A PARAMETRIC SIMILARITY METHOD: COMPARATIVE EXPERIMENTS BASED ON SEMANTICALLY ANNOTATED LARGE DATASETS *

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ABSTRACT

We present the parametric method $SemSim^p$ aimed at measuring semantic similarity of digital resources. SemSim^p is based on the notion of *information content*, and it leverages a reference ontology and taxonomic reasoning, encompassing different approaches for weighting the concepts of the ontology. In particular, weights can be computed by considering either the available digital resources or the structure of the reference ontology of a given domain. SemSim^p is assessed against six representative semantic similarity methods for comparing sets of concepts proposed in the literature, by carrying out an experimentation that includes both a statistical analysis and an expert judgement evaluation. To the purpose of achieving a reliable assessment, we used a real-world large dataset based on the Digital Library of the Association for Computing Machinery (ACM), and a reference ontology derived from the ACM Computing Classification System (ACM-CCS). For each method, we considered two indicators. The first concerns the degree of confidence to identify the similarity among the papers belonging to some special issues selected from the ACM Transactions on Information Systems journal, the second the Pearson correlation with human judgement. The results reveal that one of the configurations of SemSim^p outperforms the other assessed methods. An additional experiment performed in the domain of physics shows that, in general, SemSim^p provides better results than the other similarity methods.

Keywords Semantic similarity reasoning \cdot weighted ontology \cdot information content \cdot statistical analysis \cdot expert judgement \cdot benchmarking.

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1 Introduction

Similarity is a fundamental research topic relevant to different applications, from recommender systems [10], text classification [40], health [1], to geographic information systems (GIS) [25, 49], just to mention a few. In particular, semantic similarity relying on the use of knowledge-based techniques [28, 67, 6, 21] represents a promising research field. Along this direction, we present the parametric semantic similarity method SemSim^p. It is derived from SemSim [17, 23], which has been conceived for evaluating semantic similarity of annotated resources (i.e., real world entities). There are no restrictions about the type of analyzed resources, they can be images, technical reports, descriptive brochures, and any other artifact. The only requirement is that a resource has to be semantically annotated, i.e., its content is described by a collection of concepts or features, referred to as a semantic annotation vector (annotation vector for short). Furthermore, such concepts cannot be freely chosen but they have to be selected from a reference ontology. In our work, the reference ontology is a taxonomy, i.e., a collection of concepts from a given application domain organized according to the ISA relationship (ISA hierarchy) [23]. In order to evaluate the semantic similarity of digital resources, SemSim requires a weighted reference ontology, where each concept is associated with a weight. Such a weight represents the specificity (or, inversely, the genericity) of the concept in the given domain that is inversely related to the cardinality of the set of the described resources (i.e., its extension) in the given domain. SemSim evaluates the semantic similarity of digital resources by exploiting the structure of the ontology. In particular, it computes the semantic similarity of pairs of annotation vectors on the basis of the similarity between concepts from the ontology, by relying on the information content approach [39]. SemSim has been assessed with experiments in several case studies [17, 23, 24], showing its efficiency and better performances with respect to well-known methods in the literature.

In this paper, we present the parametric method *SemSim^p*, which is an evolution of *SemSim*. It essentially depends on two parameters: the method used for computing the weights associated with the concepts of the ontology, and a normalization factor adopted when the two compared annotation vectors have different cardinalities. The objective is the validation of *SemSim^p* by means of a comparative assessment, showing that *SemSim^p* configured with a new selection of parameters improves the performance of *SemSim*, as well as it outperforms some of the most representative semantic similarity methods proposed in the literature. In particular, we assessed *SemSim^p* by contrasting it against six of the most popular similarity methods for comparing annotation vectors, organized in two groups. One group, containing Dice [18], Jaccard [30], and Sigmoid [38], relies on set-theoretic methods, since the similarity scores are derived by applying set-theoretic operations on the annotation vectors associated with the digital resources. The second group, formed by WNSim [57], and the methods proposed by Rezaei & Fränti [51] and Haase et al. [26], includes taxonomy-based methods, which require pairs of concepts in the annotation vectors to be compared.

Evaluating a similarity reasoning method is not a simple task, it presents two orders of difficulties: one relies on the choice of the set of resources (dataset) to be analyzed, and the other is the actual benchmark, i.e., the reference against which it is possible to measure the performance of the selected method. With regard to benchmarking techniques, the most used one is based on human judgement [41] [62]. In essence, considering a set of resources with their annotation vectors, a group of people is asked to pairwise match and assign them a similarity score. However, it is well-known that the human decision about similarity can be subjective, depending on the perspective adopted in looking at the resources, the relevant features, the purpose in mind and, finally yet importantly, the selected context. Secondly, a robust experiment requires a statistically relevant number of resources to be addressed. However, the greater the number of resources the harder the effort of people to perform the evaluation task.

We performed two different experiments based on the articles published in the Digital Library of the Association for Computing Machinery (ACM-DL). Since it is unrealistic to ask a group of people to pairwise check thousands of annotation vectors, producing millions of similarity scores, the key idea of this experimentation is to use some ACM special issues as benchmarks, because they contain papers whose semantic similarity, on average, is supposed to be greater than the one of a collection of papers randomly selected. In fact, such papers are gathered by the editor according to the research topic indicated in the call for paper. In particular, the first experiment is based on a statistical analysis without human intervention, and the second one on expert judgement (EJ), limited to the ACM special issues. The results of both the experiments reveal that one of the configurations of *SemSim^p* outperforms the other assessed methods. In order to confirm these results, a further experiment was performed by relying on the articles published by the American Physical Society (APS). This additional experiment shows that, in general, *SemSim^p* provides better results with respect to the selected similarity methods.

The paper is organized as follows. In the next section, the related work is introduced. In Section 3 the parametric $SemSim^p$ method is presented. In Section 4, the experiments are described, starting with the context description and the related research questions. In Section 5 the experimental results are discussed, and in Section 6 the conclusion is presented.



Figure 1: Histogram of all the papers indexed by SCOPUS with "semantic similarity" (retrieval date: Nov, 2019).

2 Related Work

Nowadays, we are witnessing an increasing interest of the research community on the topic of semantic similarity, both at theoretical and practical levels. In fact, it encompasses a variety of fields spanning from artificial intelligence, social sciences to medicine, genetics, etc. In order to better emphasize the role of the semantic similarity research topic, we assessed its impact on the literature by considering the SCOPUS abstract and citation database. In this context, we ran a query² aimed at retrieving all the papers tagged by the keyword "semantic similarity" in the time interval from 1992 to 2019, and we retrieved 4,463 papers. Figure 1 shows the distribution per year of the obtained papers, where their increment in the considered time interval is evident. As we observe, more than 200 papers have been tagged by year in the interval from 2008 to 2019, and the highest number of papers, that is about 500, is related to 2018. Each paper is also associated with one or more sectors that are shown in Table 9 in Annex A according to a descending order of number of papers.

Among the retrieved sectors, we distinguished the *technical* sectors from the *application* ones. In the former, the papers likely present technical details, for instance, algorithms to compute semantic similarity or implementations of semantic similarity solutions. The latter, i.e., the application ones, are illustrated in Figure 2. They concern social sciences, decision sciences, arts and humanities, biochemistry, genetics and molecular biology, medicine, etc. Among these sectors, *Social Sciences, Decision Sciences*, and *Arts and Humanities* involve a relevant high number of papers tagged with "semantic similarity", which are 23.3%, 13.3%, and 13.0% papers, respectively.

From a methodological point of view, methods for evaluating similarity can be categorized as follows [8]: *knowledge-based* [28, 67, 6, 21] (the focus of this paper), *corpus-based* [65] that can be further classified according to kernel-based models [12, 4], *deep neural network-based* [61, 66], and *hybrid methods* [27]. Currently, the focus of research is shifting towards deep neural network-based methods. However, these methods require high computational resources and lack interpretability, and the need for determining a balance between computational efficiency and performance is still a challenge [8]. With respect to these methods, in this work, we rely on a knowledge-based approach that, as illustrated in this paper, shows good performances and computational efficiency.

This section gives an overview of the existing works from the literature addressing the main topics of this paper. Indeed, it is organized as follows: Section 2.1 focuses on the methods for weighting concepts in an ontology, Section 2.2 recalls some methods for computing similarity between sets of concepts and, in particular, the ones selected for comparison with $SemSim^p$ in our experiment, and Section 2.3 is about the approaches for evaluating them.

²The query was run on the 19th November, 2019.



Figure 2: Percentage of papers indexed by SCOPUS with "semantic similarity" by application sectors.

2.1 Ontology Weighting Methods

Extensional methods, also referred to as distributional [54], in general compute the information content of a concept on the basis of the frequency distribution of the corresponding terms in a corpus of text documents. Therefore, these methods leverage on the extensional semantics of the concepts since their probability can be calculated by considering the number of occurrences of each concept in the text corpora. Extensional approaches were used by Jiang & Conrath [32], Lin [39], and Resnik [50] to estimate semantic similarity between concepts. They also encompass the inverse document frequency (IDF) method, and the combination of term frequency (TF) and IDF [42, 53]. In our work, we derived the concept frequency method and the annotation frequency method, respectively, from the one used by Resnik [50] and IDF (see Section 3).

The intensional methods, also referred to as intrinsic [54], compute the information contents of concepts on the basis of the conceptual relationships existing between them and mainly, on the basis of their taxonomic structure. With this regard, the method of Seco et al. [56] is based on the number of concepts' hyponyms and the total number of concepts in the taxonomy. An extension of the mentioned method is presented by Meng et al. [43], where also the depth of concepts in the taxonomy, i.e., the degree of generality of concepts, is considered. In [54], the authors claim that the taxonomical leaves are enough to describe and differentiate two concepts because *ad-hoc abstractions* (e.g., abstract entities) rarely appear in the universe of discourse, but have an impact on the size of the taxonomy. In order to estimate the weight of a concept, Hayuhardhika et al. [29] propose to use the density factor of a concept, which is based on the sum of incoming and outgoing connections with other concepts versus the total number of concepts' weights. In our paper, we focused on taxonomic structure and the other ontological relationships to derive concepts' weights. In our paper, we focused on taxonomies (i.e., structures organized according to ISA relationships) because, in general, they are used for classification purposes by actual communities (e.g., the ACM and APS communities).

With respect to the previous proposals, in our work both the extensional and the intensional approaches have been addressed and experimented.

2.2 Similarity between Sets of Concepts

In this section, since we represent a resource as a collection of concepts, we recall some proposals concerning the similarity between sets of concepts. In particular, we start from the approaches that were selected for the experiments conducted in this paper.

Traditionally, in order to evaluate the similarity between sets of concepts (features), the Dice [18] and Jaccard [30] measures were adopted, which can also be formulated according to the well-known Tversky model [63]. Furthermore, the Sigmoid similarity measure [38], which is an improvement of Dice, was also considered. As mentioned in the Introduction, these are the three set-theoretic methods that were considered in our experimentation, as formally recalled in Section 4.3.4. The formal definitions of these three methods are provided in Table 10 in Annex C.

With regard to the methods relying also on a taxonomy, we recall three similarity measures, the ones introduced by Rezaei & Fränti [51], and Haase et al. [26], and the WNSim similarity [57], that were also used in order to evaluate $SemSim^p$. They are formally given in Table 11 in Annex C. In particular, in [51], a similarity measure between sets of

keywords was presented, which is based on matching the individual concepts of two groups by applying the well-known Wu and Palmer measure [64], by using the WordNet taxonomy. In [26], in order to compute the similarity of pairs of concepts belonging to different sets, the authors use the edge-based similarity measure proposed by Li et al. [37], which combines the shortest path lengths and the depths of subsumers in the taxonomy non-linearly. In [57], the authors propose WNSim, a method for computing similarity between sets of keywords representing sentences in documents, by leveraging the Leacock and Chodorow similarity between concepts [36]. Both the methods proposed, respectively, by Haase et al. [26] and Shajalal & Aono [57] are asymmetric since, in comparing the two sets, the selection of the first one is relevant. Note that, as opposed to the mentioned methods, $SemSim^p$ is symmetric.

Among the other proposals that are based on the taxonomy, it is worth mentioning the paper of Cordì et al. [11], where the problem of defining a similarity metric between sets of concepts belonging to the same ontology is addressed. Essentially, two sets of concepts, named as *source* and *target* in the mentioned paper, have a similarity degree equal to 1 if all the concepts in the source are in the target, up to a normalization factor. However, the similarity metric proposed by these authors is based on the Dijkstra's algorithm, i.e., on the evaluation of the minimal path between nodes in the graph. Analogously to the approach of Haase et al. [26], concepts which are closer according to their positions in the taxonomy are semantically more similar than concepts that have a greater distance. Chen et al. [9] present a semantic similarity measure for web service discovery. It can be applied to both textual descriptions and interface signatures. However, these two proposals are based on an enriched notion of semantic distance which relies on weighted paths combining different relationships of an ontology (e.g., is-a and has-a), and therefore we did not address them in our experimentation that leverages the information content of an ISA hierarchy.

Finally, in the paper of Jia et al. [31], semantic similarity has been investigated in the clinical context, in order to measure patient disease similarity. In the paper, the authors recall the most representative metrics proposed in the literature for evaluating the similarity between sets of concepts, including Dice, Jaccard, and the information content approach. However, the authors state that the choice of the most appropriate algorithm under various clinical scenarios is still a challenge, especially when the sizes of the sets to be compared are large or unbalanced, and they claim the need for further investigations about this research topic.

2.3 Approaches to Semantic Similarity Evaluation

Traditionally, semantic similarity between concepts or words is assessed by developing experiments where people are asked to express a similarity value between terms. In some cases, such experiments bring to the definition of the so called *golden datasets*. In this context, a golden dataset is defined as a list of pairs of terms, each associated with a numerical value representing the semantic similarity between the terms as derived from the human judgement evaluation. The use of a golden dataset is important since it can be employed as a benchmark in the evaluation and comparison of different similarity methods. Among the existing golden datasets we recall: **R&G**, which is composed of 65 pairs of words representing general concepts evaluated by 51 college undergraduates according to a scale from 0 to 4, where the higher the semantic similarity, the higher the score [52]; **M&C**³ is composed of 30 pairs of words, which represent a subset of R&G evaluated by 38 persons [46]; **R122** is composed of 122 pairs of words representing generic concepts evaluated by 14 up to 22 people, out of a total of 92 participants [59].

In our case, we could not use one of the available golden datasets. In fact, there are no golden datasets including similarity scores for all possible pairs of concepts in the set and, in particular, concerning the ACM-CCS keywords, which is the domain of our experimentation.

The statistical method used for the experimentation analysis presented in our paper is similar to the approach used by Köhler et al. [35] to identify candidate diseases that best explain a set of clinical features. In fact, they propose a statistical model to assign a *p-value*⁴ to the similarity score obtained by searching *n* terms, corresponding to the probability of having a similarity score higher than, or equal to, the one obtained by randomly sampling with the Monte Carlo method [33] the same number of query terms. If the highest-scoring candidate disease has a significant *p-value*, this indicates that the syndrome is highly likely. Otherwise, the clinical features are not specific enough to allow a diagnosis. More generally, De Nicola & D'Agostino [13] analyzed a semantic social network [45] and used a statistical approach based on *p-value* to assess the diversity of groups of people with regard to some features characterizing them, as for instance performance indicators or some others related to psychological aspects. With respect to these works where the diversity of groups is not an assumption, we changed the perspective as we assumed that there exist samples of similar digital resources (i.e., the special issues) that can be considered as a benchmark, and we used a statistical approach based on *t-value* [5] (see Section 4.3.2) in order to assess the best method to evaluate semantic similarity.

³https://github.com/alexanderpanchenko/sim-eval/blob/master/datasets/mc.csv

⁴According to Mertens and Recker [44], the *p-value* indicates the probability of obtaining the observed result or anything more extreme than that actually observed in the available sample data.



Figure 3: A simple taxonomy.

3 The Parametric SemSim^p Method

In this section, we present the parametric semantic similarity method $SemSim^p$, which is based on SemSim introduced in [23]. The *SemSim* method has been revised from two points of view. One takes into account the methods conceived to assign weights to concepts. The other one, instead, refers to a normalization factor embedded in the method, which is a coefficient that captures different counts of the annotation vectors cardinality. Such a coefficient allows the similarity measures to be normalized to values between 0 and 1. To this end, we recall some basic notions already introduced in [23, 24]. Then, we describe the $SemSim^p$ method, and the different values that the normalization factor can assume. Successively, we discuss some methods to assign weights to concepts in order to calculate their semantic similarity.

3.1 Basic Notions

According to the definitions introduced by [23, 24], an ontology Ont is a taxonomy defined by the pair:

$$Ont = <\mathcal{C}, ISA > \tag{1}$$

where $C = \{c_i\}$ is a set of concepts, and *ISA* is the set of pairs of concepts in C that are in subsumption (\sqsubseteq) relationship:

$$ISA = \{(c_i, c_j) \in \mathcal{C} \times \mathcal{C} | c_i \sqsubseteq c_j\}$$
⁽²⁾

where $c_i \sqsubseteq c_j$ means that c_i is a child of c_j in the taxonomy. Note that, in this work, we focus on taxonomies that are trees (i.e., tree-shaped taxonomies). A *Weighted Reference Ontology* (*WRO*) is then defined as follows:

$$WRO =$$
(3)

where w, denoting the concept weighting function, is a probability distribution defined on C, such that given $c \in C$, w(c) is a decimal number in [0, 1]. A simple tree-shaped taxonomy is introduced in Figure 3. It will be used in Section 3.3 in order to present the different ontology weighting methods.

Using the WRO, each resource is annotated by means of a semantic *annotation vector*. An annotation vector av is a collection of concepts of the ontology Ont, introduced to capture the semantic content of the corresponding resource. It is represented as follows:

$$av = (c_1, ..., c_n), c_i \in \mathcal{C}, i = 1, ..., n.$$
 (4)

3.2 The *SemSim^p* algorithm

The *SemSim^p* method has been defined in order to calculate a semantic similarity degree between annotation vectors [23]. This method is based on two parametric functions, $consim_h$ (see Eq. (5)) and $semsim_{h,\mu}$ (see Eq. (8)), the former used to compute the similarity of pairs of concepts (or features), whereas the latter conceived to calculate the similarity of pairs of annotation vectors.

In particular, given two concepts c_1 , c_2 , the similarity between them is given as follows:

$$consim_h(c_1, c_2) = \frac{2 \times IC_h(lcs(c_1, c_2))}{IC_h(c_1) + IC_h(c_2)}$$
(5)

where $lcs(c_1, c_2)$ is the *least common subsumer* of the concepts c_1 and c_2 in the taxonomy, i.e., the least abstract concept of the ontology that subsumes both of them and, for any concept $c \in C$, $IC_h(c)$ is defined as follows:

$$IC_h(c) = \begin{cases} -log(w_h(c)) & \text{if } h = \{CF, AF, TD\}\\ iic(c) & \text{if } h = \{IIC\} \end{cases}$$
(6)

where *CF* (*Concept Frequency*), *AF* (*Annotation Frequency*), *TD* (*Top-Down topology-based*), and *IIC* (*Intrinsic Information Content*) are ontology weighting methods that will be presented in the next section. Note that $IC_h(c)$, in the case $h = \{CF, AF, TD\}$, is the information content of the concept c as introduced in [39], whereas in the case $h = \{IIC\}$, it is defined according to [56].

Now, let us consider two annotation vectors, say $av_1 = (c_{11}, \ldots, c_{1n})$ and $av_2 = (c_{21}, \ldots, c_{2m})$, respectively. The $semsim_{h,\mu}$ function computes the $consim_h$ for each pair of concepts belonging to the set $S = av_1 \times av_2$, i.e., the Cartesian product of av_1 , and av_2 .

We focus on the pairs that show high affinity, and to this end, in line with the maximum weighted matching problem in bipartite graphs [19], a concept belongs to at most one pair. Accordingly, $\mathcal{P}(av_1, av_2)$ is the set of sets of pairs, defined as follows:

$$\mathcal{P}(av_1, av_2) = \{ P \subset S | \quad \forall (c_{1i}, c_{2j}), (c_{1q}, c_{2k}) \in P, \\ c_{1i} \neq c_{1q}, c_{2j} \neq c_{2k}, |P| = min\{n, m\} \}$$

$$(7)$$

The $semsim_{h,\mu}$ function identifies the set of pairs of concepts of the av_1 and av_2 that maximizes the sum of the $consim_h$ values. Formally, we have:

$$semsim_{h,\mu}(av_1, av_2) = \frac{\max_{P \in \mathcal{P}(av_1, av_2)} \left\{ \sum_{(c_{1i}, c_{2j}) \in P} consim_h(c_{1i}, c_{2j}) \right\}}{\mu(n, m)}$$
(8)

where μ , referred to as *similarity normalization factor*, is defined as follows:

$$\mu(n,m) = \begin{cases} \max(n,m) \\ \min(n,m) \\ ave(n,m) \\ gav(n,m) \end{cases} (arithmetic average(n,m) = \frac{n+m}{2}) \\ gav(n,m) \\ (geometric average(n,m) = \sqrt{nm}) \end{cases} (9)$$

Note that in Eq. (8) the semantic similarity between annotation vectors is *symmetric*.

Below, the rationale underlying the choice of the similarity normalization factor mentioned above is briefly illustrated.

When computing the similarity degree of two resources r_1 and r_2 , where r_1 and r_2 are annotated with the annotation vectors av_1 composed of n_1 concepts, and av_2 composed of n_2 concepts, respectively, two cases can be distinguished: either the two annotation vectors have the same cardinality, or they have different cardinalities.

In the first case, that is $n_1 = n_2$, each concept in av_1 can be matched with one concept in av_2 , and vice-versa. Therefore, the four options lead to the same normalization factor, and the similarity degree is computed by considering the whole semantic descriptions of both the resources. In the second case, assuming for instance $n_1 > n_2$, there is a part of information about av_1 (i.e., $n_1 - n_2$ concepts) that is ignored when computing the similarity value.

In the following, the effects of the four proposed normalization factors are illustrated when $n_1 \neq n_2$, for instance with $n_1 > n_2$. If the normalization factor is chosen as the maximum between n_1 and n_2 , that is n_1 , we intend to privilege richer annotations, and therefore the "missing information" in av_2 weakens the similarity between the resources. If the normalization factor is chosen as the minimum between n_1 and n_2 , that is n_2 , we assume that a more "compact" annotation vector holds the essence of the resource r_1 , and the remaining concepts are redundant. In particular, the choice of the normalization factor as the maximum considers the missing information (in the shorter annotation) as a deficiency. Conversely, the choice of the normalization factor as the minimum deems the additional information (in the longer annotation) as a redundancy. Therefore, the choice about the maximum or the minimum emphasize differences and commonalities between the compared annotation vectors, respectively.

Choosing the normalization factor as the arithmetic average implies a compromise between the two above cases. This case somehow considers the missing and the redundant information in annotating the compared resources in the same

manner. Finally, the geometric average behaves essentially as the arithmetic average but is more sensitive to small values.

Algorithm The *semsim^p* semantic similarity function.

```
1: function SEMSIM-P(T, av1, av2, weightingMethod, normOp)
      if weightingMethod is an extensional method then
2:
3:
         avs = loadAnnotationVectors();
4:
         T = weightingTaxonomy(T, weightingMethod, avs);
 5:
      else
 6:
         T = weightingTaxonomy(T, weightingMethod);
 7:
      end if
8:
      consimMatrix[][] = empty matrix;
9:
      for i=0 to av1.size()-1 do
10:
         for j=0 to av2.size()-1 do
11:
            consimMatrix[i][j] = consim(av1[i], av2[j], T);
12:
         end for
      end for
13:
14:
      bestPairing = hungarianAlgorithm(consimMatrix);
15:
      temp = 0:
16:
      for all bp in bestPairing do
         temp = temp + bp.value;
17:
18:
      end for
19:
      normFactor = normalization(av1.size(), av2.size(), normOp);
      return temp / normFactor;
20:
21: end function
```

The algorithm for the $semsim^p$ function relies on the Hungarian algorithm for solving the *maximum weighted matching* problem in bipartite graphs [19], and is illustrated in the following in pseudocode. The function takes as input a taxonomy (i.e., T), the annotation vectors of the two documents to be compared (i.e., av1 and av2), a weighting method (i.e., weightingMethod) that is one out of AF, CF, TD, and IIC, and normOp that specifies which normalization function out of *min*, *max*, *ave*, and *gav* must be applied.

The first step is the assignment of weights to concepts in the taxonomy (lines 2-7). In case the weighting method is an extensional one (i.e., AF or CF), all the annotation vectors are loaded in the avs variable, and the weightingTaxonomy function is invoked with the taxonomy, the weighting method and the annotation vectors (lines 3-4). In case the weighting method is an intensional one (i.e., TD or IIC), the annotation vectors are not needed to assign weights to concepts, and therefore the weightingTaxonomy function is invoked only with the taxonomy and the weighting method. Then, the similarity values between each concept from av1 and av2 (i.e., av1[i] and av2[j]) are computed and stored in the consimMatrix (lines 8-13). The hungarianAlgorithm function is invoked with the consimMatrix to identify the pairing between the paired concepts is computed and the value is stored in the temp variable (lines 15-18). The function ends by dividing the value of the temp variable by the computed normalization factor, i.e., normFactor (lines 19-20).

Independently of the chosen weighting method and normalization factor, in accordance with the computational complexity of the Hungarian algorithm, the *semsim*^p method is polynomial in the size of n, specifically $O(n^3)$, where n is the cardinality of the larger of av1 and av2.

3.3 Ontology Weighting Methods in SemSim^p

In this section, we illustrate two types of methods, namely *extensional* and *intensional*, which are introduced to compute the probability of concepts (weights) in a tree-shaped taxonomy. Extensional methods compute concept weights by taking into account both the topology of the ISA hierarchy and the content of the annotated dataset. Intensional methods allow concept weights to be derived on the basis of the sole topology of the ISA hierarchy. The former need a statistically significant number of annotated resources and provide more adherence to the current state of the reality, whereas the latter can always be applied. These two types of methods are illustrated with the support of a running example based on the toy ontology shown in Figure 3, and the dataset composed of the four annotated resources, namely r_1 , r_2 , r_3 , and r_4 , shown in Table 1.

Resource	Annotation Vector
r_1	$av_1 = (Worker, Student)$
r_2	$av_2 = (Employee)$
r_3	$av_3 = (Student)$
r_4	$av_4 = (Employee, Freelance)$

Table 1: Running example dataset

3.3.1 Extensional Methods

The extensional methods illustrated in this section are the Concept Frequency (CF) and the Annotation Frequency (AF).

Concept Frequency method. The CF method is based on the standard approach of computing the relative frequency of a concept from a taxonomy in a corpus of documents [50]. According to this approach, given a concept c, its relative frequency (referred to as $w_{CF}(c)$ weight) is the number of occurrences of c and its descendants, divided by the number of occurrences of all concepts in the set of all the annotation vectors. Formally we have:

$$w_{CF}(c) = \frac{n(c^+)}{N},\tag{10}$$

where c^+ is the set formed by c and its descendants in the taxonomy, $n(c^+)$ is the total number of occurrences of the concepts in c^+ , and N is the total number of occurrences of the concepts in all the annotation vectors of the dataset.

For instance, considering the running example, in the case of the concept *Worker*, the *Worker*⁺ set is {*Worker*, *Employee*, *Freelance*} and $n(Worker^+)$ is equal to 4. In fact, considering the annotation vectors of Table 1, the concepts *Worker* and *Freelance* appear once, and the concept *Employee* appears twice. Furthermore, the total number of occurrences of all the concepts in the set of the four annotation vectors is equal to 6. Consequently: $w_{CF}(Worker) = \frac{4}{6} = \frac{2}{3}$.

Annotation Frequency method. The AF method is basically inspired by the well-known notion of *inverse document frequency (IDF)*. It is a part of the *term frequency* (TF)-IDF notion used in information retrieval to evaluate the relevance of a term in a document, extracted from a corpus of documents.

Given a concept *c*, its *IDF* is computed as the *logarithm* of the ratio of the number of documents in the collection to those containing *c*:

$$IDF(c) = \log_b \frac{|AV|}{|AV_{c^+}|} \tag{11}$$

where, AV is the set of all the annotation vectors in the dataset, and AV_{c^+} is the subset of AV containing the concept c or at least one of its descendants.

In our case, given a concept c, its relative frequency (referred to as $w_{AF}(c)$ weight) in the AF method is the number of annotation vectors containing c or a descendant of its, divided by the total number of annotation vectors, as follows:

$$w_{AF}(c) = b^{-IDF(c)} = \frac{|AV_{c^+}|}{|AV|}$$
(12)

where, according to our approach, b = e.

Considering the concept *Worker* in the running example, according to the AF method, we have that $|AV_{Worker^+}|$ is equal to 3, because the concept *Worker* and its descendants, namely *Employee* and *Freelance*, appear in 3 annotation vectors, namely av_1 , av_2 , and av_4 . Therefore, since 4 is the total number of annotated resources, the following holds: $w_{AF}(Worker) = \frac{3}{4}$.

3.3.2 Intensional Methods

The intensional methods illustrated in this section are the Top-Down topology-based (TD) and the Intrinsic Information Content (IIC).

Top-Down topology-based method. The TD method has been introduced in [22] and extensively experimented in [23], where it has been referred to as *probabilistic* method. It essentially computes the probabilities of concepts in the reference ontology by adopting a *uniform probabilistic distribution* along the ISA hierarchy following a top-down

approach. Specifically, the root of the ISA hierarchy has the probability equal to 1, and the probability of a concept c (referred to as $w_{TD}(c)$) of the ontology is obtained as follows:

$$w_{TD}(c) = \frac{w(parent(c))}{|siblings(c) + 1|}$$
(13)

In the running example, according to this approach, we have $w_{TD(Worker)} = \frac{1}{2}$, since *Worker* is one of the two children of the root *Person*.

Intrinsic Information Content method. The IIC method has been conceived to compute the information content of a concept in a taxonomy [56] defined as a function of its descendants. In particular, the basic assumption is that the more descendants a concept has the less information it expresses. Therefore, leaves in the taxonomy are the most specific ones, and consequently, their information contents are maximal.

Given a taxonomy, the Intrinsic Information Content (*iic*) of a concept c is given as follows:

$$iic(c) = 1 - \frac{log(|desc(c)| + 1)}{log(|\mathcal{C}|)}$$
 (14)

where desc(c) is the set of the descendants of the concept c, and C is the set of the concepts in Ont.

Note that the denominator in Eq. (14) ensures the *iic* values are in [0, 1]. Furthermore, the information content of the root node in the taxonomy is equal to 0.

Now let us consider the taxonomy shown in Figure 3. The intrinsic information content of the concept *Worker* is defined as follows: $iic(Worker) = 1 - \frac{log(2+1)}{log(5)} = 0.32$ since the descendants of *Worker* and the total number of concepts in the taxonomy are 2 and 5, respectively.

4 Case Study and Experiments

4.1 Context description

The first domain of our experimentation concerns the papers published in computer science by the ACM and, in particular, appeared in two journals, which are the ACM Transactions on Information Systems (TOIS) and the ACM Transactions on Database Systems (TODS) journals. The total number of articles we considered in the experiment is 1,103, which corresponds to the number of papers published in these journals in the time window from January 1990 to June 2017. One of the primary goal of the Digital Library of the Association for Computing Machinery (ACM-DL) is the quick discovery and the easy accessibility to the content of the articles by the reader. For this reason, most of the papers published in the ACM journals were manually annotated by the authors according to the ACM Computing Classification System (ACM-CCS). The latest version of the ACM-CCS was developed in 2012. This replaces the traditional 1998 version, and is used as one of the de facto standard classification systems in the computing field. It consists of more than 2,000 subjects covering all the fields of computer science. These subjects are not mutually exclusive and reflect the state of the art of the computing discipline, therefore they are supposed to be expanded and updated with the forthcoming subject areas in computer science.

4.2 Research Questions and Indicators

We set up 16 different configurations of *SemSim^p*. Each configuration is characterized by one of the previously mentioned four methods to compute the weights of the concepts (i.e., CF, AF, TD, and IIC), and one of the four different options to compute the similarity normalization factor (i.e., max, min, ave, and gav). Furthermore, in this analysis we considered the Dice, Jaccard, Sigmoid, WNSim similarity methods and the ones proposed respectively by Rezaei & Fränti [51] and by Haase et al. [26] with the purpose of comparing them with *SemSim^p*.

In order to evaluate the performance of these methods, we identified the following research questions:

- **RQ1.** Assuming that we have a collection of papers selected by following some similarity criteria, which is the similarity method that allows us to assert with the highest degree of certainty that these papers were not gathered together randomly?
- **RQ2.** Assuming that we have a limited number of papers, in order to identify their mutual similarity, which is the method that provides results closer to those given by human experts?

To the purpose of answering to these research questions, we defined two indicators, namely the degree of confidence, indicated also as **I1**, for **RQ1**, and the Pearson correlation, indicated also as **I2**, for **RQ2**.

I1 is based on a statistical inference method, called *null hypothesis significance testing* [44], by which an hypothesized factor (i.e., asserted hypothesis) is tested against an hypothesis of no effect or relationship (i.e., null hypothesis) on the basis of empirical observations [48]. In our work, the *hypothesis* "the papers in a given collection are similar" is compared to the *null hypothesis* that "they are not similar" since they have been selected randomly. Assuming that the papers in a given collection are similar, we compare the similarity methods against the given assumption, then the best similarity method is the one that allows to assert with the highest probability that the papers in the collection are similar. Since the probability that the asserted hypothesis is true corresponds to the degree of confidence (**I1**), the higher **I1**, the better the method.

In order to answer to the second research question, we asked five experts to evaluate the mutual semantic similarity of the papers in the given sets, and we computed the Pearson correlation (I2) between similarity methods' results and expert judgement.

4.3 Study settings

As anticipated in Section 1, in the presence of a large dataset, it is unrealistic to ask a group of people to pairwise check thousands of resources, producing millions of similarity scores. For this reason, we selected some sets of papers among the 1,103 TOIS and TODS papers mentioned above. In particular, we focused our attention on the seven TOIS special issues published in the aforementioned time window, i.e., from January 1990 to June 2017⁵. A special issue can be considered as a *set* of papers selected by the editor on the basis of their topics, i.e., on the basis of the similarity of their contents, which should be determined by the research topic indicated in the call for paper. Hence, we assumed that the mutual similarity of special issue papers has been already implicitly validated by the corresponding editors. Therefore, we performed a first experiment validating *SemSim^p* against the editor decision in assembling papers in each special issue. In particular, we expect that a special issue gathers papers with semantic cohesion significantly higher than the average of a sufficiently great number (i.e., 100,000) of sets of papers, randomly sampled from the whole set of 1,103 papers, having the same cardinality as the special issues.

Successively, in a second experiment, we asked some experts in computer science for an assessment of the similarity of the papers contained in each of the seven special issues. In particular, for each special issue, five experts of our research institutes were asked to evaluate the mutual similarity of the papers of the special issue. This evaluation was performed at two levels: first by addressing the ACM-CCS keywords of the papers, then also by analyzing their abstracts, because sometimes the keywords do not represent the content of a paper in an exhaustive way. The overall experimentation set up was organized according to two phases: preprocessing of the ACM dataset and experimental set up⁶.

4.3.1 Preprocessing of the ACM dataset

This phase was devoted to acquire the ACM data and prepare them in order to be used to perform the experiments. It consists of six steps:

- Collection of the ACM papers and keywords extraction;
- Engineering the ontology derived from ACM-CCS;
- Semantic annotation of the ACM papers;
- Weighting the ontology concepts;
- Computation of similarity values;
- Selection of samples of mutually similar papers.

Collection of the ACM papers and keywords extraction. During this step, the papers of the TOIS and TODS journals in the mentioned time range were collected. Afterwards, the ACM-CCS keywords were extracted by means of basic text processing techniques. In general authors who want to publish with the ACM are required to provide and to associate with their articles the appropriate keywords from the ACM-CCS. The ACM provides an accurate categorization of the papers since the keywords are checked first by the reviewers during the revision process and, successively, by the editors of the journals, before publication.

⁵In this time interval, no special issue was published on the TODS journal.

⁶The ACM dataset used for performing the experimentation can be accessed at the following link: http://dx.doi.org/10.17632/r4vbkhgxx3.2 [60]

The result of this step is a text file containing the list of papers published from January 1990 to June 2017 in the TODS and TOIS journals with the corresponding ACM-CCS keywords. Each item of the list includes a numeric identifier, the year of publication, the title of the paper, the author(s), and the ACM-CCS keywords.

Engineering the ontology derived from ACM-CCS. The aim of this step was to build an ontology [14, 16, 20] in an appropriate format to compute semantic similarity values by means of the $SemSim^p$ algorithm. In the ACM, the CCS is a Directed Acyclic Graph (DAG) [55], where each node is labeled with a subject area of computer science, and arcs denote a hierarchical relationship. As mentioned in Section 3, the SemSim^p method requires a tree-shaped ontology to compute the similarity values. Therefore, to the purpose of the experiment, we built a tree-shaped taxonomy on the basis of the ACM-CCS as follows. For each path in the ACM-CCS ending in a root (i.e., a node without parents), we added a concept in the ontology, which is identified by the concatenation of the labels of the ACM-CCS nodes along the considered path. Accordingly, if a node in the ACM-CCS has two parents, it has two paths ending in some roots and leads to the generation of two concepts in the ontology, in order to remove the multiple inheritance. Then, each of the new concepts is linked to only one parent according to the specialization relationship. For instance, in the ACM-CCS, both the nodes "Cross-computing tools and techniques"⁷, and "Dependable and fault-tolerant systems and networks" have "Reliability" as a child. In turn, these two parents have "General and Reference", and "Computer systems organization" as parents, respectively, which are roots. Therefore, the following concepts were added to the ontology: "Reliability_Cross-computing tools and techniques_General and Reference_owl: Thing", and "Reliability_Dependable and fault-tolerant systems and networks_Computer systems organization_owl: Thing", where "Thing" is the unique root of the ontology we constructed. Furthermore, the former concept is a specialization of "Cross-computing tools and techniques_General and Reference_owl:Thing" because "Reliability" is a child of "Cross-computing tools and techniques" in the ACM-CCS.

A fragment of the ACM-CCS 2012 is shown in Figure 9 in Annex B, in particular, part of the sub-tree having "Information systems" as a root. Therefore, the "Information systems" node has five children ("Data management systems", "Information systems applications", "Information storage systems", "World Wide Web", and "Information retrieval"). Note that the relationship between a child and a parent node is a ISA relationship because we assumed the corresponding concepts as *competences* on the topics related to the ACM-CCS keywords. For instance, an expert in "Database management system engines" has also competences in "Data management systems" (which is the computer science area labeling its parent node) and has also competences in the areas labeling all its ancestors along the ISA hierarchy, therefore in this case also in "Information systems", which is one of the root nodes of the ACM-CCS.

In our experiment, the online categorization revised by the ACM was used as published in June 2017. The result of this step is an ontology on computer science concepts, organized as a tree and available in the OWL/RDF format⁸. It consists of 2,113 concepts and 2,114 ISA relationships. The ontology was automatically built from an html version of the ACM-CCS keywords.

Semantic annotation of the ACM papers. This step was devoted to annotate all the selected papers with the concepts of the ontology that was built in the previous step, and to associate with each paper the corresponding annotation vector. Consider, for instance, one of the papers of the Special Issue 3 on *User Interface Software and Technology* and, in particular, the paper labeled Title 1, as shown in Table 2. This paper has been categorized by the authors by specifying the following keywords (referred to as *Categories and Subject Descriptors* in the ACM):

```
C.2.4 [Computer-Communication Networks]: Distributed Systems - distributed
applications, distributed databases;
D.2.2 [Software Engineering]: Tools and Techniques - user interfaces;
D.2.6 [Software Engineering]: Programming Environments - user interactive;
D.3.3 [Programming Languages]: Language Constructs - input/output;
H.1.2 [Models and Principles]: User/Machine Systems - human factors;
H.4.1 [Information Systems Applications]: Office Automation;
1.7.1 [Text Processing]: Text Editing.
```

Since this paper was published in 1992, these keywords have been specified according to previous versions of the ACM-CCS 2012. Successively, after the release of the 2012 version, paper categorizations have been revised by the ACM and, for each paper, the list of updated keywords can be found online in the *index term* menu, where classification

⁷Note that, for the sake of clarity, ACM-CCS keywords are in quoted Courier, whereas the concepts in the developed ontology are in quoted *italic*.

⁸https://www.w3.org/TR/owl-ref/

Title	Short title
A High-Level and Flexible Framework for Implementing Multiuser User Interfaces.	Title 1
A Model for Input and Output for Multilingual Text in a Windowing Environment.	Title 2
EmbeddedButtons: Supporting Buttons in Documents.	Title 3
Lessons Learned from SUIT, the Simple User Interface Toolkit.	Title 4
A General Framework for Bidirectional Translation between Abstract and Pictorial Data.	Title 5

Table 2: Papers of the Special Issue 3.

numbers (such as C.2.4 or D.2.2 above) have been omitted. For instance, in the previous example, the category H.4.1 [Information Systems Applications]: Office Automation; has been replaced with the following one: [Information Systems]: Information Systems Applications, Enterprise information systems – enterprise applications. Therefore, in our experiment, the ontology concept corresponding to the above ACM-CCS path has the following identifier: "Enterprise applications_Enterprise information systems_owl:Thing".

Weighting the ontology concepts. As mentioned in the previous sections, in the $SemSim^p$ approach, each node has to be associated with a weight. To this aim, this step was devoted to evaluate the weights of the ACM concepts according to the CF, AF, TD, and IIC methods presented in Section 3.3.

In Figure 4, the ontology derived from the ACM-CCS is drawn as a graph, where nodes and arcs represent concepts and ISA relationships, respectively. In particular, the size of each node is proportional to the associated weight computed according to the extensional (CF and AF) and the intensional (TD and IIC) methods. The *owl:Thing*⁹ node, i.e., denoting the most general concept, is white and the other ones are green. In Figure 5, the fragment of the ontology related to the information systems subject area, corresponding to the bottom right sides of the graphs of Figure 4, is detailed. Note that, due to our focus on the TOIS and TODS journals, i.e., the information systems area, the sizes of the nodes corresponding to the extensional methods are more heterogeneous with respect to those corresponding to the intensional ones, whose weights depend only on the structure of the concepts, differ depending on the different weighting methods. Note that, in general, different weights lead to different similarity values of the *SemSim*^p method, according to the Eq. (5), on which it is based. Both the figures were realized by using the Gephi¹⁰ software [3].

Computation of similarity values. This phase was devoted to compute the similarity matrices containing the semantic similarity values of all possible pairs of the collected papers according to the 16 *SemSim^p* configurations, as well as the other selected methods. As the number of collected papers is 1,103, each resulting similarity matrix has more than 1,000,000 values.

Selection of samples of mutually similar papers. This step was devoted to select samples of papers that are mutually similar. As mentioned before, we assumed that special issues were assembled together by editors following some similarity criteria, and we addressed all the special issues from January 1990 to June 2017. The titles of the special issues are presented in Table 3, whereas in Table 4, the number of papers of each special issue and the number of ACM keywords of each paper are shown. As illustrated before, for the sake of brevity, only the titles of the papers included in the Special Issue 3 are shown in Table 2.

4.3.2 Experimental set up

This phase consists of two steps. The former concerns the set up of the semantic cohesion experiment, and the latter the expert judgement experiment.

Setting up the semantic cohesion experiment. This step concerns the statistical analysis in order to quantify the semantic cohesion of each special issue (i.e., the average of the similarity values of all pairs of papers in the issue). As shown in Table 4, each selected special issue consists of either 4 or 5 papers. Accordingly, two sets of 100,000 samples of 4 and 5 papers were randomly selected, respectively.

⁹*owl:* stands for the OWL namespace, i.e., http://www.w3.org/2002/07/owl#.

¹⁰https://gephi.org



Figure 4: Ontology derived from the ACM-CCS with the node sizes proportional to the weights computed by means of the extensional CF, AF, and intensional TD, IIC weighting methods.

For each special issue, the semantic cohesion was computed by applying the *SemSim^p* configurations, as well as the other selected methods. Then, the same computations were performed for each of the randomly selected samples of 4 and 5 papers, and the average similarity values were used to build different frequency distributions. Finally, we performed the hypothesis testing for the null and asserted hypotheses (see Section 4.2). In particular, the *t-value* and the corresponding degree of confidence of the asserted hypothesis were computed for each of the considered similarity methods and for each special issue. The *t-value* (*t*) was computed as follows:

$$t = \frac{sc_i - \overline{sc_R}}{\sigma} \tag{15}$$

where sc_i is the semantic cohesion (i.e., the average similarity value) of the special issue *i*, $\overline{sc_R}$ is the average of the sample semantic cohesion values (i.e. the average of the sample semantic similarity averages) and σ is the standard deviation of the sample semantic cohesion values. Note that, considering the population of semantic similarity values, σ is equal to the population standard deviation divided by the square root of the sample size [5].

On the basis of the t-test, we are able to identify the best result, i.e., the similarity method that maximizes the degree of confidence of the asserted hypothesis (I1) and, hence, the probability that the assertion that a special issue gathers similar papers is true.



Figure 5: An excerpt from the ontology derived from ACM-CCS related to the *information system* sub-tree, with the node sizes proportional to the weights computed by means of the extensional CF, AF, and intensional TD, IIC weighting methods.

	Title	Short title
ĺ	Special Issue on Computer-Human Interaction.	Sn Ise 1
	Volume 9 Issue 2, April 1991	59.133.1
	Special Issue on Research and Development in Information Retrieval.	Sn Ice 2
	Volume 9 Issue 3, July 1991	5p.155.2
ĺ	Special Issue on User Interface Software and Technology.	Sn Ice 3
	Volume 10 Issue 4, Oct. 1992	5p.155.5
Ì	Special Issue on Social Science Perspectives on IS.	Sp Icc 4
	Volume 12 Issue 2, April 1994	5p.155.4
Ì	Special Issue on Video Information Retrieval.	En los F
I	Volume 13 Issue 4, Oct. 1995	5p.188.5
Ì	Special Issue on Contextual Search and Recommendation.	Sn Ice 6
	Volume 33 Issue 1, March 2015	Sp.188.0
Ì	Special Issue on Trust and Veracity of Information in Social Media.	Sp Ice 7
l	Volume 34 Issue 3, May 2016	Sp.188.7

Table 3: Titles of the selected TOIS special issues.

In order to better present the rationale underlying the first experiment, Figure 6 shows the semantic cohesion distribution for the 100,000 randomly selected samples with cardinality 5, as well as the semantic cohesion of the Special Issue 6 (sc_6) computed by using *SemSim^p* configured with the annotation frequency as weighting method, and the geometric average as similarity normalization factor. The average value of semantic cohesion for the resulting distribution is labelled by \overline{sc}_R , whereas σ labels its standard deviation. It is worth noting that sc_6 is more than 4σ times higher than \overline{sc}_R . This leads to t = 5.2621. According to the t-test method defined in the literature and the value of the *Student's t distribution* computed by using the cumulative distribution function [5], the degree of confidence of the hypothesis that the Special Issue 6 is a collection of similar papers is 99.84 % (see Table 6). The same analysis was performed for each Table 4: Number of papers (# papers) of the selected TOIS special issues and number of ACM keywords (# keywords) of each paper. NA means that the paper 5 is not available because the special issue contains 4 papers.

	Sp.Iss.1	Sp.Iss.2	Sp.Iss.3	Sp.Iss.4	Sp.Iss.5	Sp.Iss.6	Sp.Iss.7
# papers	4	4	5	4	4	5	5
# keywords of paper 1	4	4	10	1	7	1	1
# keywords of paper 2	2	2	7	2	4	3	1
# keywords of paper 3	7	8	6	7	6	4	2
# keywords of paper 4	5	6	9	3	8	1	4
# keywords of paper 5	NA	NA	3	NA	NA	1	2

of the semantic similarity methods considered in this paper and for each of the seven special issues.



Figure 6: Statistical analysis of semantic cohesion for the Special Issue 6 computed by using $SemSim^p$ configured with the annotation frequency as weighting method, and the geometric average as similarity normalization factor.

Setting up the expert judgement experiment. This step was devoted to setting up the experiment in order to determine the semantic similarity method that provides similarity values that best fit with those provided by expert judgement. To this purpose, as mentioned before, we asked five experts of our research institutes, having at least 18 years of experience in the database and information systems fields, to evaluate the mutual similarity values for all the papers included in each special issue. Each special issue was evaluated by three experts. The workload for each expert was assigned having

in mind an objectivity-quality of result trade-off. To this aim, we avoided to overwhelm experts with heavy activities that would have diminished the quality of the evaluation. This analysis was performed at two levels: first by focusing on the ACM-CCS keywords of the papers, then by also analyzing their abstracts. Afterwards, the Pearson correlation values (I2) between the similarity values obtained from the expert-based experiment focusing on keywords and the automatically-computed ones were evaluated. The best result, in this case, is the similarity method that maximizes the Pearson correlation. Indeed, I2 was evaluated by considering the experiment based on keywords because abstracts are not used by the semantic similarity methods addressed in this work. The expert-based experiment also focusing on abstracts was used in Section 5 in order to discuss the annotation quality issue.

4.3.3 Software

In order to support the phases presented above, we developed different modules of software by using two programming languages. In particular, the components dealing with the pre-processing of the ACM and American Physical Society (APS) datasets, which were needed for setting up the two experiments, the statistical analysis, and the component about the data visualization were implemented by using the Python programming language¹¹. The module for the automatic generation of the ontology starting from the ACM-CCS, as well as the *SemSim^p* method were implemented by using the Java programming language¹².

4.3.4 Selected similarity methods for comparison

As mentioned, in this work, we address the similarity of the ACM papers represented by means of sets of concepts (features), i.e., their annotation vectors. In the experimentation, we selected the well-known Dice [18], and Jaccard [30] measures and, furthermore, Sigmoid [38], WNSim [57], and the methods of Rezaei & Fränti [51], and of Haase et al. [26]. In particular, the first three are representatives of the so-called *set-theoretic methods*, since they are based on set-theoretic operations applied to the sets of features (the paper annotation vectors), whereas the remaining three are representatives of the *taxonomy-based methods*, since they also rely on a taxonomy. These measures are formally provided in Tables 10 and 11.

Note that, as anticipated in Section 2.2, WNSim and the method proposed by Haase et al. are asymmetric, i.e., the order used to compare two annotation vectors is relevant. However, since in our experimentation the order of comparison is not significant, we computed the average of the similarity between a pair and the corresponding symmetric one. In Tables 5 and 7 and Figures 7 and 8, these measures are indicated, respectively, as WNSim_{sym} and Haase et al._{sym}, where _{sym} stands for symmetric.

We did not include similarity methods based on machine learning in the comparison because most of them require access to the content of the digital resources (e.g., the text of the articles), which can not be always available. Conversely, we considered the methods that only require resources to be semantically annotated.

4.4 Comparison results

The results obtained from the two experiments are presented in Tables 5, 6 and 7. Note that $semsim_{AF,max}$ corresponds to the original semsim function presented in [23]. Table 5 includes the semantic cohesion for each special issue, computed by applying the $SemSim^p$ configurations, and the other selected methods, and according to the expert judgement. EJ_{key} stands for the expert judgement performed by only considering the ACM-CCS keywords, whereas EJ_{abs} considers both the keywords and the abstracts of the papers. Table 6 illustrates, for each special issue, the degree of confidence (I1) and the Pearson correlation values obtained by focusing on keywords (I2) for all the $SemSim^p$ configurations. For each method, the average values of all the special issues for both the indicators are shown in the "Average" column. Analogously, Table 7 shows the data corresponding to the other selected methods¹³, and $semsim_{AF,gav}$, which is the best performing $SemSim^p$ configuration. In the last two tables, the best results are highlighted in bold.

For each considered method, the scatter plot in Figure 7 shows the average degree of confidence and the average Pearson correlation both computed over all the special issues. In the legend, the associated labels in the plot represent

¹¹The code for the statistical analysis, the ACM and APS datasets, and the used ontologies are available at: http://dx.doi.org/10.17632/pv3hvmbppk.1 [15]

¹²The implementation of the *SemSim^p* method is part of the *SemanticRelatednessInRDFGraph* software project available at: https://github.com/ftaglino/SemanticRelatednessInRDFGraph

¹³Given the Pearson correlation $P = \frac{\sum_i (s_i - \bar{s}) \cdot \sum_i (e_i - \bar{e})}{\sum_i (s_i - \bar{s})^2 \cdot \sum_i (e_i - \bar{e})^2}$, where s_i is the similarity between pairs of papers and e_i is the similarity assigned by experts, in the case of the Special Issue 7, for Dice, Jaccard, and Sigmoid, P cannot be computed because $s_i = 0$ for all the pairs. In fact, the set intersection between the annotation vectors of any two papers in this special issue is empty.

the similarity normalization factors (see Section 3.2), where X stands for maximum, N for minimum, A for arithmetic average, and G for geometric average, and the weighting methods are associated with different markers (see Section 3.3). Furthermore, W, S, D, J, H, R standing for the WNSim_{sym}, Sigmoid, Dice, Jaccard, Haase et al._{sym} and Rezaei & Fränti methods, respectively, are included.

Table 5: Semantic cohesion of the selected special issues computed by similarity method and according to expert judgement. EJ_{key} stands for the expert judgement performed by only considering the ACM-CCS keywords, whereas EJ_{abs} considers both the keywords and the abstracts of the papers.

Similarity method	Sp.Iss.1	Sp.Iss.2	Sp.Iss.3	Sp.Iss.4	Sp.Iss.5	Sp.Iss.6	Sp.Iss.7
semeim	0.21	0.18	0.28	0.26	0.47	0.37	0.05
semsim gr	0.21	0.10	0.28	0.20	0.47	0.39	0.05
SemsimTD	0.22	0.21	0.28	0.23	0.48	0.35	0.00
semsim _{11C} max	0.22	0.25	0.28	0.23	0.47	0.42	0.09
someim + E	0.42	0.38	0.49	0.73	0.68	0.71	0.00
semsimar,	0.42	0.38	0.49	0.73	0.08	0.76	0.09
Semsim_p	0.43	0.43	0.50	0.71	0.69	0.83	0.12
semsimuc min	0.13	0.57	0.30	0.60	0.69	0.80	0.15
concorner im	0.10	0.24	0.25	0.27	0.55	0.44	0.06
semsim _{AF,ave}	0.28	0.24	0.35	0.37	0.55	0.44	0.06
semsim _{CF,ave}	0.29	0.28	0.35	0.30	0.56	0.48	0.08
semsim _{TD,ave}	0.29	0.35	0.35	0.33	0.56	0.53	0.11
$semsim_{IIC,ave}$	0.29	0.33	0.34	0.33	0.55	0.51	0.10
semsim _{AF,gav}	0.29	0.26	0.37	0.42	0.56	0.49	0.06
$semsim_{CF,gav}$	0.31	0.31	0.37	0.41	0.57	0.52	0.09
$semsim_{TD,gav}$	0.31	0.38	0.37	0.38	0.57	0.57	0.12
$semsim_{IIC,gav}$	0.30	0.36	0.36	0.39	0.57	0.55	0.11
Dice	0.13	0.11	0.18	0.19	0.43	0.23	0
Jaccard	0.08	0.06	0.10	0.13	0.28	0.18	0
Sigmoid	0.03	0.03	0.04	0.06	0.11	0.08	0
WNSim _{sym}	0.16	0.12	0.16	0.41	0.53	0.24	0
Rezaei & Fränti	0.42	0.52	0.47	0.49	0.62	0.70	0.32
Haase et al.sym	0.41	0.51	0.45	0.54	0.64	0.75	0.25
EJ _{kev}	0.33	0.38	0.38	0.27	0.54	0.41	0.18
EJabs	0.23	0.28	0.41	0.39	0.58	0.39	0.39

4.5 Threats to validity

This Section reports the approach that was adopted to cope with the threats to validity of the experiment in order to evaluate the performance of an ontology-based similarity method. It relies on the notion of quality of a software engineering experiment that, according to Kaner & Bond [34] and Sjøeberg et al. [58], depends on its **construct**, **internal** and **external** validities.

Threats to **construct validity** deal with limitations of the experimental set up. In particular, the experiment could be limited by the general problem of *lack of ontological quality* of the considered taxonomy, by the *dataset size*, by the *annotation quality*, and by the *lack of availability of subject matter experts* for validation tasks.

The lack of ontological quality concerns the syntactic, semantic, and social dimensions [7]. In order to deal with it, we used the ontology derived from the ACM-CCS 2012. The syntactic quality is guaranteed by the Protégé ontology management system¹⁴ that allowed us to validate the OWL code automatically generated from the ACM-CCS keywords. Then the social and semantic dimensions of ontological quality are both guaranteed by the fact that the ontology was built on the basis of the ACM-CCS 2012, which is widely accepted and used in the computer science community.

Threats to dataset size deal with the choice of the appropriate size of the dataset. From one side, the risk is to choose a "toy case study" that does not reflect the complexity of the reality. From the other side, the risk is to have a too large dataset for which it is not feasible neither to ask experts to analyze it, nor to identify some criteria in order to select representative samples of data to be verified by expert judgement. To reduce these risks, we used a large dataset including an ontology of 2,114 concepts and 1,103 annotated papers, and we selected the special issues from TOIS as representative samples to be evaluated by human experts.

With regard to the annotation quality, as mentioned, in order to guarantee a good level of annotation, we selected two top quality journals, where most of the papers have been manually annotated by authors with keywords. Such annotations

¹⁴See https://protege.stanford.edu [47].

trations. The table also includes		
e SemSim ^p configu		Sn Ise 7
by using all the		Sn Iss 6
ssue obtained		Sn Ise 5
each special is		Sn Iss 4
[2 values for	column.	Sn Ise 3
on correlation]	the "Average"	Sn Ise 2
I1 and Pearse	indicators in	Sn Ise 1
of confidence	es for both the	Average
Table 6: Degree (the average value	

0						0										
	Avera	age	Sp.1s	s.1	Sp.Is:	52	Sp.Iss	<u>.</u> 3	Sp.Is:	4.8	Sp.Is	s.5	Sp.Is:	s.6	Sp.Ise	27
Similarity method	II	12	II	12	II	12	II	12	II	12	11	12	11	12	II	12
$emsim_{AF,max}$	84.95%	09.0	92.8%	0.8	87.28%	0.54	99.13%	0.42	96.64%	0.15	99.78%	0.42	99.81%	0.93	19.23%	0.92
$emsim_{CF,max}$	82.18%	0.59	86.74%	0.78	84.78%	0.43	97.55%	0.46	91.82%	0.21	%9.66	0.4	%99.66	0.94	15.1%	0.92
$msim_{TD,max}$	75.38%	0.56	70.01%	0.71	83.11%	0.25	90.33%	0.51	72.5%	0.32	98.84%	0.39	99.24%	0.93	13.62%	0.78
$msim_{IIC,max}$	77.45%	0.58	75.07%	0.73	83.45%	0.31	92.08%	0.55	78.77%	0.3	99.1%	0.42	99.35%	0.94	14.36%	0.82
$msim_{AF,min}$	85.17%	0.61	92.6%	96.0	89.85%	0.31	98.33%	0.64	99.38%	0.67	99.15%	0.51	99.81%	0.22	17.04%	0.92
$msim_{CF,min}$	82.52%	0.59	85.69%	0.98	88.17%	0.16	95.26%	0.63	98.58%	0.7	98.32%	0.5	99.65%	0.25	11.96%	0.91
$msim_{TD,min}$	76.03%	0.56	65.77%	0.96	87.09%	-0.05	82.14%	0.67	93.73%	0.73	94.86%	0.49	%60.66	0.3	9.5%	0.78
$msim_{IIC,min}$	77.87%	0.58	71.64%	0.97	87.17%	0.02	85.06%	0.71	95.63%	0.72	96.01%	0.52	99.26%	0.28	10.31%	0.82
$emsim_{AF,ave}$	85.80%	0.66	94.31%	0.9	%0.0%	0.53	99.22%	0.6	98.35%	0.3	99.75%	0.5	99.81%	0.89	19.14%	0.92
$emsim_{CF,ave}$	83.57%	0.66	89.22%	0.89	88.35%	0.4	97.79%	0.64	95.96%	0.35	99.55%	0.48	99.67%	0.93	14.43%	0.91
$msim_{TD,ave}$	77.83%	0.62	73.09%	0.84	87.39%	0.17	90.77%	0.67	83.32%	0.45	%69.86	0.47	99.21%	0.94	12.34%	0.78
$:msim_{IIC,ave}$	79.67%	0.65	78.17%	0.85	87.53%	0.26	92.48%	0.71	87.95%	0.43	98.98%	0.5	99.34%	0.95	13.21%	0.82
$msim_{AF,gav}$	85.67%	0.69	94.07%	0.94	90.21%	0.52	99.11%	0.69	98.79%	0.45	%69.66	0.52	99.84%	0.83	17.96%	0.92
$emsim_{CF,gav}$	83.43%	0.69	88.63%	0.93	88.58%	0.41	97.46%	0.72	%60.76	0.5	99.43%	0.5	99.71%	0.88	13.14%	0.91
$msim_{TD,gav}$	77.73%	0.65	71.36%	0.89	87.57%	0.18	89.32%	0.74	87.27%	0.58	98.3%	0.48	99.29%	0.92	11.0%	0.78
$msim_{IIC,gav}$	79.52%	0.68	76.75%	0.9	87.7%	0.28	91.28%	0.78	91.01%	0.57	%69.86	0.52	99.41%	0.92	11.83%	0.82

Table 7: Degree of confidence **I1** and Pearson correlation **I2** values for the best performing *SemSim^p* configuration, and the other selected methods. The table also includes the average values for both the indicators in the "Average" column.

	Avera	ge	Sp.1s	-	Sp.1s.	s.2	sp.ls	.3	Sp.Is	s.4	Sp.Iss	5	Sp.Iss	.6	Sp.1ss	5.7
ity method	II	12	11	12	II	12	II	12	11	12	11	12	II	12	II	12
$m_{AF,gav}$	85.67%	0.69	94.07%	0.94	90.21%	0.52	99.11%	0.69	98.79%	0.45	%69.66	0.52	99.84%	0.83	17.96%	0.92
Dice	84.76%	0.64	90.13%	0.69	86.53%	0.69	98.37%	0.72	96.92%	0.52	99.87%	0.73	99.51%	0.46	21.97%	
ccard	82.37%	0.65	83.31%	0.72	78.23%	0.71	95.69%	0.73	95.89%	0.45	<i>%LL</i> 66	0.74	99.67%	0.58	24.05%	•
gmoid	80.88%	0.63	80.84%	0.72	74.16%	0.67	92.02%	0.68	94.66%	0.45	99.4%	0.71	99.49%	0.58	25.56%	
Sim _{sym}	84.33%	0.61	92.0%	0.83	78.87%	0.69	98.79%	0.72	98.92%	0.59	99.88 <i>%</i>	0.66	99.72%	0.35	22.13%	0.46
i & Fränti	74.73%	0.46	%60.09%	0.81	84.75%	-0.06	79.81%	0.51	79.83%	-0.08	94.91%	0.59	98.90%	0.84	24.80%	0.61
et al	77.89%	0.69	68.94%	0.93	88.64%	0.28	81.91%	0.77	91.65%	0.7	96.92%	0.67	99.5%	0.82	17.65%	0.68



Figure 7: Scatter plot showing the average degree of confidence and the average Pearson correlation values computed for all the special issues and all the addressed methods.

have also been checked by the reviewers of the papers and the editors of the journals and revised by the ACM in order to be compliant with the last release of the ACM-CCS (see Section 4.3). Then we performed two expert judgement evaluations (i.e., one focusing on keywords and the other also on abstracts) that allowed us to further discuss this issue in Section 5.

The lack of availability of subject matter experts was addressed by considering a special issue as a "cluster" of mutually similar papers related to a specific topic (i.e., the special issue research theme). This assumption allowed us to perform the first experiment without involving human experts in evaluating the semantic similarity scores of a high number of pairs of papers. This is not the case of the second experiment, where the number of papers in each special issue was limited (i.e., 4 or 5) and it was quite easy to find experts available for the similarity evaluation as they were not overwhelmed in performing such a task.

Internal validity threats, instead, deal with the randomness of the results due to, for instance, the *evaluator subjective ness* and the *explosion of the number of similarity values* to be considered that could lead to a burden of work affecting the quality of the evaluation. The first risk was reduced by designing the semantic cohesion experiment, centered on a statistical approach, where the human intervention was limited to the selection of papers done by the special issue editors. However, since the editors may have not grouped the papers by similarity but, for instance, by discipline coverage, we did a further verification with the expert judgement experiment. The second risk was reduced by asking experts to evaluate only the papers collected in the special issues. Indeed, they represent a limited but significant amount of samples of papers, considered similar by the authoritative opinion of the editors. Finally, **external validity** threats concern the generalizability of the results. In this work, such a risk was reduced by addressing different topics in the computer science domain by selecting seven special issues. In addition, a further experiment in the physical domain was performed, as illustrated in the next subsection.

4.5.1 APS Experiment for External Validity

The domain of this experimentation concerns the papers published by the American Physical Society (APS) in the Physical Review Letters, a journal covering the full arc of fundamental and interdisciplinary physics research. In the experiment, we considered 52,762 articles published in this journal from 1980 to 2013, and annotated according to the Physics and Astronomy Classification Scheme (PACS), a classification system of the APS, organized as a taxonomy. There are several updated editions of the PACS until 2010. Since 2016, the PACS has been replaced by the PhySH (Physics Subject Headings). In this paper, we consider the PACS 2010 regular edition, consisting of 4,574 subjects covering all the fields of physics.

Analogously to the statistical part of the ACM experiment, we evaluated the performance of the 16 different configurations of $SemSim^p$, Dice, Jaccard, Sigmoid, WNSim similarity methods and those proposed, respectively, by Haase et al., and Rezaei & Fränti. In particular, we computed the degree of confidence I1 in order to answer to **RQ1**.

Concerning the selection of special issues, similar to the ACM experiment, we considered a collection of 21 papers regarding high-temperature superconductors, which was assembled by the APS editorial office¹⁵. However, randomly sampling 21 mutually similar papers out of 52,762 multidisciplinary ones is an extremely rare event. Hence, the likelihood that the semantic cohesion of the 21 mentioned papers is higher than the one of 100,000 sets of randomly selected papers with the same cardinality is close to 100% for every method. For this reason, in line with the statistical experiment performed on the ACM dataset, we selected 4 papers from the mentioned collection. For the sake of clarity, in the rest of this paper, we refer to this collection of 4 papers as the *APS virtual special issue*.

We built the reference ontology in accordance with the structure and format of the PACS codes¹⁶. It gathers 4,575 concepts and 4,574 ISA relationships, and it has a tree-shaped structure with 6 levels. Analogously to the ACM dataset, we evaluated the weights of the APS concepts according to the CF, AF, TD, and IIC weighting methods. The dataset used to compute the weights for the extensional methods (i.e., CF and AF) consists of all the 52,762 papers. Conversely, we restricted the statistical experiment to 2,000 randomly selected papers from this dataset, which include the 4 papers of the APS virtual special issue.

Finally, we computed the *t-value* and the corresponding degree of confidence (I1) of the asserted hypothesis, i.e., the papers of the APS virtual special issue are similar. Table 8 shows the results of this experiment for all the methods ordered from the highest to the lowest values.

Table 8: Degree of confidence (I1) for the APS virtual special issue obtained by using all the methods.

Similarity method	I1
$semsim_{AF,max}$	99.86%
$semsim_{TD,max}$	99.86%
$semsim_{CF,max}$	99.84%
$semsim_{IIC,max}$	99.84%
$semsim_{TD,ave}$	99.84%
$semsim_{AF,ave}$	99.83%
Haase et al.sym	99.83%
$semsim_{CF,ave}$	99.82%
$semsim_{TD,gav}$	99.82%
$semsim_{AF,gav}$	99.82%
$semsim_{IIC,ave}$	99.81%
$semsim_{CF,gav}$	99.80%
$semsim_{IIC,gav}$	99.79%
Rezaei & Fränti	99.79%
$semsim_{TD,min}$	99.70%
$semsim_{AF,min}$	99.69%
$semsim_{CF,min}$	99.66%
$semsim_{IIC,min}$	99.65%
WNSim _{sym}	97.91%
Dice	97.39%
Jaccard	96.24%
Sigmoid	95.30%

¹⁵See https://journals.aps.org/prl/heating-up-of-superconductors. Last access on 16th April, 2022.
¹⁶See https://web.archive.org/web/20131122200802/http://www.aip.org/pacs/pacs2010/about.
html

5 Discussion

5.1 ACM experiments

In Figure 7, as mentioned in Section 4.4, the scatter plot shows the average degree of confidence and the average Pearson correlation values computed for all the seven special issues, and for all the addressed methods.

Note that, concerning **I1**, $SemSim^p$ configurations with the extensional weighting methods (AF and CF) provide better results with respect to those with the intensional ones (TD and IIC) and, in particular, AF shows the highest degree of confidence. Furthermore, independently of the weighting methods, the configurations with A (arithmetic average), as similarity normalization factor, provide the best degree of confidence values, although they are very close to those with G (geometric average). We also observe that all the $SemSim^p$ configurations with AF outperform the other selected methods.

With regard to **I2**, the *SemSim^p* configuration with AF, as weighting method, and G, as similarity normalization factor, shows better results with respect to the other configurations and all the selected methods except for Haase et al._{sym}, which has a comparable **I2** value. Furthermore, given a *SemSim^p* weighting method, the configuration with G provides the best average Pearson correlation values, and significantly outperforms that with A.

The study also reveals that, by focusing on the degrees of confidence I1 of $SemSim^p$ with the G and A similarity normalization factors, the results according to the AF weighting method are very close (0.13%) whereas, according to the indicator I2, they differ significantly (3%).

Overall, given the above mentioned results, in our opinion the $SemSim^p$ configuration with the AF weighting method and the G similarity normalization factor is recommended. In fact, the configuration with A slightly outperforms that with G with respect to **I1** (but such a difference can be neglected), whereas the difference between G and Aconfigurations with respect to **I2** is relevant and cannot be ignored.

Finally, Figure 8 shows the average degrees of confidence and the average Pearson correlation values in a scatter plot related to all the SemSim^p configurations, WNSim_{sym}, Haase et al._{sym}, and the method of Rezaei & Fränti for the Special Issue 7. In this case, the degrees of confidence of $SemSim^p$ configurations are low and, hence, the **RQ1** assumption (see Section 4.2), related to the assembly of the papers by following some similarity criteria, seems not to be satisfied. This is also confirmed by the semantic cohesion related to keywords (EJ_{key} in Table 5), which is the lowest value (0.18) among the others. We believe that this is due to the low quality of the annotation for this specific special issue (see threats to construct validity in Section 4.5). In fact, the semantic cohesion value increases (0.39) in the case it is estimated by also considering the abstracts (EJ_{abs}) , because the evaluation has been performed according to a richer amount of information. Indeed, as shown in Table 5, this is evident by looking at the difference (0.21) between the semantic cohesion related to EJ_{key} and the one related to the EJ_{abs} , which is greater with respect to the other cases. The reason of the low quality of the annotation is that in 2 out of 5 papers of the Special Issue 7, the selected keywords are too generic (e.g., Information Retrieval, see Figure 9), therefore they do not adequately describe the contents of the papers. Furthermore, as shown in Table 4, in general the papers of the Special Issue 7 have been annotated with fewer keywords. This also applies to the Special Issue 6, but in this case the selected keywords are hierarchically related (they belong to the same paths of the ISA hierarchy). Therefore the RQ1 assumption holds for the Special Issue 6, as well as the special issues 1-5.

5.2 The APS experiment

The experiment with APS is different with respect to the ACM ones. Firstly, it concerns a different application domain, i.e., physics. Then, within this field, the considered papers cover the whole range of physics and are therefore less focused than the topics addressed by the ACM TODS and TOIS journals, which mainly concern information systems. Accordingly, as shown in Table 8, the degree of confidence of the asserted hypothesis (**I1**) is very high for all the assessed methods, since it is quite easy to identify the virtual special issue among the sets of randomly sampled papers. Our study reveals that all *SemSim^p* configurations significantly outperform the WNSim_{sym}, Dice, Jaccard, and Sigmoid similarity methods. The *SemSim^p* configurations with M (maximum), A, and G, together with the Haase et al._{sym} and Rezaei & Fränti methods are the best performing ones, and almost equivalent because their difference is less than 0.07%.

In general, the APS experiment confirms that $SemSim^p$ provides the best results. The main difference with respect to the ACM experimentation is that the choice of the weighting method plays a less relevant role in determining the best method. This is probably due to the above-mentioned inherent characteristics of the APS articles, which are less focused than the ACM ones. This is because the 52,762 papers cover all the fields of the physics and, then, when



Figure 8: Scatter plot concerning the average degree of confidence and the average Pearson correlation values for all the *SemSim^p* configurations, WNSim_{sym}, Haase et al._{sym}, and the method of Rezaei & Fränti concerning the Special Issue 7.

weights are computed with the extensional methods, i.e, AF and CF, they are comparable to those obtained according to the intensional ones, i.e, TD and IIC.

6 Conclusion

In this work, the parametric semantic similarity method $SemSim^p$ has been introduced. It is based on a reference ontology, which is used to semantically annotate a set of digital resources. This method was successfully validated by means of a comparative assessment, which was performed through an experimentation that includes both a statistical analysis and an expert judgement evaluation. To this end, we adopted a large dataset of 1,103 papers collected from the Digital Library of the ACM and an ontology derived from the ACM Computing Classification System, which is one of the standard classification systems in the computing field. Then, we adopted the APS dataset in the domain of physics to assess the generalizability of the results.

For the ACM dataset, where the annotated digital resources mainly focus on one subject, i.e., information systems (see Section 5.2), the comparative assessment allowed us to elaborate the following considerations about the *SemSim^p* configurations. In particular, the one with the annotation frequency weighting method (AF) and the geometric average similarity normalization factor (*gav*) is recommended, since it exhibits the highest correlation with expert judgement and a high degree of confidence. However, for the datasets for which a significant amount of annotated resources is not available, *SemSim^p* allows the use of the intensional methods. In particular, when it is configured with IIC and the geometric average similarity normalization factor (*i.e.*, *gav*), it still provides results comparable to the best performing methods (i.e., Dice, Jaccard, WNSim_{sym}, Sigmoid, and Haase et al._{sym}). In fact, Dice, WNSim_{sym}, Jaccard, and Sigmoid

outperform this $SemSim^p$ configuration with regard to I1, but it is not the case with regard to I2. Conversely, this $SemSim^p$ configuration outperforms Haase et al._{svm} with regard to I1, but it is slightly outperformed with regard to I2.

We also assessed the adoption of different normalization factors with the aim of improving *SemSim* [23]. Indeed, the presented analysis reveals that the best performance of *SemSim^p* is achieved with the *ave* and the *gav* similarity normalization factors.

Note that, in this work, we addressed the problem of expert judgement related to the difficulty of asking a significant number of experts to pairwise check thousands of resources, producing millions of similarity scores. In particular, we adopted a new solution to assess similarity methods, which relies on a large dataset consisting of 1,103 annotated papers and seven ACM special issues, and the assumption that the papers published in a special issue are gathered by the editors according to a given research topic indicated in the call for paper.

The APS experimentation, where the annotated digital resources are less focused, reveals that, in general, *SemSim^p* provides better results than other similarity methods but the choice of the weighting method is less relevant.

As future work, we plan to experiment $SemSim^p$ in the health sector in order to further investigate its applicability to different contexts, and define the guidelines to identify the best $SemSim^p$ configuration depending on the specificities of the collected dataset of a given domain.

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Annex A

Table 9: Number of papers indexed by SCOPUS with "semantic similarity" grouped by application sectors.

Sectors	Number of papers
Computer Science	3,680
Mathematics	1,116
Engineering	980
Social Sciences	429
Decision Sciences	247
Arts and Humanities	241
Biochemistry, Genetics and Molecular Biology	180
Medicine	171
Business, Management and Accounting	140
Materials Science	58
Physics and Astronomy	58
Psychology	55
Earth and Plenatary Sciences	45
Neuroscience	35
Health Professions	30
Chemical Engineering	23
Environmental Science	22
Economics, Econometrics and Finance	20
Chemistry	18
Agricultural and Biological Sciences	17
Energy	16
Pharmacology, Toxicology and Pharmaceutics	9
Immunology and Microbiology	5
Nursing	3
Veterinary	1
Undefined	1
Multidisciplinary	32

Annex B

Information systems

• Data management systems

- Database design and models
 - * Relational database model
 - * Entity relationship models
 - * Graph-based database models
 - · Hierarchical data models
 - · Network data models
 - * Physical data models
 - * Data model extensions
 - \cdot Semi-structured data
 - · Data streams
 - · Data provenance
 - \cdot Incomplete data
 - \cdot Temporal data
 - · Uncertainty
 - \cdot Inconsistent data
- Data structure
- Database management system engines
- Query languages
- Database administration
- Information Integration
- Middleware for databases
- Information systems applications
 - Enterprise information systems
 - * Intranets
 - * Extranets
 - * Enterprise resource planning
 - * Enterprise applications
 - * Data centers
- Information storage systems
- World Wide Web
- Information retrieval

Figure 9: An excerpt of the ACM-CCS keywords.

Annex C

Method	Formula
Dice	$sim(av_1, av_2) = \frac{2 av_1 \cap av_2 }{ av_1 + av_2 }$
Jaccard	$sim(av_1, av_2) = \frac{ av_1 \cap av_2 }{ av_1 \cup av_2 }$
Sigmoid	$sim(av_1, av_2) = \frac{e^{ av_1 \cap av_2 } - 1}{(e^{ av_1 \cap av_2 } + 1)(av_1 - av_2 + av_2 - av_1 + 1)}$

Table 10: Formulas of the set-theoretic similarity methods selected for comparison.

Method Formula $sim(av_1, av_2) = \frac{\sum_{c_i \in av_1} max_{c_j \in av_2}(sim^{lch}(c_i, c_j)) \cdot IDF(c_i)}{\sum_{c_i \in av_1} IDF(c_i)}$ WNSim where $sim^{lch}(c_i, c_j) = -log \frac{length(c_i, c_j)}{2 \cdot maxdepth}$ IDF is defined according to Eq. (11) in Section 3.3.1 $length(c_i, c_j)$ is length of the shortest path between c_i and c_j maxdepth is the maximum depth of the taxonomy $sim(av_1, av_2) = \frac{\sum_{c_i \in av_1} S(c_i, c_j)}{|av_1|}$ where Rezaei & Fränti $|av_1| \ge |av_2|$ $c_j \in av_2$ is the concept paired with c_i according to Section 2.2 $S(c_i, c_j) = \frac{2 \cdot depth(lcs(c_i, c_j))}{depth(c_i) + depth(c_j)}$ depth(c) is the length of the shortest path between c and the root of the taxonomy $lcs(c_i, c_j)$ is the least common subsumer of c_i and c_j $sim(av_1, av_2) = \frac{1}{|av_1|} \sum_{c_i \in av_1} max_{c_j \in av_2} S(c_i, c_j)$ Haase et al. where $S(c_i, c_j) = \begin{cases} e^{-\alpha l} \cdot \frac{e^{\beta h} - e^{-\beta h}}{e^{\beta h} + e^{-\beta h}} & \text{if } c_i \neq c_j \\ 1 & \text{otherwise} \end{cases}$ $\alpha = 0.2$ $\beta = 0.6$ $h = depth(lcs(c_i, c_j))$ $l = length(c_i, c_j)$

Table 11: Formulas of the taxonomy-based similarity methods selected for comparison.