Subjective and generic distance in ViewpointS: an experiment on WordNet

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ABSTRACT

We first briefly recall the ViewpointS knowledge representation formalism and discuss the genericity it enables in terms of semantic distance computation. ViewpointS enables representation and storage of individual viewpoints in a shared knowledge graph. Knowledge providers (i.e., agents) express their individual opinions by emitting viewpoints on the semantic similarity or proximity between resources of the knowledge graph which can either be agents, documents (i.e., knowledge supports) or concepts (i.e., descriptors). In this paper, we benchmark the ViewpointS approach against other classic semantic distances (graph based or information content based) on a WordNet experiment. Our goal is to demonstrate the value of keeping the subjectivity of the represented knowledge, while having a generic approach that can handle any kind of knowledge and compute similarity between any kinds of objects.

CCS Concepts

• Knowledge Representation and Reasoning→Semantic Networks.

Keywords

Subjective Knowledge Representation; Knowledge Graphs, Semantic distances, Semantic similarity, WordNet.

1. INTRODUCTION

Evaluating semantic similarities has always been a challenging problem for computers [1]. Whereas a child can easily state than a truck and a car are "closer" than a truck and a plane, this is not straightforward for a computer to evaluate formally those similarity (or proximity). And the issue becomes even bigger when subjectivity or human interpretation comes into play. Automatically evaluating semantic distances between entities becomes then very cumbersome and the methods that have been proposed generally tend to be specific (e.g., dependent on the structure of the data) in order to bring out relevant results. One environment in which human interpretation is at the center is the Web. Indeed, since Web 2.0 has democratized the sharing, recommendation and creation of content via social networks, blogs and fora, and since semantic Web technologies have begun to structure the knowledge deposited, generated and stored on the Web, two kinds of content have emerged. These types of content differ in the ways they are produced and structured. On one hand, contribution-based social Web platforms allow the production of a wealth of data with little or no structure; these data evolve rapidly (e.g., folksonomies [2]). On the other hand, highly structured knowledge is constituted consensually by circles of experts (e.g., ontologies [3] or linked data [4] or other structured datasets) even if in certain domains there is still a lack of formalized knowledge in ontologies.

In the ViewpointS approach, our objective is to create a knowledge representation formalism that retains the best qualities of each type of content. Our objective is to support and give value to both (i) the structure which characterizes semantic Web datasets and (ii) the evolution and maintenance rates of shared knowledge on the social Web as proposed as in Gruber's work [5] or [6]. ViewpointS is also a knowledge formalism catching the subjectivity of knowledge. By this we mean there is no absolute truth but only subjective viewpoints, the interpretation of which being itself a subjective process. Knowledge providers (agents) can express their individual semantics by emitting viewpoints on the similarity or the proximity of two resources. These resources can be documents, concepts or agents. In the following, we will show that the ViewpointS approach enables the automatic computation of semantic similarities based on the topology of the underlying knowledge graph; and furthermore, this capability is fully generic i.e., independent from the structure of the data.

A major source of inspiration for our approach has been the Theory of Neuronal Group Selection by Edelman's approach [7]. According to this theory, the human brain is not a store of fixed or coded attributes to be called up and assembled as in a computer; instead, it results from a process of continual re-categorization within a network (the cortex) of about 30 billion neurons and 1 million billion synapses. One central and striking assumption in this theory is that most of the brain global/macro capacities rely on a single local/micro mechanism: the variation of the synapses' strengths as a feedback of individual value-systems to experience. In ViewpointS, the key idea is twofold: i) the unit of knowledge is a connection (we call it viewpoint) between two knowledge resources and ii) the wiring harness of viewpoints between a given pair of knowledge resources plays the role of 'synapse interconnecting two neurons'; we therefore call it synapse. In a previous contribution [8] we demonstrated the learning ability of the ViewpointS knowledge graph. In this paper, we show the potential of the subjective knowledge representation for the

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computation of semantic distances through a benchmark on the WordNet dataset[1].

We start in the following section with a state of the art on semantic distance computation methods and the past benchmarks that have been done with WordNet. Then section 3 details the ViewpointS approach. Once we have identified in the literature methods having proved efficient for a WordNet use case, we benchmark those methods against our approach. The benchmarking method and its results are discussed in section 4. Finally, we summarize our results in section 5 and expose our plans for developing the approach.

2. STATE OF THE ART

2.1 Knowledge representation

Our main point, in relation with current studies on the merging of social and semantic web, is the following: we always start from incorporating the (human or artificial) Agent as presented in [2], we show in our formalism section that it plays a key role in our representation of knowledge: the whole approach builds upon the micro-expressions of individual semantics (viewpoints). It must be noted that our mechanism for evaluating and confronting viewpoints does not use any additional contribution as is the case in [9].Thus, the emphasis is placed on what emerges from the knowledge graph, as reported in [10]. Indeed, the authors of [10] studied the possibility of the emergence of a collective representation of knowledge with a "bottom-up" vision of system interactions; this is what happens in ViewpointS.

2.2 Semantic distance measures

In the literature one may find several studies like [11]–[13] using the Wordnet dataset for benchmarking semantic relatedness methods. Those semantic measures– which the user could find implemented in libraries such as SML (Semantic Measurement Library) [14] – can be categorized as follows: (i) semantic relatedness measures based on the topology of a graph (e.g., based on the length of paths in a graph such as [15]) and (ii) relatedness measures between concepts using their information content such as the Resnik's measure [16] which rather uses the information on nodes than topological information. It may happen that shortest path based methods weight the edges depending on a depth in a taxonomy [17]. There are also hybrid methods such as Lin's [18]. Indeed, the Lin's measure uses both the information content of the two concepts for which we want to know the semantic distance but it also includes the information content of the least common subsumers of the two concepts. In our benchmark, we will focus on two measures that already have been benchmarked on the WordNet dataset and we will use the SML implementation of Lin and Wu & Palmer methods. We will focus on those three measures because they have already been tested in benchmarks on WordNet and they are quite representatives of the different approaches of computing semantic relatedness.

According to us, there are several limitations in the two categories of semantic relatedness methods mentioned above. Firstly, many of the shortest paths based measures need a taxonomical structure in a knowledge base to operate e.g., such as the is_a hierarchy in an ontology. If – like the knowledge engineering community seems to go for – we want to integrate both highly structured semantic data and social contributions we think we need to break free from this constraint. Moreover, if our goal is the integration of the social and the semantic Web, we need to be able to compute generic semantic distance measures between agents (human or artificial), documents and concepts. We need semantic distances capable of computing without preliminary adaptation, distances between agents and documents, between agents, between documents, etc. Finally, we believe that it is a plus that our topological semantic relatedness measure respects the metric properties of distance (symmetry, separation and triangular inequality). We propose in the next section the ViewpointS formalism and two semantic distance measures based on it.

3. VIEWPOINT'S FORMALISM

3.1 The Knowledge Graph

ViewpointS is a formalism dedicated to subjective knowledge; it holds that any proximity or distance relationship between two resources is expressed by an agent as a viewpoint. A typed viewpoint connects these two resources. These viewpoints are individually interpreted by a perspective chosen by the user / contributor. This perspective allows assigning a weight to each viewpoint, depending on who issued it, on when it was created, and on its semantic type or other more complex criteria. In the ViewpointS formalism, human agents (e.g., Web users) or artificial agents (e.g., data mining tools, knowledge extractors, ontologies) are equally considered as knowledge providers emitting viewpoints. We call resources agents, knowledge supports (documents, videos, Web pages, messages, posts, etc.) and descriptors (topics, tags). Resources are bound by the viewpoints within the knowledge graph (KG); in other words, KG is a bipartite graph formed of a set of resources R and a set of ViewpointS V.

A viewpoint (Figure 1) is a tuple (a, {r1, r2}, θ, t) containing the following information:

- a, the agent who issued the viewpoint:
- {r1, r2}, the couple of resources semantically connected by a;
- θ, the viewpoint's type;
- t, the viewpoint's creation date.

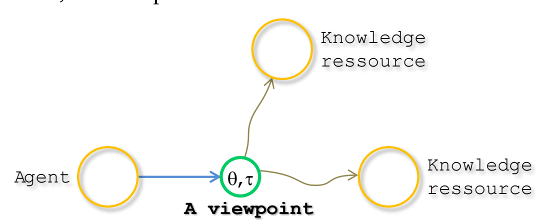

Figure 1: A viewpoint.

For instance, the viewpoint (Guillaume, {paper 707, acm:Knowledge representation and reasoning}, dc:subject, 27/02/15) expresses that the agent Guillaume associates 'paper 707' to the Knowledge representation and the reasoning concept of ACM's taxonomy with the relation DublinCore subject. (Mario, {Mario, Luigi}, foaf:knows, 13/07/1985) means that Mario expressed in 1985 that he knows (as in FOAF) Luigi. To identify the meaning of the viewpoints' types, we adopt, when possible, existing Semantic Web types. The ViewpointS approach is implemented in a Java API under open source license[2].

3.2 Subjective knowledge quantification

In order to exploit the knowledge, we build perspectives defining rules for quantifying the viewpoints. It may be default rules

[1] wordnet.princeton.edu

[2] https://github.com/sifrproject/viewpoints_kernel

adopted by a group of users in a recurrent context or specific rules filtering KG according to preferences such as: ignoring the viewpoints anterior to a given date, privileging the viewpoints emitted by some agents or privileging viewpoints of a given type. The preliminary step in building a knowledge map consists in grouping all the viewpoints connecting any given pair of knowledge resources into a higher level link called a synapse. The strength of the synapse is based on the aggregation of the weights of all viewpoints in the synapse. The two functions of evaluation (Map) and aggregation (Reduce) of viewpoints form a perspective which allows the exploitation of subjective knowledge. For the same KG, several interpretations, defined as Knowledge Maps (KM), can be made, depending on the way agents evaluate and aggregate viewpoints. For instance, an agent might give a lot of importance to viewpoints emitted by friends or with a specific type or included in a specific date range. The Knowledge Map is a graph made of resources (R) and synapses (S) to which common graph algorithms can be easily applied. The perspective is under the responsibility of the user, who decides which way he wants to interpret the KG. The two functions of evaluation and aggregation of viewpoints can be extended at will to suitably match one's needs. Figure 2 illustrates the interpretation process of KG. Also, the specific architecture of the perspective inspired by the map-reduce approach opens the way to a massive parallelization of computation.

An important aspect, directly inspired from the Web 2.0, lies in the built-in feature for integrating agent feedback. Within their perspective, agents exploit the viewpoints for browsing KM and reversely update the KG through viewpoints expressing their feedback. Along these exploitation/feedback cycles, shared knowledge is continuously elicited against the beliefs of the agents in a selection process. The knowledge map is defined as a graph in which semantic similarities within the knowledge resources are computed according to a given perspective. All KG exploitation methods are then subjective methods, i.e., always tied to a perspective. The semantic distance methods presented below are generic methods that can adapt to any specific use by tuning the perspective. Perspective can be tuned in various ways in order to evaluate each viewpoint accordingly to his type, emitter or creation date. Here the viewpoints are evaluated only with their type. Each viewpoint type is associated with a weight.

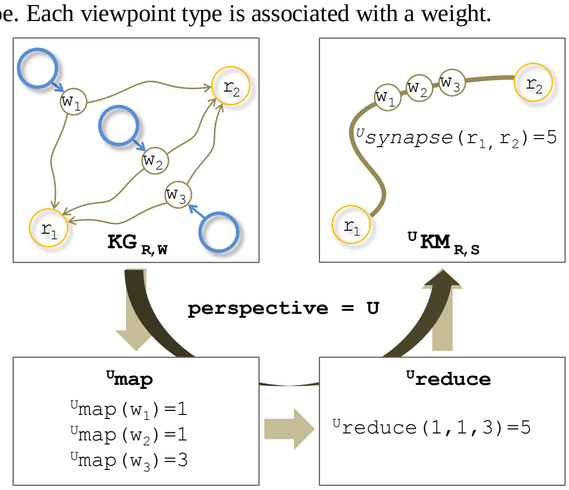

Figure 2: Interpretation of Knowledge Graph (KG) into Knowledge map (KM).

3.3 Semantic distance measures

3.3.1 Shortest Path Distance (SPD)

We start with a very simple shortest path based semantic distance by adapting the Dijkstra algorithm. We summarize our Dijkstra-inspired-algorithm by considering two steps. Firstly it 'propagates' distances on all the nodes on all the paths starting from a given node. Doing so we restrict the exploration to non-cyclic paths with a maximal length. Then it computes the shortest path between the starting node and a destination node. SPD is therefore a metric distance and we enforce this within the kernel code by unit testing that this property remains true.

3.3.2 Multiple Paths Distance (MPD)

We designed the multiple paths distance as an evolution of SPD taking in account all the paths shorter than a maximal length between two resources. Multiple Paths Distance (MPD) proceeds the same as SPD constructing a traversal tree containing paths from a starting node. Let us consider the set of paths p_i between two resources each one with a given length d_i. We compute the synapse s_i equivalent to each path p_i. At this point several equivalent synapses connect the two resources. We sum those equivalent synapses to obtain the super-equivalent synapse equivalent to the bunch of paths and base the distance between the resources on its value. More formally for two resources r_1, r_2:

$$d_{MPD}(r_1,r_2) = \frac{1}{\frac{1}{d_1} + \frac{1}{d_2} + \frac{1}{d_3} + \cdots + \frac{1}{d_n}}$$

In the next section, we detail how we compare SPD and MPD with two of the semantic distance measures previously discussed.

4. BENCHMARKS

We begin in the next sub-section explaining our benchmark method when using the WordNet dataset. Then we discuss the results we have obtained.

4.1 Method

We propose a semantic distance benchmark on words. For this, we adopted a semantic distance gold standard containing the distances between 353 common words belonging to the WordNet dataset according to a group of persons (wordsim 353 [19]).

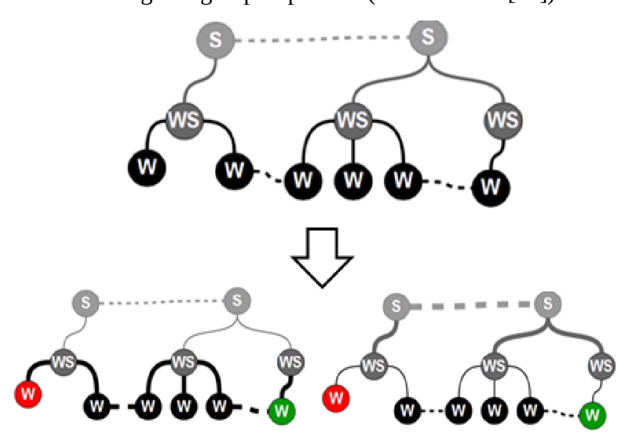

Figure 3: Two different perspectives give two different interpretations and exploitations of WordNet. The thickness of edges represents the strength of the synapse paths. There are two different Knowledge Maps resulting from two different evaluations of the viewpoints types. Based on two perspectives the length of the shortest path between the red and the green word changes.

WordNet's structure is described in Figure 3. We extract three types of resources: the Word, the WordSense and the Synset. *Words* have different meanings and then are bound to WordSenses. *WordSenses* are grouped in synonyms sets (*SynSets*). Several semantic relations tie two SynSets: hyperonymy, meronymy and more generally semantic proximity. WordSenses can also be bound together by a SeeAlso relation. For instance, the word "bank" is tied to two meanings: the financial institution and the side of a river. A SynSet constituted by different WordSenses of financial institutions is connected by a hyperonymy relation to the SynSet "institutions". For each one of these relations a viewpoint is created with the suitable type (ex.: a isA viewpoints for the hyperony relations). For instance, the SynSet constituted by the WordWenses (dog, domestic dog, Canis familiaris) is the hyperonym of the (canine, canid) SynSet.

The WordNet is interpreted in our benchmark by several perspectives, each giving priority to an ordered set of relations. Each one of these perspectives reflects a specific meaning or knowledge goal that we illustrate in Figure 3. The first perspective in Figure 3 focuses on paths through Words and WordSenses via the SeeAlso relation. On the other hand the second perspective gives priority to semantic relations between SynSets. Figure 4 illustrates the Knowledge Graph resulting from the indexation of this little example on WordNet. For the readability of the illustration we didn't represented the emitter of all the Viewpoints since there is only one viewpoint emitter which is the WordNet 3.1 artificial agent. This artificial agent represents the dataset. For instance, the WordSense "dog" is tied by a viewpoint emitted by the WordNet agent to the SynSet "(dog, domestic dog, canis familiaris)".

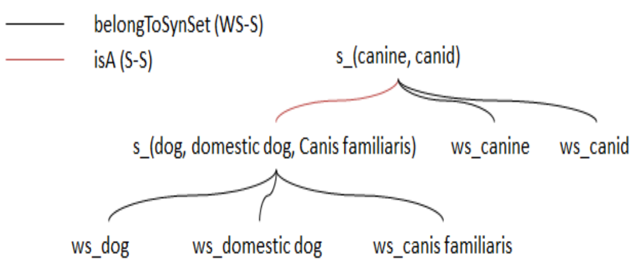

Figure 4: Example based on some WordSenses and Synsets.

Table 1: Perspective giving weights to the WordNet relations types: SeeAlso (SA), Hyperonym (H), Meronym (M) and Similar (S)

P1	**P2**	**P3**	**P4**	**P5**	**P6**
SA(5)	H(7)	H(7)	S(7)	SA(7)	SA(7)
S(5)	S(5)	M(5)	H(5)	H(7)	S(7)
	M(4)	S(4)	M(4)	M(5)	H(5)
				S(4)	M(4)

We firstly compare our SPD and MPD distances to the wordsim 353 gold standard distances. We then compare the SPD and MPD distances to Lin and Wu & Palmer measures (used through their SML implementation). Finally, we propose a summary of results comparing all the semantic distance methods to the wordsim 353 gold standard. The Table 1 shows the priority order given by the respective perspectives (P1 to P6) between relation types in WordNet. We also give for each relation type its associated weight. By default all the relation types have a weight of 1. This priority order results from the weight given by the Map function. For instance, in P4, it gives maximal priority (i.e., maximal weight) to the Similar relation. The basic relations (WordSense-Word and WordSense-SynSet) keep a fixed value along all our experimentations.

4.2 Results

Results will be expressed in terms of precision percentage according to the chosen gold standard. Precision is obtained by the following formula with a tested distance d_{test} and a gold standard distance d_{gold}:

$$precision = 100 - \frac{abs(d_{test} - d_{gold}) \times 100}{d_{gold}}$$

Precision values displayed in the following charts are average precisions on 353 comparisons with the wordsim 353 distances. The results in Figure 5 shows the precision of SPD and MPD compared to the wordsim 353 distances with each perspective. We first observe that changes in the perspective tuning have a much greater impact on SPD than on MPD. The shortest path distance result changes radically between two perspectives because the shortest path used in the distance calculation changes with different tunings of the perspective. In the multiple paths approach, changes in the perspective tuning only have a moderate effect. Not surprisingly, the MPD with the perspective that gives emphasis on semantic relatedness relations between SynSets and on hyperonymy and meronymy is the one that gives the best results. MPD draws indeed better value from the diversity or relations than SPD. MPD-P4 is therefore best combination of method and perspective for computing the semantic distance between words according to the wordsim 353 gold standard.

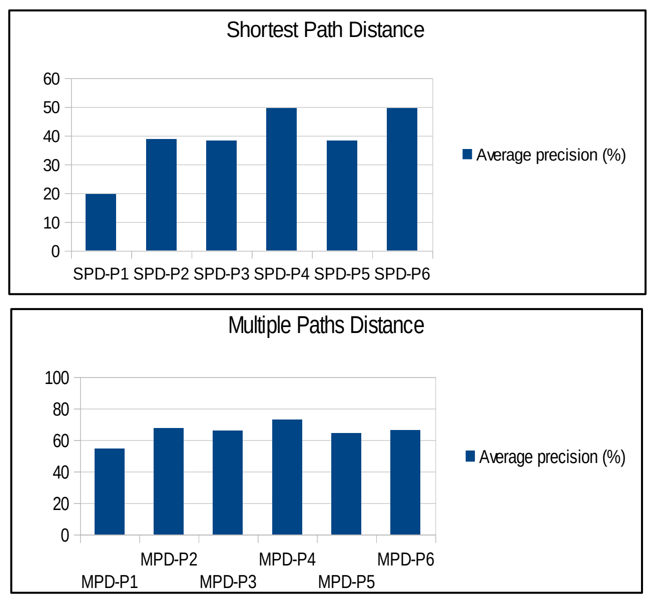

Figure 5: Benchmark comparing SPD and MPD to the wordsim 353 distances.

We then compare in Figure 6 the distances computed with SPD and MPD to Lin's measure results and, in Figure 7, and to Wu & Palmer's distance. It seems according to the figures 6 and 7 that each kind of method – either shortest path or multiple paths based – is well suited to achieve results very closed to the two categories of semantic distances. SPD as a shortest path based method obtains the best results when we compare it to the Wu & Palmer method. Also, MPD can get the closest results to Lin method which is based mainly on information content. However the best perspective tuning is not any longer P4.

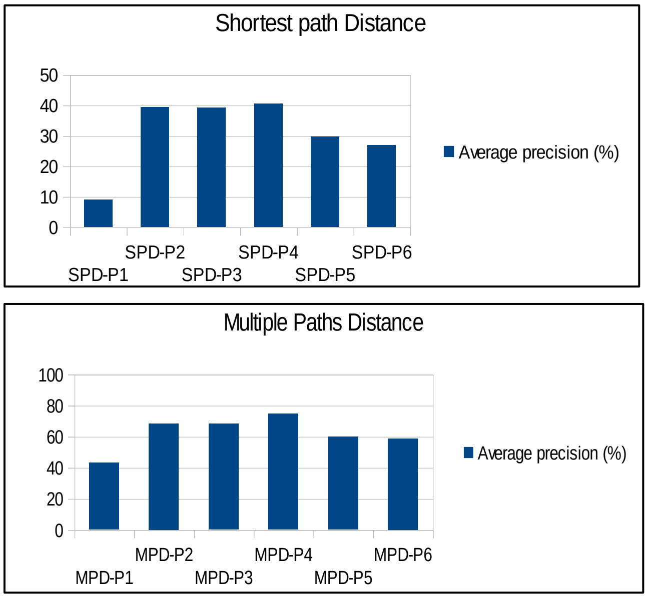

Figure 6: Benchmark comparing SPD and MPD to Lin's measure.

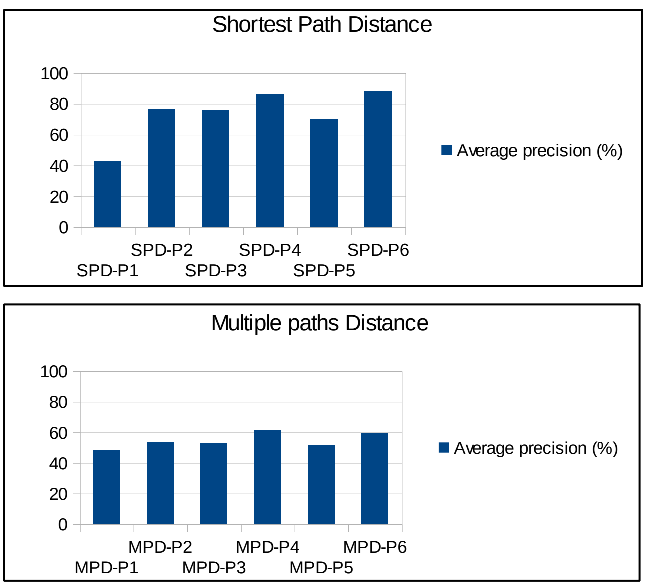

Figure 7: Benchmark comparing SPD and MPD to Wu & Palmer's measure.

Finally, we summarize bours benchmarks in Figure 8 by comparing all the methods to the wordsim 353 gold standard: MPD-P4, Lin, Wu & Palmer and we included also in this final result the Jiang & Conrath method [20] which is another IC based method adapting Resnik measure but it considers the information content of lowest common subsumer and the two compared concepts to calculate the distance between the two concepts.

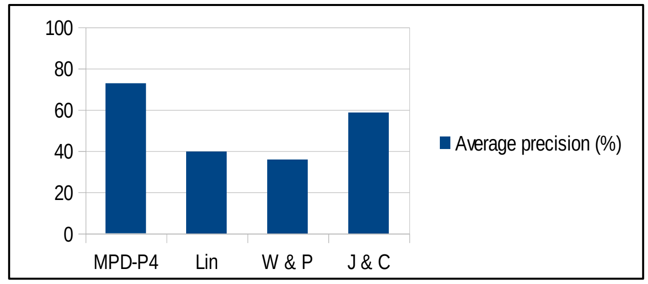

Figure 8: Benchmark summary using wordsim 353 gold standard.

5. DISCUSSION & PERSPECTIVES

We have presented a model and formalism where both the explicit semantics of the linked data and the contributions of Web 2.0 users can be expressed as fine-grained subjective units of knowledge called viewpoints within an evolutionary knowledge graph, and then put in perspective within knowledge maps in [21].

We have shown the advantage of separating methods and perspectives: this yields a generic semantic distance calculation method which can be tuned without specialization. We have actualized this tuning when customizing the perspectives in order to reach closest results to our gold standard. The subjectivity in ViewpointS is twofold: (i) we represented WordNet as subjective knowledge (i.e., open to interpretation) and (ii) having a knowledge goal in mind we selected a specific way to interpret this knowledge. We have applied the two generic distances SPD and MPD to a knowledge base with a taxonomic structure and have used Lin and Wu & Palmer measures (classic literature semantic similarity measures) in a benchmark. Using the appropriate perspective it seems that we yield better precision with respect to the wordsim 353 gold standard. The perspective mechanism allows us to have generic methods achieving relatively close results to those of "classic" similarity/distance measures in the literature. The next step in the development of the ViewpointS approach is to enhance the automatic tuning of the best perspective with respect to a given specific use case. Since finding the optimal tuning is a combinatorial problem we intend to rely on genetic algorithms. This class of algorithms is able to evolve a population of perspectives in order to sort out in short time optimal perspectives for a specific use.

To end with, we are currently working on the design of an API offering intuitive browsing of the knowledge and one-click feedback exploiting the context.

We are planning for several applications which may help us evaluate the ViewpointS approach: Amongst them, one will consist in cross scientific discovery of agronomic knowledge (CIRAD) and another will deal with biomedical data within the SIFR project[3].

6. AKNOWLEDGEMENTS

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