Ontological Distance Measures for Information Visualisation on Conceptual Maps

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Abstract. Finding the right semantic distance to be used for information research, classification or text clustering using Natural Language Processing is a problem studied in several domains of computer science. We focus on measurements that are real distances: i.e. that satisfy all the properties of a distance. This paper presents one *ISA*-distance measurement that may be applied to taxonomies. This distance, combined with a distance based on relations other than *ISA*, may be a step towards a real semantic distance for ontologies. After presenting the purpose of this work and the position of our approach within the literature, we formally detail our *ISA*-distance. It is extended to other relations and used to obtain a MDS projection of a musical ontology in an industrial project. The utility of such a distance in visualization, navigation, information research and ontology engineering is underlined.

Keywords: *ISA*-distance, Semantic Distance, MDS, Ontology Visualisation, Conceptual Maps, Ontology Engineering.

1 Introduction

Searching for information in a huge amount of data is a challenging task. Visual assistance, such as conceptual and knowledge maps, may help the human operator by showing him/her data that are close to each other: which papers concern a given subject, which people are interested in a given molecule, which picture may best illustrate his/her speech, etc. We underlined the interest of conceptual and knowledge maps for indexing, navigating or retrieving information through massive data sets in [7]. The objective is now to reinforce the semantic of the maps by projecting ontologies onto those maps, using a MultiDimensional Scalling (MDS) method, in such a way that concepts and other *objects* are gathered together by means of semantic distance.

In face of the growth in the amount of available information, various domains of computer science propose solutions often based on ontologies or taxonomy and use

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similarity or semantic distance measurements. Few of these distances respect the three properties of distance: *positiveness*, *symmetry* and *triangle inequality*. This paper presents an ISA-distance (based on the *ISA* relationship) that respects those properties. It may be a first step towards a real semantic distance and can be used to apply MDS onto the concepts of an ontology.

The remainder of the paper is organised as follows. The next section presents the state-of-the-art concerning semantic distance measurement and positions our approach within the literature. Our method is then introduced, formally described and illustrated by means of simple examples. This distance measurement was applied to an industrial project where musical landscapes are used to visually index music titles and compose playlists semi-automatically. The distance measurement is therefore extended to other semantic relations. Then it is used to obtain a knowledge map in the music domain, through the MDS projection of the concepts of the ontology. We also demonstrate how this distance may support engineers and domain specialists in assessing semantic consistency when designing an ontology for a particular domain. These results, together with their limits and perspectives are discussed before the conclusion.

2 State-of-the-Art Concerning Semantic Distance

The different strategies and methodologies used for semantic distance measurement aim at estimating a kind of similarity between concepts. Several domains of computer science have tried to find a semantic distance measurement. The state-of-the-art below presents the various approaches and their vocabulary.

The major reason for finding such a distance concerns information retrieval. Initially, information systems used exact correspondence between request and data but, to avoid silence, current methods allow approximate requests and use distance measures to find pertinent information, widening the scope of the search. One of the first methods was proposed by J. Sowa in [16]: given a lattice of concept types, the distance between concept a and concept b is given by the length of the shortest path from a to b that does not pass through the absurd concept ($\perp$).

Other distance measurements have been proposed by the *Object* community. For example Jérome Euzenat uses the unary distance proposed by [2] in order to determine the neighbourhood of an object in classification systems [9]. This distance between two concepts corresponds to the number of edges between them in the graph.

People working in the NLP (*Natural Language Processing*) community, are often interested in analysing and comparing sets of documents, and applying clustering methods to them. Several similarity measurements are therefore used [1, 12]. A document is commonly represented as a vector of terms. The basis of the vector space corresponds to distinct terms in a document collection. The components of the document vector are the weights of the corresponding terms, which represent their relative importance in the document and the whole document collection. The measurement of distances may be ensemblist, using Dice or Jaccard coefficients, or geometric, using cosines, Euclidian distance, distributional measure or Jensen-Shannon divergence. The problem with these approaches is the lack of precision due to vectorisation and the fact that some concepts may be considered as totally independent even if they are semantically close. For example, considering synonyms as independent concepts may adversely affect the distance estimation. Some solutions have been proposed using *Synonym Rings*[1], as in the WordNet ontology [4].

However, this context is rather remote from ours. While in NLP people search for the most representative set of concepts that may characterise a document and find a similarity distance between them, we are looking for a distance between the concepts themselves. This is also the problematic of [3], in which semantic relatedness and semantic distance are distinguished. Semantic relatedness uses all the relations in the ontology (WordNet), while semantic distance only takes into consideration the hyponymy relation. In our approach, initially, we also limit the calculus to the hyponym relation and then we extend it to other semantic relations.

To determine the semantic distances between concepts, it is possible to use a vectorial representation of each concept, as proposed in [11]. Each dimension of this vector consists of a concept, as in the above mentioned approach, except that concepts are associated with other concepts and not with documents. Using these vectors, a numeric distance can be calculated between two concepts, using numeric methods (cosines, Euclidian distance, etc.). In our application, there is no correspondence between concepts using vectors and, more generally, it is always difficult to associate a numeric value to a non-numeric parameter in order to apply traditional mathematical calculus. We therefore prefer directly to use the links available in the ontology and their semantics.

Concerning the database community, one semantic distance model has been proposed in [15]. However, the formalism used is very generic and, while we try to comply with most of the recommendations given, it is difficult to satisfy all of them.

The semantic web community, in particular researchers interested in ontologies, has also proposed several algorithms to determine the distance between concepts[2] [5]. Most of them are based on edge-measurement of the shortest path between concepts, which is not satisfactory because it does not take into account the degree of detail of the ontology. Other methods are based on the lowest super-ordinate (most specific common subsumer); in ontologies, concepts often have several *parents* and only taking the closest one into account may hide other aspects of the concepts. Moreover, it compromises the respecting of triangle inequality. The probabilistic measure of similarity proposed by Resnik [14], takes multiple inheritances into account, but does not satisfy all the properties of a distance.

3 From Ontology to Semantic Distance

This section details the semantic distance that we propose. It starts with an intuitive description, followed by formalisation and examples. We follow the notation of [5], using upper case for sets of concepts and lower case for single concepts.

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1 http://en.wikipedia.org/wiki/Synonym_Ring

2 See for example: Laakso, A.: Semantic similarity. Wikipedia web pages at http://www.laakshmi.com/aarre/wiki/index.php/Semantic_similarity

3.1 Intuitive Approach

Two concepts are close if there is a concept that subsumes both of them and if this concept is slightly *more general*; to estimate its degree of generalisation we consider the number of concepts encompassed by it. In the simple case where the ontology is a tree and concept *a* subsumes concept *b*, we want the distance from *a* to *b* to be the number of concepts encompassed by *a* but not *b*. The number of such concepts is thus used to estimate the degree of generalisation of *a* compared to *b*.

NOTE – If *a* subsumes *b* and *b* subsumes *c*, using such a distance ensures that:

$$d(a,c) = d(a,b) + d(b,c) \tag{1}$$

In a concept hierarchy supporting multiple inheritances the subsumers of a concept (for example *s* and *s'*, which subsume *y* in Fig. 1) may be seen as several points of view regarding this concept. The intuitive approach presented above needs to be extended to the general case. Considering a concept hierarchy like the one modelled in Fig. 1, one can easily understand that concepts *a* and *x*, which are subsumed by *s*, are closer than *a* and *b*. More generally, all concepts subsumed by *s* are closer to *a* than *b*, with respect to the point of view of *s*. Therefore, the higher the number of concepts subsumed by *s*, the greater the distance between *a* and *b*.

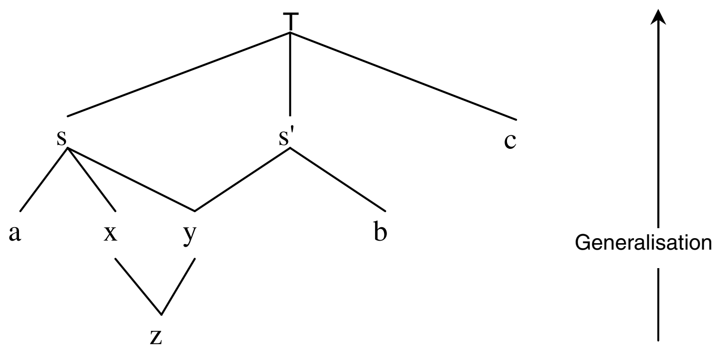


Fig. 1. Hierarchy that may represent a taxonomy of concepts. Note that the orientation of edges is top-down, i.e. "*z is an x*".

Using these two intuitive notions of distance, we set out to define a distance measurement where the distance between two concepts (for example *a* and *b*) is a function of the number of concepts closer to *a* than *b*, and to *b* than *a*, respectively. This means that the distance must take into account all points of view with regard to a concept. To be more significant, common sub-concepts must be removed from the distance.

3.2 Definition and Proof

Using an ontology, the similarity between concepts can be estimated on the basis of several indicators. The concepts can be linked by various kinds of relations, and the similarity can hardly be estimated without taking into account their semantics. Among these relations, the ISA relation defining the generalization between concepts plays a key role as the backbone of any ontology. Since one concept can be a specialization of several others, the ISA part of the ontology can be represented by a Direct Acyclic Graph (DAG) whose nodes represent the concepts of the ontology and whose oriented edges represent the specialization relation.

Given a graph (V,E) where V is the set of vertices and E the set of edges, a is a father of b if edge $(a,b) \in$ V, and a is an ancestor of b iff there is a path between a and b. The set of concepts having a as ancestor is denoted by $desc(a)$, while its set of ancestors is denoted by $ansc(a)$. Given two nodes a and b, node x is one of their exclusive ancestors iff it is the ancestor of exactly one of them i.e. $x \in ansc(a) \cup ansc(b) - ansc(a) \cap ansc(b)$. The set of the exclusive ancestors of a and b is denoted by $anscEx(a,b) = anscEx(b,a)$.

We use $d_{ISA}(a,b)$ to denote the distance between two concepts a and b based on the ISA relationship, defining it as follows:

$$d_{ISA}(a,b) = |desc(ancEx(a,b)) \cup desc(a) \cup desc(b) - desc(a) \cap desc(b)| \qquad (2)$$

If the *ISA*-graph is a tree and $b \in desc(a)$, we can observe that the exclusive ancestors of a and b are on the path between a and b. Thus, $desc(ancEx(a,b)) \subset desc(a)$ and $desc(b) \subset desc(a)$, therefore:

$$d_{ISA}(a,b) = |desc(a) - desc(a) \cap desc(b)| \text{ as expected (c.f. Section 3.1)}$$

Let us now consider the satisfaction of the three axioms (*positiveness, symmetry and triangle inequality*) for this distance definition.

Theorem d_{ISA} is a distance if the three following axioms are verified:

i) $\forall\ a, b\ d_{ISA}(a,b) \geq 0$ and $d_{ISA}(a,b) = 0 \Leftrightarrow a = b$ (*positiveness*)
ii) $\forall\ a, b\ d_{ISA}(a,b) = d_{ISA}(b,a)$ (*symmetry*)
iii) $\forall\ a, b, c\ d_{ISA}(a,c) + d_{ISA}(c,b) \geq d_{ISA}(a,b)$ (*triangle inequality*)

i) $\forall\ a, b\ d_{ISA}(a,b) \geq 0$ comes directly from the definition of d_{ISA} as a cardinality of a set. For the second part of the *positiveness* axiom we have: $\Rightarrow d_{ISA}(a,b) > 0$ implies that either $desc(a) \cup desc(b) - desc(a) \cap desc(b)$ or $desc(ancEx(a,b)) - desc(a) \cap desc(b)$ is not empty. In first case, there is at least one x such that ($x \in desc(a)$ et $x \notin desc(b)$) or ($x \in desc(b)$ et $x \notin desc(a)$). The existence of x ensures that $a \neq b$. In second case, there is at least one ancestor that is not common to a and b (otherwise $desc(ancEx(a,b))$ will be empty). The existence of this exclusive ancestor ensures that $a \neq b$.
$\Leftarrow$ having $a = b$ trivially implies that both $desc(a) \cup desc(b) - desc(a) \cap desc(b)$ and $desc(ancEx(a,b))$ are empty sets and therefore that $d_{ISA}(a,b) = 0$

ii) By definition of the distance, since $anscEx(a,b) = anscEx(b,a)$

iii) It is sufficient to prove that any element of the set $S_{ab}=\{desc(ancEx(a,b)) \cup desc(a) \cup desc(b) - desc(a) \cap desc(b)\}$ is an element of at least one of the two sets $S_{ac}= \{desc(ancEx(a,c)) \cup desc(a) \cup desc(c) - desc(a) \cap desc(c)\}$ and $S_{bc}=\{desc(ancEx(c,b)) \cup desc(c) \cup desc(b) - desc(c) \cap desc(b)\}$.

If $x \in S_{ab}$, either

- $x \in \{desc(a) \cup desc(b) - desc(a) \cap desc(b)\}$
- or $x \in \{desc(ancEx(a,b)) - desc(a) \cap desc(b)\}$.

In the first case, let us assume $x \in desc(a)$ and $x \notin desc(b)$ the proof is similar for the alternative case where $x \in desc(b)$ and $x \notin desc(a)$. Therefore either $x \notin desc(c)$, and $x \in \{desc(a) \cup desc(c) - desc(a) \cap desc(c)\}$ or $x \in desc(c)$ and thus $x \in \{desc(c) \cup desc(b) - desc(c) \cap desc(b)\}$. In both cases $x \in S_{bc}$.

In the second case, $x \in \{desc(y) - desc(a) \cap desc(b)\}$ with $y \in ancEx(a,b)$), note that this implies that x is not a descendant of both a and b. Let us now assume that y is an ancestor of a and not of b (the proof is similar for the alternative case where y is an ancestor of b and not of a). Either $y \in Anc(c)$ or not. If it does, $y \in AncEx(c,b)$. In this case if $x \in desc(c)$ and since x is not a descendant of both a and b, then $x \in \{desc(a) \cup desc(c) - desc(a) \cap desc(c)\}$ or $x \in \{desc(c) \cup desc(b) - desc(c) \cap desc(b)\}$. If $x \notin desc(c)$ then $x \notin \{desc(b) \cap desc(c)\}$ and therefore $x \in \{ desc(c) \cup desc(b) - desc(c) \cap desc(b)\}$.

If $y \notin Anc(c)$, $y \in AncEx(a,c)$ and the proof is the same as above, inversing a and b.

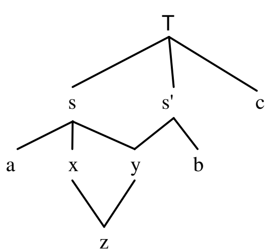
3.3 Simplified Example

To illustrate our *ISA*-distance calculus, let us consider some distances using a small example. Considering the hierarchy given in Fig. 1, the ISA-distance between x and y is obtained as follows:

$$\begin{aligned} d_{ISA}(x,y) &= |\, desc(ancEx(x,y)) \cup desc(x) \cup desc(y) - desc(x) \cap desc(y) \,| \\ &= |\, desc(s') \cup desc(x) \cup desc(y) - \{z\} \,| \\ &= |\, \{s',y,b,z\} \cup \{x, z\} \cup \{y, z\} - \{z\}| = |\, \{s',y,b,x\}| = 4.0 \end{aligned}$$

The full distance matrix concerning the hierarchy given in Fig. 1 is presented in Table 1. One can verify the three distance properties on this matrix.

Table 1. Distance Matrix between the Nodes given in Fig. 1



	T	b	y	a	x	s'	s	z	c
T	0.0	8.0	7.0	8.0	7.0	5.0	4.0	8.0	8.0
b	8.0	0.0	6.0	7.0	7.0	3.0	7.0	7.0	5.0
y	7.0	6.0	0.0	5.0	4.0	5.0	5.0	4.0	8.0
a	8.0	7.0	5.0	0.0	3.0	7.0	4.0	4.0	6.0
x	7.0	7.0	4.0	3.0	0.0	6.0	3.0	2.0	6.0
s'	5.0	3.0	5.0	7.0	6.0	0.0	5.0	6.0	5.0
s	4.0	7.0	5.0	4.0	3.0	5.0	0.0	4.0	6.0
z	8.0	7.0	4.0	4.0	2.0	6.0	4.0	0.0	6.0
c	8.0	5.0	8.0	6.0	6.0	5.0	6.0	6.0	0.0

Moreover, note that proposition (1) holds for concepts having tree-like relationship; for instance $dist(\top,a) = dist(\top,s) + dist(s,a) = 5 + 3 = 8$.

4 Applications, Results and Perspectives

4.1 Results in Ontology Visualisation

The following example is extracted from a current industrial project[3] which aims at modelling and representing music knowledge as an ontology which is projected onto a two dimensional map for navigation and indexing purpose [7]. In this simple extract, we only consider two types of concepts: music periods and composers (music works are not considered to keep the discussion simple). The semantics of the relations between them is *BELONGS-TO*. Periods are children of the root. This model can be represented as a Direct Acyclic Graph (DAG). The traditional approach for an aesthetic visualisation of a DAG is a hierarchical model whereby nodes are displayed in layers according to their rank in the graph hierarchy [17, 8]. We now show how our semantic distance produces an alternative representation that conserves part of semantic information which is otherwise poorly represented.

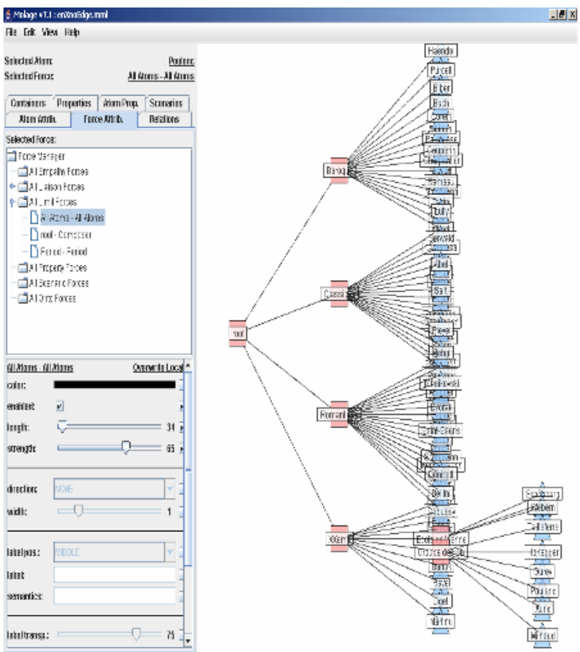


Fig. 2. Hierarchical visualisation of the ontology (works are not shown)

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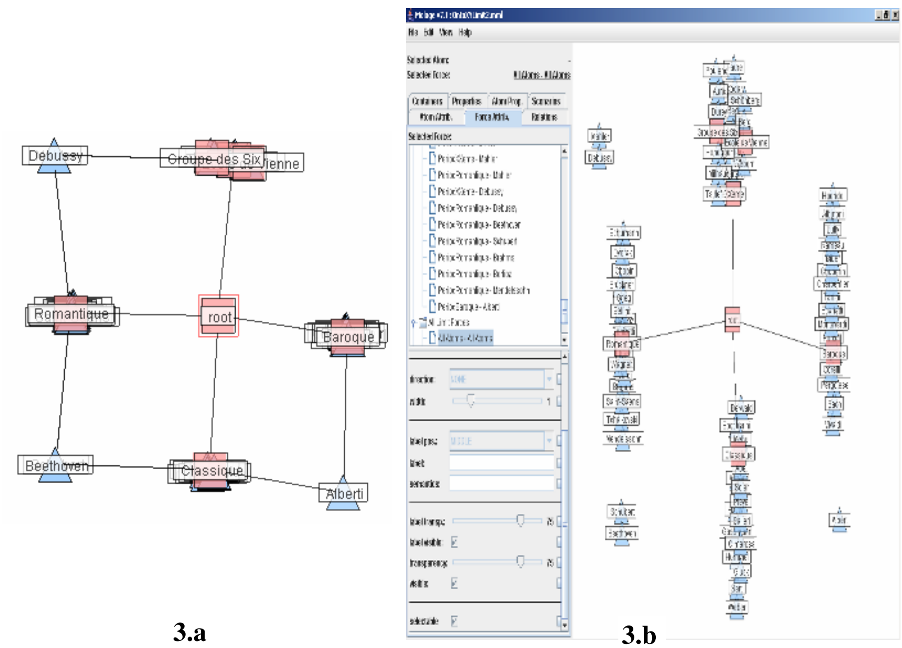
[3] This project was realised with Nétia *inc. http://www.netia.net/us/*

In the following snapshots, all the displays were performed using our knowledge mapping environment called Molage that implements different graph drawing algorithms among which MultiDimensional Scaling (MDS) and Force Directed Placement [6, 7]. Fig. 2 presents an aesthetic hierarchical display[4] of the music model performed with Molage (with a limited number of edge crossings [8]). The periods are on the second layer, most of composers are on the third layer, two sub-periods for the XXth century ('Le groupe des Six' and 'Ecole de Vienne') are also on this third layer, and their children on the fourth layer. In order to read the labels, another Molage force called the 'Limit force' was applied to separate the different nodes that are on the same layer along the *y* axis. The result is understandable, but presents several pitfalls. It looses particular semantic information since those composers that are linked to two periods like *Alberti*, *Debussy* or *Malher* are not highlighted in the mass of all composers. The different periods are not separated according to their respective influence, but merely because of the fact that we want to limit the number of edge crossings in the display. It is necessary to keep visible links to associate each composer to his (her) period(s). A display with most of the composers on the third layer is a sub-optimal usage of the plane with empty and cluttered spaces. Finally, with such a display, a concept, such as *Romantic*, is far on the Euclidian plane from its instances which are the composers that represent this period. This is a problem when we want to use the Euclidian plane for indexing as we do in our application [7].



3.a 3.b

Fig. 3. Visualisation using our distance

[4] Note that labels are in French because it has been done in a French project.

Our distance measurement may now be applied to this ontology in order to maintain strong semantics. In this application we consider concepts to be defined in an extensive way. For example, each musical period is characterised by composers who composed works during a certain period. In the same way, a composer may be considered through his complete works.

Fig. 3.a shows the result of applying the distance described in Section 0 followed by an MDS projection. Music periods are identified as *pink squares*[5], and composers as *blue triangles.* One can see that all composers of a unique period are piled up under their period. However, some composers are between several musical periods. *Beethoven* is considered as a turning point between the *classical* and *romantic* periods. He is therefore positioned in a cluster between the two periods (like *Schubert*). One can also notice a kind of chronological circle around the root (square without label) from *Baroque* period to the *Classical*, then the *Romantic* ending with the *XX^th^ Century*. In order to identify the composers beneath a period, in Fig. 3.b we applied the 'Limit force' as we did for the hierarchical display in Fig. 2.

The semantic distance in Fig. 3.b can now be compared to the hierarchical model in Fig. 2. The belonging of composers to a particular period is clearer and their links to their period is no longer necessary. The space is better utilized and there is less cluttering. Composers that belong to two different periods like *Alberti* or *Beethoven* are better identified since they are positioned between the corresponding periods. Composers and their periods are gathered which is what we expected when using this projection for indexing new composers. Indeed it suffices to drop a composer near a cluster to automatically index it with the right periods. All problems in the hierarchical model seem to be overcome. However, the two sub-periods of the *XX^th^ century* are now so near (see Fig. 3.a) that it is difficult to identify which composers belong to which period in Fig. 3.b. In conclusion, when applied to a simple ontology model, our distance method gives a different view from the traditional hierarchical model with more semantic expression. However there are still side effects that have to be dealt with when specialising concepts. In fact, the distance driven display resembles a radial display with good aesthetic properties while maintaining semantic constraints that can be used for better navigation and possible indexing.

4.2 Results in Ontology Engineering

To assess our approach, we also intended to use the evaluation protocol proposed in [10]. We therefore performed a simulation using MeSH. The distances obtained were not very satisfactory. After analysis, it appeared that some concepts in MeSH are related to others in a surprising way (see Fig. 4.a). For example, *Headache* and *Migraine (Migraine Disorder)* have no common close subsumer. *Headache* is subsumed by *Pain* whereas *Migraine* is not. Therefore, *Pain* being a very general concept, both appear very distant on Fig. 4.b. It therefore appears that our distance and projection method reveals a pitfalls in the Mesh ontology.

With regard to this example, the distance we propose and the associated visualisation may be used by ontology modellers. During the building of an ontology

[5] Shapes enable readers of the black and white printed version to ignore colours.

the projection emphasises ontological inconsistencies, e.g. semantically closed concepts that appear far from one another on the projection, thus revealing bad or missing relations. It may also be used for ontology validation.

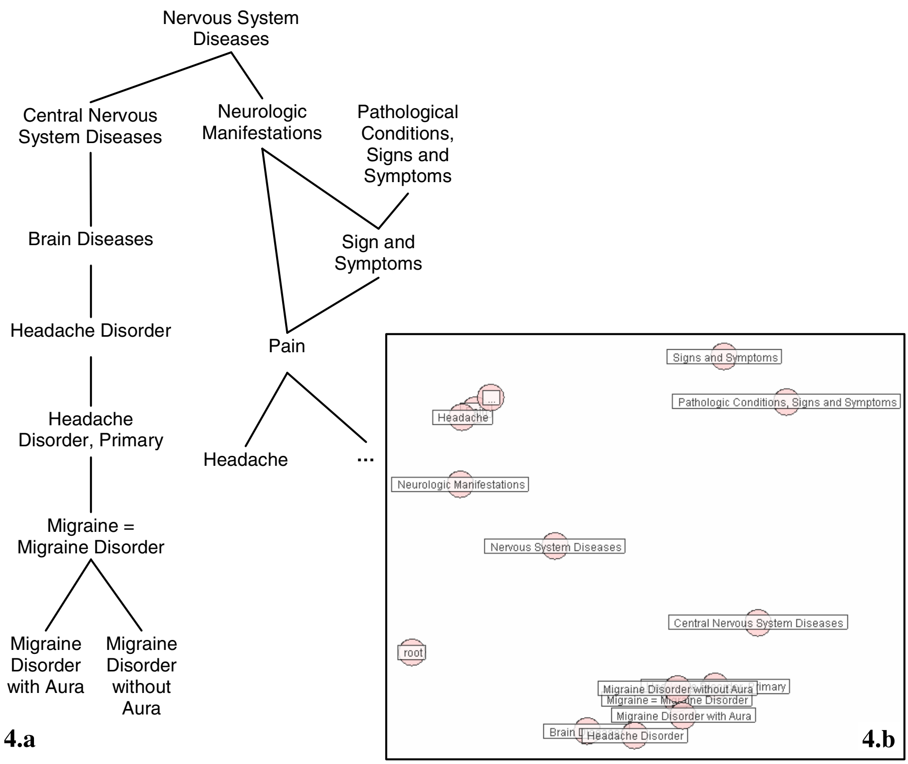


Fig. 4. A Fragment of the MeSH Taxonomy and is projection in Molage

4.3 Perspectives

For better results, our method needs to be completed. Only considering the ISA relation is not sufficient. It would be interesting to combine this distance with others that take into account the meronymy relation or some functional relations. Our future work will concern this extension to other relations.

Another perspective concerns the inclusion of a level of detail that can be associated with each concept of the ontology. Building an ontology often consists in listing the "words" that are used in a particular domain, determining which are synonyms and the concepts that are designated by those words. From the list of domain concepts, relations between them are defined, in particular the ISA-relation, which is used to structure them in a concept hierarchy. However, knowledge engineers and domain experts may describe some parts of the ontology at a high level of granularity (very deeply) whereas some other parts are described more succinctly. It is necessary to associate a value to each concept that specifies whether the concept is close to instances or a general concept and that represents the level of detail [13]. Combining this level of detail with the distance measurement presented in this paper would enable different visualisations in function of usage: ontology engineering, navigation through massive amounts of data, indexing, etc. We can imagine, for example, that a knowledge engineer would restrict the visualisation to high-level concepts, whereas a music indexer would only be interested in low-level concepts and instances.

5 Conclusion

This paper introduces an ISA-distance measurement that can be applied to taxonomies. It respects the three properties of distance: *positiveness*, *symmetry* and *triangle inequality*. We applied it in an industrial context to project a music ontology using MDS projection, in order to build a musical landscape to be used for music title indexing. This distance makes two contributions to the ontological engineering community. The first one concerns the visualisation of ontologies. Building the landscape using our distance measurement, we obtain a conceptual map where concepts are gathered together according to their semantics. The second one concerns the support of ontology building and validation. Knowledge engineers and domain experts involved in the building of an ontology may use this distance measurement as a means of verifying the proximity of concepts that are assumed to be close and thus validating the hierarchy of concept types.

Our perspective is to combine the *ISA*-distance with others that take into account several kinds of relations. In this way, using these distances in the MDS projection of an ontology offers an alternative to the traditional hierarchical representation, which is confusing and misleading when the true structure is a DAG.

While some improvements are necessary, this distance may be seen as the first step towards a real semantic distance for ontology modelling and visualising.

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