Supporting Customer Choice with Semantic Similarity Search and Explanation^{*}

Anna Formica, Michele Missikoff, Elaheh Pourabbas, and Francesco Taglino

National Research Council, Istituto di Analisi dei Sistemi ed Informatica “A. Ruberti”
Viale Manzoni 30, I-00185 Rome, Italy
{name.surname}@iasi.cnr.it

Abstract. Semantic search and retrieval methods have a great potentiality in helping customers to make choices, since they appear to outperform traditional keyword-based approaches. In this paper, we address *SemSim*, a semantic search method based on the well-known information content approach. *SemSim* has been experimented to be effective in a defined domain, namely the tourism sector. During experimentation, one of the first requests raised from the users concerned the possibility to explain, besides the typical output of a semantic search engine, why a given result was returned. In this paper we investigate *SemSim* with the aim of providing the user with an explanation about the motivations behind the ranked list of returned options, with graphical representations conceived to better visualize the results of the semantic search.

Keywords: Similarity Reasoning, Weighted Reference Ontology, Information content, Digital Resources.

1 Introduction

Similarity reasoning represents a promising application of semantic technologies that is constantly gaining importance in information management. It also represents one of the key pillars of a new generation of search engines, capable of processing a user request from a conceptual perspective instead of basing the research on keyword-matching mechanisms. Along this direction, several semantic approaches have been proposed in the literature, based on the use of reference ontologies. Such approaches require that both the user request and the elements of the search space are semantically annotated, i.e., are associated with semantic expressions built upon the concepts of a reference ontology. This approach, referred to as *semantic* search and retrieval, appears to outperform traditional keyword-based approaches. However, the application of semantic search is restricted to focused domains due to the cost needed to develop the required semantic infrastructures (basically, reference ontology and semantic annotations).

In a previous paper [5] the authors have proposed *SemSim*, a semantic search method based on the idea that the similarity between conceptual structures depends on the amount of information content they share. In turn, the information content carried by a

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conceptual structure depends on the information content carried by the concepts (features) of the reference ontology (an *ontology* is a formal, explicit specification of a shared conceptualization [7]) for the given domain, at a given time. Intuitively, the information content of a concept, in our approach, depends on the number of objects in the search space that carry such a concept. In brief, a concept associated with fewer objects has a better selection coefficient and therefore a greater information content. Conversely, a concept that can be found in a large number of objects has less selectivity and therefore carries a more limited information content. Then, we introduced the notion of a *weighted ontology*, where each concept is associated with a weight corresponding to the frequency of the search objects that carry such a concept. It is quite obvious that concepts up in the hierarchy will have higher weight (and therefore less information content) than more specific concepts, positioned down in the hierarchy [11].

The core of the *SemSim* method consists in the derivation of the semantic similarity between concept structures, one representing a user request and one representing a target resource. Currently, we are experimenting the method, and the possibility to obtain, besides the typical output of a semantic search engine (i.e., a list of target objects, ranked according to a similarity score), a synthetic explanation of why the similarity engine achieves the displayed results. Therefore, the objective of this work is to extend the *SemSim* method by providing the user with such an explanation about the mechanism adopted in deriving the ranked list of objects. It is worth noting that often the outcome is not intuitive, since *SemSim* aims at maximizing the global information sharing of the user request and target object (i.e., the summation of the common information contents for all the concepts characterizing a given search object) therefore, avoiding ‘easy’ matching mechanisms.

The paper is organized as follows. After the next section presenting the related work, Section 3 recalls some basic notions of the *SemSim* method. In Section 4, a qualitative analysis of *SemSim* is presented, and in Section 5 two different visualizations of the analyzed results are given. Finally, Section 6 concludes.

2 Related Work

In the large majority of papers proposed in the literature [3,13], semantic search is performed by using WordNet [16], see for instance [8,15]. WordNet (a lexical ontology for the English language) provides, for a given concept (noun), the natural language definition, hypernyms, hyponyms, synonyms, etc, and also a measure of the *frequency* of the concept, by using noun frequencies from the Brown Corpus of American English [6]. We did not adopt the WordNet frequencies for two reasons. Firstly, we deal with specialized domains (e.g., systems engineering, tourism, etc.), requiring specialized domain ontologies. WordNet is a generic lexical ontology (i.e., not focused on a specific domain) that contains only simple terms. In fact, multi-word terms are not reported (e.g., terms such as “private house” or “country resort” are not defined in WordNet). Secondly, there are concepts in WordNet for which the frequency is not given (e.g., “accommodation”).

The work presented in [8] shares some analogies with our approach with regard to the need of computing weights without relying on large text corpora. Therefore, they propose a method, referred to as CP/CV, such that each node in the taxonomy is

associated with a concept vector, built on the basis of the topology of the ontology and the position of concepts therein. Then, the similarity of concepts is evaluated according to the *cosine* similarity of the related concept vectors. Conversely, in our work the similarity of concepts is conceived to determine the similarity of two concept vectors.

Regarding the methods to compute the similarity between concept vectors, our work proposes a two stages method, firstly computing the pair-wise concept similarity (*consim*), and then deriving the similarity between vectors of concepts (*semsim*). Pair-wise concept similarity is performed according to the information content approach [11]. With regard to the second stage, we adopted a solution inspired by the *maximum weighted matching problem* in bipartite graphs. In the literature the *Dice*, *Jaccard* and *Cosine* [12] methods are often adopted in order to compare vectors of concepts. However, in these methods the matchmaking of two concept vectors is based on their intersection, without considering the position of the concepts in the ontology. According to the *Weighted Sum* approach [2] a fixed value (i.e., 0.5) is assigned to each pair of hierarchically related concepts. Our proposal is based on a more refined semantic matchmaking, since the match of two concepts is performed according to their shared information content, and the vector similarity is based on the optimal concept coupling.

Within the semantic web search approaches supported by ontologies, we selected [1] and [10] as representative works. In the mentioned papers, semantic search methods have been conceived for retrieving the relevant resources based on OWL¹ (Ontology Web Language) ontologies. Basically, the relevant resources are identified by weighting the instances and properties defined in the assertional knowledge (ABox). Conversely, in our approach, weights are assigned to the features which correspond to the concepts of the terminological knowledge (TBox), and the identification of the relevant resources is performed on the basis of the ranked feature vectors.

3 The Semsim Method: An Overview

In [5] two different *SemSim* methods were addressed, namely the *probabilistic* and the *frequency* approaches. In the mentioned paper, we have shown that the *SemSim* method based on the frequency approach has a higher correlation with *Human Judgment (HJ)* than some of the most representative approaches defined in the literature. In this section, we recall the frequency approach, which is the focus of our paper. The *Universe of Digital Resources (UDR)* is the totality of digital resources that are semantically annotated with a reference ontology. In our work we address a simplified notion of ontology, *Ont*, consisting of a set of concepts organized according to a ISA hierarchy. In particular, *Ont* is a *taxonomy* defined by the pair $Ont = \langle C, H \rangle$, where C is a set of concepts and H is a set of ordered pairs of concepts of C such that if $(c_i, c_j) \in H$, then c_j ISA c_i , i.e., c_i is a more general concept with respect to c_j .

Given two concepts $c_i, c_j \in C$, the *least upper bound* of c_i, c_j , $lub(c_i, c_j)$, is always uniquely defined in C (we assume the hierarchy is a lattice). It represents the least abstract concept of the ontology that is a more general with respect to c_i and c_j .

¹ <http://www.w3.org/TR/owl2-primer/>

Consider an ontology $Ont = \langle C, H \rangle$. A *request feature vector* (*request vector* for short) rv is defined by a set of ontology concepts (the order of the concepts is irrelevant), i.e., $rv = (c_1, \dots, c_n)$ where $c_i \in C$.

Analogously, given a digital resource $dr_i \in UDR$, an ontology feature vector ofv_i associated with dr_i is defined by a set of ontology concepts describing the resource as follows: $ofv_i = (c_{i,1}, \dots, c_{i,m})$, where $c_{i,j} \in C, j = 1, \dots, m$.

A *Weighted Reference Ontology* (WRO) is a pair $WRO = \langle Ont, w \rangle$, where w is a function defined on C , such that given a concept $c \in C$, $w(c)$ is a rational number in the interval $[0, \dots, 1]$.

In the following, let H^* be the reflexive and transitive closure of H . According to the frequency approach, the weight associated with the concept c in the ontology $Ont = \langle C, H \rangle$, indicated as $w_f(c)$, is defined as follows:

$$w_f(c) = \frac{|\{ofv : (c' \in ofv, (c, c') \in H^*)\}|}{|UDR|}$$

Therefore, the weight assignment is computed on the basis of the given ontology feature vectors and weights are assigned according to a bottom-up approach in order to take into account the essence of the ISA hierarchy. For instance, in our running example in the tourism domain, suppose the digital resources are vacation packages for visiting a European capital, which are offered by a tourism agency. Each package is annotated with one ontology feature vector defined by using the concepts of the WRO shown in Figure 1. Suppose we have a UDR containing 22 vacation packages, each annotated as shown in Table 1.

Table 1. Annotation of vacation packages based on ontology feature vector

$ofv_1 = (\text{InternationalHotel}, \text{FrenchMeal}, \text{Cinema}, \text{Flight})$	$ofv_{12} = (\text{SeasideCottage}, \text{VegetarianMeal}, \text{Shopping})$
$ofv_2 = (\text{Pension}, \text{VegetarianMeal}, \text{ArtGallery}, \text{ShoppingCenter})$	$ofv_{13} = (\text{Campsite}, \text{IndianMeal}, \text{Museum}, \text{RockConcert})$
$ofv_3 = (\text{CountryResort}, \text{MediterraneanMeal}, \text{Bus})$	$ofv_{14} = (\text{RegularAcc}, \text{RegularMeal}, \text{Museum}, \text{Bazaar})$
$ofv_4 = (\text{CozyAcc}, \text{VegetarianMeal}, \text{Museum}, \text{Train})$	$ofv_{15} = (\text{InternationalHotel}, \text{PictureGallery}, \text{Flight})$
$ofv_5 = (\text{InternationalHotel}, \text{ThaiMeal}, \text{IndianMeal}, \text{Concert}, \text{Bus})$	$ofv_{16} = (\text{Pension}, \text{LightMeal}, \text{ArcheologicalSite}, \text{CarRental}, \text{Flight})$
$ofv_6 = (\text{SeasideCottage}, \text{LightMeal}, \text{ArcheologicalSite}, \text{Flight}, \text{ShoppingCenter})$	$ofv_{17} = (\text{AlternativeAcc}, \text{LightMeal}, \text{RockConcert}, \text{Bus})$
$ofv_7 = (\text{RegularAcc}, \text{RegularMeal}, \text{Salon}, \text{Flight})$	$ofv_{18} = (\text{CozyAcc}, \text{VegetarianMeal}, \text{Exhibition}, \text{ArcheologicalSite}, \text{Train})$
$ofv_8 = (\text{InternationalHotel}, \text{VegetarianMeal}, \text{Ship})$	$ofv_{19} = (\text{CountryResort}, \text{VegetarianMeal}, \text{Concert}, \text{Bus})$
$ofv_9 = (\text{FarmHouse}, \text{MediterraneanMeal}, \text{CarRental})$	$ofv_{20} = (\text{Campsite}, \text{MediterraneanMeal}, \text{ArcheologicalSite}, \text{Attraction}, \text{CarRental})$
$ofv_{10} = (\text{RegularAcc}, \text{EthnicMeal}, \text{Museum})$	$ofv_{21} = (\text{AlternativeAcc}, \text{LightMeal}, \text{Concert}, \text{Bus})$
$ofv_{11} = (\text{RegularAcc}, \text{LightMeal}, \text{Cinema}, \text{Bazar})$	$ofv_{22} = (\text{FarmHouse}, \text{LightMeal}, \text{RockConcert}, \text{Train})$

Consider the feature *VegetarianMeal* (a leaf in the taxonomy tree) which appears in each of the six *ofvs* of the set $\{ofv_2, ofv_4, ofv_8, ofv_{12}, ofv_{18}, ofv_{19}\}$ (see Table 1). The relative frequency of this feature over the whole resources (the 22 packages) is $w_f(\text{VegetarianMeal}) = 6/22 = 0.27$ (see Figure 1).

Fig. 1. WRO of our running example

In order to assign a weight to a more general concept, we have to consider not only the set of *ofvs* containing the concept but also the sets of *ofvs* containing its descendants in the ISA hierarchy. For instance, consider *LightMeal* which has only two children as descendants, namely *VegetarianMeal* and *MediterraneanMeal*. *MediterraneanMeal* appears in the *ofvs* of the set $\{ofv_3, ofv_9, ofv_{20}\}$. *LightMeal* is contained in the *ofvs* of the set $\{ofv_6, ofv_{11}, ofv_{16}, ofv_{17}, ofv_{21}, ofv_{22}\}$, therefore its weight is given by the cardinality of the union of the three sets above, divided by the total number of *ofvs*, i.e., $w_f(LightMeal) = 15/22 = 0.68$. Note that, in the case of overlapping sets of *ofvs*, the union set in the above formula guarantees that w_f does not exceed one.

Let us consider a tourist who wants to visit a European capital and, in order to buy a vacation package, he/she expresses the following preferences:

"I would like travel by bus, sleep in a campsite, have ethnic food, and enjoy rock concerts".

It can be formulated according to the request feature vector notation as follows:

$$rv_1 = (Campsite, EthnicMeal, RockConcert, Bus).$$

The *SemSim* method allows the user to choose among the vacation packages offered by the tourism agency of our running example (shown in Table 1) the one that better satisfies his/her needs. In particular, it evaluates the similarity between feature vectors (*semsim*), which is based on the notion of similarity between concepts (features), referred to as *consim*.

Given a WRO, the *consim* method relies on the information content approach defined by Lin [11]. According to the standard argumentation of information theory, the information content of a concept c is defined as $-\log w(c)$, where w is the weight associated with the concept c in the WRO. Therefore, as the weight of a concept increases the informativeness decreases hence, the more abstract a concept the lower its information content. Given two concepts c_i and c_j , their similarity, $consim(c_i, c_j)$, is defined as the maximum information content shared by the concepts divided by the sum of the information contents of the concepts. Note that we assume the ontology is a tree, therefore the least upper bound of c_i and c_j , $lub(c_i, c_j)$, is always defined and provides the maximum information content shared by the concepts in the taxonomy. Formally, we have:

$$consim(c_i, c_j) = 2 \times \frac{\log w_f(lub(c_i, c_j))}{\log w_f(c_i) + \log w_f(c_j)}$$

For instance, consider the pair of concepts *VegetarianMeal* and *MediterraneanMeal* of the WRO shown in Figure 1. The *consim* measure between *VegetarianMeal* and *MediterraneanMeal* is defined as follows:

$$consim(VegetarianMeal, MediterraneanMeal) = 2 \log w_f(LightMeal) / (\log w_f(VegetarianMeal) + \log w_f(MediterraneanMeal)) = 0.24.$$

In fact, *LightMeal* is the *lub* between *VegetarianMeal* and *MediterraneanMeal*, and therefore provides the maximum information content shared by the comparing concepts.

As anticipated, the *SemSim* method allows us to compute the semantic similarity between the request vector rv and an ofv , $semsim(rv, ofv)$, by using the *consim* similarity above. We start by computing the *consim* for each pair of concepts of the Cartesian product of the two vectors. However, we are not interested in all possible pairs because in many cases the comparison is meaningless (e.g., contrasting *Vegetarian-Meal* with *Concert*). Hence, we restrict our analysis to the pairs that exhibit high affinity. In particular, we consider the *stable marriage problem* [14], which is the problem of finding a stable matching (i.e., there does not exist any better alternative pairing) between sets of elements. For instance, assuming rv and ofv represent a set of boys and a set of girls respectively, we analyze all possible sets of marriages, when polygamy is not allowed. Our solution, for the computation of the semantic similarity makes use of the Hungarian algorithm as an implementation for solving the *maximum weighted matching* problem in bipartite graphs [9] which runs in polynomial time. Essentially, the method aims to identify the set of pairs of concepts of the two vectors that maximizes the sum of the *consim* similarity values:

$$semsim(rv, ofv) = \frac{\max(\sum consim(c_i, c_j))}{\max(n, m)}$$

where: $i = 1..n, j = 1..m, n = |rv|, m = |ofv|, c_i \in rv$, and $c_j \in ofv$.

For instance, in the case of the request vector rv_1 defined above and the ofv_{21} shown in Table 1, the following set of pairs of concepts (enclosed in parenthesis) has the maximum *consim* sum, as shown below:

$consim(Campsite, AlternativeAcc.) = 0.70$
 $consim(EthnicMeal, LightMeal) = 0.04$
 $consim(RockConcert, Concert) = 0.79$
 $consim(Bus, Bus) = 1$

Therefore: $semsim(rv_1, ofv_{21}) = (0.70 + 0.04 + 0.79 + 1) / 4 = 0.63$, where the sum of *consim* has been normalized according to the maximum cardinality of the contrasted vectors (in this case 4).

4 Semsim Experimental Analysis

In [5] we have presented an experiment where *SemSim* has been compared to some of the most representative similarity methods defined in the literature. In the experiment four request vectors have been defined, $rv_i, i = 1, ..., 4$, corresponding to the vacation preferences of four different tourists, which are recalled in Table 2. The correlation between each selected similarity method and human judgment (*HJ*) has been evaluated, where *HJ* values had been obtained by asking to a group of 21 people, randomly selected from our Institute staff, to indicate the similarity among each rv_i and the vacation packages $ofv_j, j = 1, ..., 22$, defined in Table 1. As already mentioned, in [5] our experiment has shown that the *SemSim* method based on the frequency approach has a higher correlation with *HJ* than the other approaches selected in the literature. Therefore, in this section, our analysis is focused on the *SemSim* method based on the frequency approach.

In Table 3, the *SemSim* values obtained according to our experiment are recalled. The *ofvs* are listed with the associated similarity values, starting from the highest up to the lowest values.

Table 2. Request Vectors

rv_1	= (Campsite, EthnicMeal, RockConcert, Bus)
rv_2	= (InternationalHotel, InternationalMeal, ArtGallery, Flight)
rv_3	= (Pension, MediterraneanMeal, Cinema, ShoppingCenter)
rv_4	= (CountryResort, LightMeal, ArcheologicalSite, Museum, Train)

Let us consider the first five *ofvs* listed in Table 3, i.e., the *ofvs* associated with the five highest *SemSim* values. For each rv_i $i = 1, \dots, 4$, a table has been defined, namely Tables 4, 5, 6, and 7 respectively, where the *ofvs* with the five highest values have been indicated. In each table, in the first row the features of the addressed request vector are listed, and in the remaining rows, the features of the selected *ofvs* are recalled. The positioning of the features of the *ofvs* in the rows has been performed in order to show the set of pairs of features (one belonging to the request vector and the other one to the *ofv*) leading to the maximum weighted matching value, according to the stable marriage problem recalled above. In the rows, the features are shown with the related *consim* values (in square brackets) and a label (one among M, H, S, C and R) specifying the kind of relation existing between the matched features, as explained below:

- M stands for *exact match*, therefore the *consim* value is 1.0;
- H stands for *hierarchical* relation, i.e. one feature is a descendant/ancestor of the other; in parenthesis the number of arcs connecting the two features is also given (e.g., H(1) stands for a parent/child relation);
- S stands for *sibling*, i.e., children of the same father;
- C stands for *cousin*, i.e., children of siblings;
- R stands for *related*, for all the remaining pairs of features of the ontology.

Let us consider for instance Table 4, related to the request vector rv_1 . According to the maximum weighted matching problem, the *ofv* with the highest *SemSim* value with rv_1 is ofv_{13} , which has four features. The pairs of features providing this value are (*Campsite*, *Campsite*), (*EthnicMeal*, *IndianMeal*), (*RockConcert*, *RockConcert*), and (*Bus*, *Museum*). Therefore, two features, namely *Campsite* and *RockConcert*, match exactly (M), *IndianMeal* is in the hierarchical relation H(1) with *EthnicMeal*, because the former is a child of the latter, and the other feature, *Museum*, is related to *Bus* according to the cousin relation (C). In square brackets we represent the *consim* values associated with these pairs, which in the case of the pair (*Bus*, *Museum*) is zero because these features do not share any information in the ontology except for *Thing*. In analyzing the four tables, as a general observation, note that the *ofvs* with higher *SemSim* values show a greater number of pairs of features with exact matches (M) with respect to the other *ofvs*. Immediately lower *SemSim* values correspond to a less number of exact matches M and a high number of parent/child relations H(1). Going down in the tables, the lowest *SemSim* values are associated with a higher number of related features (R), because R does not represent any specific relation between the features in the ontology. For instance, in the case of the request vector rv_2 , in the first

row of Table 5 we have the ofv_{15} showing two exact matches and one sibling relation, and in the second row we find the ofv_7 , for which one single match and three parent/child relations are present.

Table 3. Ranking results for request vectors

rv_1		rv_2		rv_3		rv_4	
Ranked Resources	Value	Ranked Resources	Value	Ranked Resources	Value	Ranked Resources	Value
ofv_{13}	0.73	ofv_{15}	0.66	ofv_{11}	0.61	ofv_{18}	0.66
ofv_{17}	0.69	ofv_7	0.60	ofv_2	0.58	ofv_4	0.63
ofv_{21}	0.63	ofv_1	0.52	ofv_1	0.35	ofv_6	0.55
ofv_5	0.54	ofv_2	0.35	ofv_{14}	0.31	ofv_{16}	0.44
ofv_{19}	0.45	ofv_{16}	0.29	ofv_6, ofv_{16}	0.28	ofv_{22}	0.42
ofv_{22}	0.44	ofv_8	0.28	$ofv_3, ofv_9,$	0.25	ofv_{19}	0.35
ofv_{10}, ofv_{20}	0.28	ofv_5	0.26	ofv_{12}	0.23	ofv_{20}	0.34
ofv_3	0.26	ofv_6	0.22	ofv_{21}	0.20	ofv_3	0.30
ofv_9	0.19	$ofv_{10}, ofv_{11},$	0.18	$ofv_5, ofv_{17},$	0.18	ofv_{17}, ofv_{21}	0.26
ofv_{18}	0.17	ofv_{14}	0.08	ofv_{19}, ofv_{22}		ofv_{13}	0.23
ofv_1	0.16	ofv_{19}, ofv_{21}	0.08	ofv_{18}	0.16	ofv_{11}	0.22
ofv_{11}	0.11	$ofv_4, ofv_{17},$	0.07	ofv_{18}	0.16	ofv_{11}	0.22
ofv_4, ofv_7	0.08	ofv_{22}	0.06	$ofv_7, ofv_8,$	0.15	ofv_{10}, ofv_{14}	0.21
$ofv_6, ofv_{15},$	0.07	ofv_{18}, ofv_{20}	0.06	ofv_{10}	0.15	ofv_{12}	0.20
ofv_{16}	0.07	ofv_3, ofv_9	0.05	ofv_{13}, ofv_{15}	0.11	ofv_8	0.12
ofv_8	0.04	ofv_{13}	0.02	ofv_4	0.08	ofv_8	0.12
ofv_2, ofv_{14}	0.03	ofv_{12}	0.00			ofv_2	0.11
ofv_{16}	0.01					ofv_9	0.10
						ofv_5, ofv_7	0.07
						ofv_1	0.06
						ofv_{15}	0.05

However, this does not hold in general. In fact in the same table, ofv_1 in the third position has one more exact match with respect to ofv_7 . The reason is that, in the case of ofv_1 , two exact matches are combined with a cousin relation which has a very low *consim* value. We have a similar situation in Table 6, for the ofv_{11} and ofv_2 in the case of the request vector rv_3 . In fact, the combination of one exact match (*Cinema*) with two parent/child relations (*Pension*, *RegularAcc*) and (*MediterraneanMeal*, *LightMeal*) leads to a higher *SemSim* value for the ofv_{11} with respect to the ofv_2 for which two exact matches (*Pension*) and (*ShoppingCenter*) are combined with a sibling relation (*MediterraneanMeal*, *VegetarianMeal*) and a cousin relation (*Cinema*, *ArtGallery*), the last one with a very low value.

Table 4. Ranking results for rv_1

rv_1	<i>Campsite</i>	<i>EthnicMeal</i>	<i>RockConcert</i>	<i>Bus</i>	<i>Semsim</i>
ofv_{13}	Campsite M [1.0]	IndianMeal H(1) [0.91]	RockConcert M [1.0]	Museum C [0]	0.73
ofv_{17}	AlternativeAcc H(1) [0.70]	LightMeal S [0.04]	RockConcert M [1.0]	Bus M [1.0]	0.69
ofv_{21}	AlternativeAcc H(1) [0.70]	LightMeal S [0.04]	Concert H(1) [0.79]	Bus M [1.0]	0.63
ofv_5	InternationalHotel C [0]	IndianMeal H(1) [0.91]	Concert H(1) [0.79]	Bus M [1.0]	0.54
ofv_{19}	CountryResort C [0]	VegetarianMeal R [0.03]	Concert H(1) [0.79]	Bus M [1.0]	0.45

Consider now the ofv_5 in Table 4. It contains one more feature than the request vector rv_1 and, according to the stable marriage problem, it will necessarily have a dangling feature in the table. This feature is *ThaiMeal*, even though in the request vector there is *EthnicMeal* which is its parent. This is due to the higher *consim* similarity value between *IndianMeal* and *EthnicMeal* (0.91) than *ThaiMeal* and *EthnicMeal* (0.78). For this reason, since *ThaiMeal* does not contribute in any way to *SemSim* value, the value in square brackets has been set to zero.

Table 5. Ranking results for rv_2

rv_2	<i>InternationalHotel</i>	<i>InternationalMeal</i>	<i>ArtGallery</i>	<i>Flight</i>	<i>SemSim</i>
ofv_{15}	InternationalHotel M [1.0]		PictureGallery S [0.64]	Flight M [1.0]	0.66
ofv_7	RegularAcc H(1) [0.63]	RegularMeal H(1) [0]	Salon H(1) [0.78]	Flight M [1.0]	0.60
ofv_1	InternationalHotel M [1.0]	FrenchMeal S [0]	Cinema C [0.07]	Flight M [1.0]	0.52
ofv_2	Pension S [0.38]	VegetarianMeal C [0]	ArtGallery M [1.0]	Shopping Center R [0]	0.35
ofv_{16}	Pension S [0.38]	LightMeal R [0]	ArcheologicalSite R [0.08]	Flight M [1.0]	CarRental [0]
					0.29

Note that in the case of a feature associated with a weight equal to zero, such as for instance *InternationalMeal* (see the ontology in Figure 1), we assume that *consim* between this feature and any other feature is equal to zero as well. This is the reason why in Table 5, in the case of the ofv_7 , the pair *RegularMeal*, *InternationalMeal* has a *consim* value equal to zero, even though they are in a parent/child relation (and the same results are obtained for the other features in the *InternationalMeal* column with different kinds of relations).

Table 6. Ranking results for rv_3

rv_3	<i>Pension</i>	<i>MediterraneanMeal</i>	<i>Cinema</i>	<i>ShoppingCenter</i>	<i>SemSim</i>
ofv_{11}	RegularAcc H(1) [0.49]	LightMeal H(1) [0.32]	Cinema M [1.0]	Bazaar S [0.62]	0.61
ofv_2	<i>Pension</i> M [1.0]	VegetarianMeal S [0.23]	ArtGallery C [0.07]	ShoppingCenter M [1.0]	0.58
ofv_1	InternationalHotel S [0.39]	FrenchMeal C [0.02]	Cinema M [1.0]	Flight R [0]	0.35
ofv_{14}	RegularAcc H(1) [0.49]	RegularMeal R [0.02]	Museum R [0.10]	Bazaar S [0.62]	0.31
ofv_6	SeasideCottage C [0]	LightMeal H(1) [0.32]	ArcheologicalSite R [0.10]	ShoppingCenter M [1.0]	Flight [0]
ofv_{16}	Pension M [1.0]	LightMeal H(1) [0.32]	ArcheologicalSite R [0.10]	CarRental R [0]	Flight [0]
					0.28

Table 7. Ranking results for rv_4

rv_4	<i>CountryResort</i>	<i>LightMeal</i>	<i>Museum</i>	<i>ArcheologicalSite</i>	<i>Train</i>	<i>SemSim</i>
ofv_{18}	CozyAcc H(1) [0.70]	VegetarianMeal H(1) [0.46]	Exhibition S [0.15]	ArcheologicalSite M [1.0]	Train M [1.0]	0.66
ofv_4	CozyAcc H(1) [0.70]	VegetarianMeal H(1) [0.46]	Museum M [1.0]		Train M [1.0]	0.63
ofv_6	SeasideCottage S [0.54]	LightMeal M [1.0]	ShoppingCenter R [0]	ArcheologicalSite M [1.0]	Flight S [0.18]	0.55
ofv_{16}	Pension C [0]	LightMeal M [1.0]	CarRental C [0]	ArcheologicalSite M [1.0]	Flight S [0.18]	0.44
ofv_{22}	FarmHouse C [0]	LightMeal M [1.0]		RockConcert R [0.11]	Train M [1.0]	0.42

Note that in some cases the *ofvs* may have high *SemSim* values even though in the presence of dangling features of the request vector. This is the case, for instance, of the *ofv*₁₅ in Table 5, which is associated with the highest *SemSim* value in the list (0.66). In fact, it presents two exact matches (*InternationalHotel*) and (*Flight*), one sibling relation (*ArtGallery*, *PictureGallery*), and the *InternationalMeal* feature of the request vector *rv*₂ that is dangling.

5 Visualization Methods for Results

In order to provide a better visualization of the results of the *SemSim* method, we show them in graphical ways. In particular, we adopt radial and radar representations. The former gives a general idea of the results, while the latter focuses on a particular *ofv*. In the radial representation, given a request vector (*rv*) we place the *SemSim* values for the different *ofvs* on concentric circumferences where the radius of each circumference corresponds to the *SemSim* value of the related *ofv*. In Figure 2, an example related to the *rv*₄ is given, where the first five *ofvs* in the ranking have been reported according to Table 7.

Fig. 2. Radial representation for *rv*₄

Fig. 3. Radar representation (*ofv*₁₈, *rv*₄)

In the radar representation, given a *rv* and an *ofv*, we show all the features of the *rv*, and for each of these features, the *consim* value obtained from the pairs formed with the concepts of the *ofv*, as shown in Table 7. For instance, *rv*₄ is composed by five features: *CountryResort*, *LightMeal*, *Museum*, *ArcheologicalSite*, and *Train*. Therefore, *rv*₄ is represented as a pentagon, where each vertex is labeled with one of its features. As illustrated in Figure 3, the radar representation shows how the *rv*₄ is approximated by the *ofv*₁₈.

6 Conclusions

In this paper, we have addressed *SemSim*, a method for the semantic search and retrieval of resources that populate a search space. *SemSim*, which has been already

experimented in the tourism sector, has been further investigated. In particular, a qualitative analysis has been given by providing the user with an explanation about the mechanism adopted in deriving the ranked list of objects. Furthermore, graphical representations about the results have also been given.

As a future work, we plan to study ontology comprising different types of ontological relations.

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