86441	125	Solid	Frozen	5.74576
54	Time	Minute	7.55932	126	State of matter	Liquid	7.45763
55	Decrease	Fall	7.77966	127	Aircraft	Helicopter	7.59322
56	Subtraction	Difference	7.40678	128	Relaxation	Yoga	6.72881
57	Category	Classification	8.38983	129	Accommodation	Hotel	8.27119
58	Time interval	Duration	7.71186	130	Science	Physics	7.37288
59	H_2O	Water	9.66102	131	Animal	Cow	7.16949
60	Asymmetry	Asymmetric	7.76271	132	Energy storage	Battery	7.13559
61	Ice particle	Ice crystal	6.11864	133	has mother	Has parent	7.93220
62	Tsunami	Tidal wave	9.16949	134	has brother	Has sibling	7.28814
63	Dosage	Dose	8.38983	135	Ethnic group	Group of people	5.84746
64	Sustainable	Sustainability	7.79661	136	Has modem	Has connectivity device	6.84746
65	Maker	Creator	5.81356	137	Has daughter	Has child	7.79661
66	Mass	Weight	7.66102	138	Has hard drive	Has storage	6.49153
67	Has effect	Cause	6.45763	139	Has child	Has daughter	6.52542
68	Has protons	Atomic number	7.28814	140 fruit	Made from grape	Made from	5.98305
69	After	Before	8.40678	141	Has storage	Has hard drive	6.93220
70	North	South	8.89831	142	Has parent	Has mother	7.84746
71	East	West	8.77966	143	Group of people	Ethnic group	5.74576
72	Below	Above	8.89831				

Table A2. List of 24 concept pairs used for the experimental evaluation.

#	Concept 1	Concept 2	Semantic relatedness value - computed	Semantic relatedness value - human
1	Money	Cash	0.6938	0.8278
2	Money	Currency	0.6938	0.7627
3	Car	Automobile	0.8023	0.9167
4	Street	Avenue	0.5006	0.7214
5	Man	Woman	0.5006	0.8968
6	Planet	Star	0.5006	0.6992
7	Wood	Forest	0.5006	0.7365
8	Book	Author	0.4190	0.8405
9	River	Lake	0.5006	0.6897
10	City	River	0.1739	0.1794
11	Man	Father	0.6938	0.6349
12	Parent	Person	0.7215	0.4952
13	Grandmother	Person	0.3756	0.3794
14	Rural area	City	0.6577	0.6000
15	Hiking	Activity	0.7215	0.5317
16	Publication	Author	0.4190	0.7579
17	Physics	Chemistry	0.5006	0.7905
18	Student	Professor	0.5006	0.5937
19	Chicken	Banana	0.1919	0.0810
20	Cake	Turkey	0.1919	0.0810
21	Pizza	Swordfish	0.1919	0.0984
22	Superset	Subset	0.8525	0.6611
23	Less than	Greater than or equal	0.8525	0.7286
24	Tiger	Animal	0.7215	0.7698

References

[1] D. Martin, M. Burstein, J. Hobbs, O. Lassila, D. McDermott, S. McIlraith, S. Narayanan, M. Paolucci, B. Parsia, T. Payne, E. Sirin, N. Srinivasan, K. Sycara, OWL-S: Semantic Markup for Web Services, W3C Member Submission, 2004. Available at http://www.w3.org/Submission/OWLS/.

[2] C. Leacock, M. Chodorow, Combining local context and WordNet similarity for word sense identification, In: C. Fellbaum, Ed., WordNet: An Electronic Lexical Database, Cambridge, MA, USA, MIT Press, 1998.

[3] C. Manning, P. Raghavan, H. Schütze, Introduction to Information Retrieval, Cambridge University Press, 2008.

[4] J. Euzenat, P. Valtchev, "Similarity-based ontology alignment in OWL-Lite", Proceedings of the 16th European Conference on Artificial Intelligence, pp. 333–337, 2004.

[5] X. Zhang, L. Jing, X. Hu, M. Ng, J.X. Jiangxi, X. Zhou, "Medical document clustering using ontology-based term similarity measures", International Journal of Data Warehousing and Mining, Vol. 4, pp. 62–73, 2008.

[6] M. Mohler, R. Mihalcea, "Text-to-text semantic similarity for automatic short answer grading", Proceedings of the 12th Conference of the European Chapter of the Association for Computational Linguistics, pp. 567–575, 2009.

[7] J.R. Anderson, "A spreading activation theory of memory", Journal of Verbal Learning and Verbal Behavior, Vol. 22, pp. 261–295, 1983.

[8] A. Tversky, "Features of similarity", Psychological Review, Vol. 84, pp. 327–352, 1977.

[9] P. Resnik, "Using information content to evaluate semantic similarity in a taxonomy", Proceedings of the 14th International Joint Conference on Artificial Intelligence, Vol. 1, pp. 448–453, 1985.

[10] A. Budanitsky, G. Hirst, "Semantic distance in WordNet: an experimental, application-oriented evaluation of five measures", Workshop on WordNet and Other Lexical Resources, Second Meeting of the North American Chapter of the Association for Computational Linguistics, pp. 29–34, 2001.

[11] C. Fellbaum, WordNet: An Electronic Lexical Database, Cambridge, MA, USA, Bradford Books, 1998.

[12] W. Mao, W.W. Chu, "Free-text medical document retrieval via phrased-based vector space model", Proceedings of the AMIA Symposium, pp. 489–493, 2002.

[13] R.L. Solso, M.K. MacLin, O.H. MacLin, Cognitive Psychology, 7th ed., Boston, MA, USA, Allyn & Bacon, 2005.

[14] Y. Wang, "The OAR model of neural informatics for internal knowledge representation in the brain", The International Journal of Cognitive Informatics and Natural Intelligence, Vol. 1, pp. 64–75, 2007.

[15] A.M. Collins, E.F. Loftus, "A spreading-activation theory of semantic processing", Psychological Review, Vol. 82, pp. 407–428, 1975.

[16] J.Z. Wang, Z. Du, R. Payattakool, P.S. Yu, C. Chen, "A new method to measure the semantic similarity of GO terms", Bioinformatics, Vol. 23, pp. 1274–1281, 2007.

[17] L. Mazuel, N. Sabouret, "Semantic relatedness measure using object properties in an ontology", Proceedings of the 7th International Conference on the Semantic Web, pp. 681–694, 2008.

[18] R. Rada, H. Mili, E. Bicknell, M. Blettner, "Development and application of a metric on semantic nets", IEEE Transactions on Systems, Man, and Cybernetics, Vol. 19, pp. 17–30, 1989.

[19] Z. Wu, M. Palmer, "Verb semantics and lexical selection", Proceedings of the 32nd Annual Meeting of the Association for Computational Linguistics, pp. 133–138, 1994.

[20] T. Slimani, B.B. Yaghlane, K. Mellouli, "A new similarity measure based on edge counting", Proceedings of the World Academy of Science, Engineering and Technology, Vol. 17, pp. 773–777, 2006.

[21] H.A. Nguyen, H. Al-Mubaid, "New ontology-based semantic similarity measure for the biomedical domain", IEEE International Conference on Granular Computing, pp. 623–628, 2006.

[22] R. Aydoğan, P. Yolum, "Learning consumer preferences using semantic similarity", Proceedings of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems, pp. 1293–1300, 2007.

[23] J. Ge, Y. Qiu, "Concept similarity matching based on semantic distance", Proceedings of the 4th International Conference on Semantics, Knowledge, and Grid, pp. 380–383, 2008.

[24] J. Miller, J. Mukerji, MDA Guide Version 1.0.1, Needham Heights, MA, USA, Object Management Group, 2003.

[25] A.G. Kleppe, "A language description is more than a metamodel", Proceedings of the 4th International Workshop on Software Language Engineering, 2007.

[26] E. Seidewitz, "What models mean", IEEE Software, Vol. 20, pp. 26–32, 2003.

[27] C. Atkinson, M. Gutheil, B. Kennel, "A flexible infrastructure for multilevel language engineering", IEEE Transactions on Software Engineering, Vol. 35, pp. 742–755, 2009.

[28] C. Atkinson, T. Kühne, "Concepts for comparing modeling tool architectures", Model Driven Engineering Languages and Systems, Vol. 3713, pp. 398–413, 2005.

[29] D. Gašević, N. Kaviani, M. Hatala, "On metamodeling in megamodels", Proceedings of the 10th International Conference on Model Driven Engineering Languages and Systems, pp. 91–105, 2007.

[30] B. Onyshkevych, "Ontosearch: using an ontology as a search space for knowledge based text processing", PhD, Carnegie Mellon University, USA, 1997.

[31] R. Knappe, "Measures of semantic similarity and relatedness for use in ontology-based information retrieval", PhD, Roskilde University, Denmark, 2005.

[32] J.J. Carroll, I. Dickinson, C. Dollin, D. Reynolds, A. Seaborne, K. Wilkinson, "Jena: implementing the semantic web recommendations", 13th International World Wide Web Conference on Alternate Track Papers & Posters, pp. 74–83, 2004.

[33] H. Rubenstein, J.B. Goodenough, "Contextual correlates of synonymy", Communications of the ACM, Vol. 8, pp. 627–633, 1965.

[34] G.A. Miller, W.G. Charles, "Contextual correlates of semantic similarity", Language and Cognitive Processes, Vol. 6, pp. 1–28, 1991.

[35] L. Finkelstein, E. Gabrilovich, Y. Matias, E. Rivlin, Z. Solan, G. Wolfman, E. Ruppin, "Placing search in context: the concept revisited", ACM Transactions on Information Systems, Vol. 20, pp. 116–131, 2002.

[36] E. Sirin, B. Parsia, B.C. Grau, A. Kalyanpur, Y. Katz, "Pellet: a practical OWL-DL reasoned", Web Semantics: Science, Services and Agents on the World Wide Web, Vol. 5, pp. 51–53, 2007.

[37] J.J. Jiang, D.W. Conrath, "Semantic similarity based on corpus statistics and lexical taxonomy", Proceedings of the International Conference on Research in Computational Linguistics, pp. 19–33, 1997.

[38] D. Lin, "An information-theoretic definition of similarity", Proceedings of the 15th International Conference on Machine Learning, pp. 296–304, 1998.

[39] E. Gabrilovich, S. Markovitch, "Wikipedia-based semantic interpretation for natural language processing", Journal of Artificial Intelligence Research, Vol. 34, pp. 443–498, 2009.

[40] A. Budanitsky, G. Hirst, "Semantic distance in WordNet: an experimental, application-oriented evaluation of five measures", Workshop on WordNet and Other Lexical Resources, pp. 29–34, 2001.

[41] D. Bollegala, Y. Matsuo, M. Ishizuka, "A relational model of semantic similarity between words using automatically extracted lexical pattern clusters from the web", The 2009 Conference on Empirical Methods in Natural Language Processing, Vol. 2, pp. 803–812, 2009.