Conceptual Vectors and Fuzzy Templates for Discriminating Hyperonymy (`is-a`) and Meronymy (`part-of`) relations.

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Abstract. Hierarchy building from dictionaries and free texts is often viewed as an application of NLP for domain modeling. The reversal (i.e. building and using such hierarchy for Word Sense Disambiguation) is also definitively useful in NLP. Indeed, we do observe that, even in very specialized texts, polysemous terms as well as blurring linguistic phenomena like metonymy or metaphor are frequent. Conceptual vectors are part of a model for meaning representation applicable to lexical disambiguation [*Lafourcade*, 2001]. We devise some strategies combining vectors and relation templates to automatically construct lexical network able to discriminate between various `is-a` and `part-of` relations.

1 Introduction

One aspect of Object Oriented knowledge discovery is to automatize acquisition of classes hierarchies from texts (either free texts or domain dependent). We postulate, that in order to reach this goal, a global (hoolistic) approach is needed. Precisely, to built a specialization hierarchy, an iterated process should be elaborated that at the same time relies on other types of relations (like Synonymy, Meronymy and the like) as they constitute, all together, essential sets of clues. Furthermore, Natural Language Processing (NLP) techniques than include syntactic and semantic analysis, and not only surface analysis and/or pattern extraction are mandatory if generic and widely application are targeted. In the framework of lexical and meaning representation, the NLP team of LIRMM currently works on strategies for automatically building hierarchical taxonomies from various lexical resources as dictionaries and free texts. Strategies are holistically based on the partial graph construction through exploitation of classical templates, already existing relation walkthrough and conceptual vectors. That is to say that instantiation of (1) relations, (2) meanings and (3) vector computation and revision are all undertaken at the same time.

The conceptual vector model is a *recall focused* approach which aims at representing thematic activations for chunks of text, lexical entries, locutions, up to whole documents. Roughly speaking, vectors are supposed to encode *ideas* associated to words or expressions. The main applications of the model are thematic text analysis and lexical disambiguation [*Lafourcade*, 2001] and can find interesting approaches for vector refinement through the lexical implementation of taxonomies. Practically, we have built a system, with automated learning capabilities, based on conceptual vectors and exploiting monolingual dictionaries for iteratively building and refining them. For French, the system learned so far 120000 lexical entries corresponding to roughly 460000 vectors (the average meaning number being 5). We are conducting the same experiment for English. The semantic graph model on the other hand, tends to be a *precision focused approach*, which constitutes a very fruitful backbone for structuring thematic vector spaces (or generator spaces). Here, the term *precision* relate to few very strong relations. It is to be opposed to the term *recall* which relates to more numerous but weaker relations. We have extended the traditional semantic network model in several *naive but useful* ways : (1) relations between items are weighted, (2) items could be either terms or acceptions (word meanings), (3) conceptual vectors can be associated to item and propagated through relations.

Beside NLP, taxonomy extraction and other general relations have definite applications in support to software engineering. The (still quite remote) goal is to add to the system (or computer) some interpreting power toward class hierarchy and domain modeling in general. Beside already known techniques based on the formal structures of the model (say in UML), some common or specialized knowledge usually confined to engineers, should be transfered to the system. Then, some inference mechanism on the model is possible, starting from relating names (of classes, attributes, etc.) to real world objects. A particular class of application is model merging, where helping clues are both formal (types) and interpretative. The goal of this work is focused on automating the recognition of interpretation information, which falls into the scope of knowledge management.

In this paper, we first expose the main principles and assumption about hierarchy bulding. Then, we present the conceptual vectors model, the fuzzy pattern extraction approach and lexical semantic networks which mixes both meanings and vocables through weighted relations. The networks building method is detailed through the relation migration from vocables to meanings, thanks to an *ant algorithm*. Some examples of concurrent use and modification of the network are given, focusing mainly on different types of `is-a` and `part-of` relations.

2 Multi-Relation Taxonomy Building Principles

The literature about experiments in (more or less) automatic taxonomy (or hierarchy) building is abundant. A good presentation of the encountered difficulties with dictionaries could be found in [*Véronis et al.*, 1993]. Building from free texts has been surveyed in [*Barrière et al.*, 01] and [*Bourigault et al.*, 03] and they constitute a rather complete and very recent state-of-the-art.

2.1 Mixing Dictionaries and Free Texts

As pointed out by [*Véronis et al.*, 1993] mining information from multiple dictionaries leads to far better results than using only one. When specialized domain modeling is at stake, extraction are more often done from free texts as ontologies of such domains are barely available (the point is precisely to construct one). Our argument here is that multiple sources should be used, with three levels in mind: dictionary definitions, encyclopedic definitions and free texts.

When using several dictionaries, definitions are more easily processed than free texts and produced fairly accurate relations. On the other hand, free texts, beside being the sole available sources for certain domains, give more distributional informations, and offer clues about relations that might not be mentioned in dictionaries. Encyclopedic articles are between these two extremes.

2.2 Building as a Non-Ending Iterated Process

Very often, hierarchy building is viewed as processing sequentially one or several sources. In the case of a dictionary, once all entries have been analyzed, the hierarchy should be built. In our views, the building should be done incrementally by adding little pieces of informations (dubbed as *clues*) at a time, and letting some induction process structuring the hierarchy. Sources may be parsed several times.

2.3 Explicitly Managing Uncertainty

More than often, uncertainty about domain or about data interpretation are considered as problems to be absolutely solved, and in case of irreconcilable constrains, the source is either eliminated or the expert questionned. We think that uncertainty should be explicitly represented and managed, as it can never be completely eliminated. This is why, we advocate that each relation in the taxonomy to be associated with a *confidence value* or (depending of the view adopted) *excitement level*. When parsing sources, this value may be increased (or lowered) according to the clues discovered or the induction undertaken. Distributional aspects of free texts are an excellent source for managing uncertainty on the basis of existing items and relations found in dictionaries.

2.4 Mixing Meanings and Vocables

As information is extracted from texts, lexical ambiguity (not to mention syntactical) is still an issue. More than often, even in dictionary definitions, word senses may not be clearly separated. Morevover, it is now well accepted in psycholinguistics that language is processed at the same time at the levels of vocable (terms, compounds, etc.) and meanings (thematically and associatively) .

This is why items present in our taxonomy are of two types: vocables and ideas. Many ideas are identifiable as word senses but not necessary all of them. For example, some ideas at the higher level are clearly not lexicalized (unless by forged compounds), like the example of *INSTRUMENTAL OBJECT* discussed in [*Véronis et al.*, 1993]. A simplified example of such graph is given in figure 1. We do explicitly associate vocables to ideas with a `meaning` relation that is constructed the same way as other relations but mostly from dictionary sources (opposed to free texts).

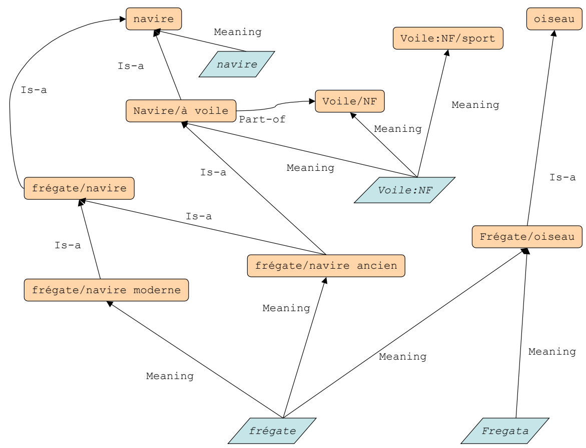

Fig. 1. Examples of multi-relation hierarchy mixing Vocable and Meanings. The *meaning* relates terms to meanings. Other relations (like *Is-a*, *part-of*, etc.) relate meaning to meanings. Relations are weighted (not shown here) to represent uncertainty and preferences.

3 Conceptual Vectors and Lexical Network Components

3.1 Conceptual Vectors

The Model of Conceptual Vector has already been presented the the context of hierarchy building in [*Lafourcade*, 2002] and what follows is a short description (towards the unfamiliar reader) of the main principles. Thematic aspects (or ideas) of textual segments (documents, paragraphs, syntagms, etc.) are represented thanks to vectors of interdependent concepts. Lexicalized vectors have been used in information retrieval for long [*Salton et al.*, 1983] and for meaning representation by the LSI (Latent Semantic Indexing) model [*Deerwester et al.*, 90] from latent semantic analysis (LSA) studies in psycho-linguistics. In computational linguistics, [*Chauché*, 90] proposed a formalism for the projection of the linguistic notion of semantic field in a vectorial space, from which our model is inspired [*Lafourcade*, 2001]. From a set of elementary notions, dubbed as *concepts*, it is possible to build vectors (conceptual vectors) and to associate them to lexical items. The hypothesis that considers a set of concepts as a generator to language has been long described in [*Rodget*, 1852] (*thesaurus hypothesis*). Polysemous words combine the different vectors corresponding to the different meanings considering several criteria as weights: semantic context, usage frequency, language level, etc. Concepts are defined from a thesaurus (in our prototype applied to French, we have chosen [*Larousse*, 1992] where 873 concepts are identified to compare with the thousand defined in [*Rodget*, 1852]). To be consistent with the thesaurus hypothesis, we consider that this set constitutes a generator space for the words and their meanings. This space is probably not free (no proper vectorial base) and as such, any word would project its meaning(s) on this space.

Thematic Projection Principle and Angular Distance. Let be $\mathcal{C}$ a finite set of n concepts, a conceptual vector V is a linear combination of elements c_i of $\mathcal{C}$. For a meaning A, a vector $V(A)$ is the description (in extension) of activations of all concepts of $\mathcal{C}$.

Let us define $Sim(A, B)$ as one of the *similarity* measures between two vectors A et B, often used in information retrieval [*Morin*, 1999] as their normed scalar product. We suppose here that vector components are positive or null. We, then, define an *angular distance* D_A between two vectors A and B as their angle.

$$\begin{aligned} Sim(A,B) &= \cos(\widehat{A,B}) = \frac{A \cdot B}{\|A\| \times \|B\|} \\ D_A(A,B) &= \arccos(Sim(A,B)) \end{aligned} \tag{1}$$

Intuitively, this function constitutes an evaluation of the *thematic proximity* and is the measure of the angle between the two vectors. We would generally consider that, for a distance $D_A(A, B) \leq \frac{\pi}{4}$, (i.e. less than 45 degrees) A and B are thematically close and share many concepts. For $D_A(A, B) \geq \frac{\pi}{4}$, the thematic proximity between A and B would be considered as loose. Around $\frac{\pi}{2}$, they have no relation. D_A is a real distance function. It verifies the properties of reflexivity, symmetry and triangular inequality. We can have, for example, the following angles (values are in degrees and examples are extracted from `http://www.lirmm.fr/~lafourcade`):

D_A(‹*tit*›, ‹*tit*›)=0°	D_A(‹*tit*›, ‹*animal*›)=32°
D_A(‹*tit*›, ‹*passerine*›)=10°	D_A(‹*tit*›, ‹*cell*›)=41°
D_A(‹*tit*›, ‹*bird*›)=19°	D_A(‹*tit*›, ‹*sadness*›)=65°

A ‹*tit*› is thematically closer to a ‹*passerine*› than a ‹*bird*› than an ‹*animal*›. Here the thematic proximity follows some kind of ontologic relation. However, ‹*cell*› nonewithstanding the polysemy begins to be poorly related. The term ‹*sadness*› has almost no thematic sharing with ‹*tit*›.

Meaning Selection. From a given thematic context under the form of a conceptual vector, it is possible to select (or weight) the meanings of a vocable. For a vocable w with k meanings $w_1 \ldots w_k$ and a context C, the weights α of the meanings are non-linearly related to the amount of mutual information between the context and a given meaning:

$$\alpha_i = \cot(D_A(V(w_i), C) = \frac{\cos(D_A(V(w_i), C)}{\sin(D_A(V(w_i), C)} \tag{2}$$

We recall that *cot* refers to the *cotangent* function, with $\cot(0) = +\infty$ and $\cot(\pi/2) = 0$. The rational is the following. The *similarity* between two objects A and B is the cosine of the angle between these two objects. Inversely the *dissimilarity* is the sine. The weight of selection of B towards A if the ratio between what is common (the similarity) on what is different (the dissimilarity).

For example, take the vocable ‹*frégate*› (Eng. frigate) with ambiguity between the boat and the bird. Let C be the vector related to ‹*plume*› (feather) which is itself ambiguous, we have the following values:

$D_A(V(\text{‹}\textit{frégate/boat}\text{›}), V(\text{‹}\textit{plume}\text{›})) = 1.1 \qquad \alpha_i = acot(1.1) = 0.5$
$D_A(V(\text{‹}\textit{frégate/bird}\text{›}), V(\text{‹}\textit{plume}\text{›})) = 0.43 \qquad \alpha_i = acot(0.5) = 2.13$

Thanks to the thematic context, the most activated meaning of ‹*frégate*› in the context of ‹*plume*› is the bird, as it has much more weight than the other interpretation. Although useful, this process may no be sufficient as more than often words and meanings are related while not being in the same semantic field. This is why, the construction and the exploitation of lexical and semantic network is necessary. The construction of such a network is done through templates but also by filtering through thematic proximity.

3.2 Vocables and Senses, Templates and Fuzzy Relations

From dictionaries, we create two types of vertex representing vocables and their meanings. The basic relation between a vocable and its meaning is named `meaning`. This particular relation can be specialized with properties like anaphora, metonymy, etc.), but for clarity we consider only the general relation ‹*word sense*$_i$› `as meaning of` ‹*vocable*›. We are directly interested in extracting the following relations, as they are often key information in Word Sense Disambiguation and they also help structuring domain knowledge:

1. hierarchical relations with distinction between `is-a` (like in ‹*horse*›`is-a`‹*animal*›), `instance-of` (like in ‹*tyranosaurus*› `is-a` ‹*Dinosaurs*›). We should note that sometimes the gap between these two relations is very thin, however some meanings clearly refers to classes (and only classes, like ‹*Dinosaurs*›). Other terms refer generally to instances but can be found in texts as classes.
2. meronymic relations with distinction between `part-of` (like in ‹*piston*› `part-of` ‹*engine*›) and `member-of` (like in ‹*soldier*› `member-of` ‹*squad*›). Some templates can be generic for both relations, but tests on properties can sometimes gives clues for which one to choose.
3. some instrumental relations like `property`, `cause`, `patient`, `agent`, etc. The `property` relates a meaning A and a meaning B, B being a property. For instance, *l'iris peut être de couleur variée* (Eng. the iris can be of various color). The `cause` relates an action to a cause. The `patient` relates an object to an action when the object can be a typical patient of this action, like in *la glace peut être cassée* (Eng. the glass can be broken) which is a good example of partly unresolved ambiguity. The vocable ‹*glace*› has at least three meanings in French (1) ice-cream, (2) frozen water and (3) mirror ; only (2) and (3) can reasonable be broken, the selection being done thanks to conceptual vector and large distributional information. In the same way, we have the typical `agent` relation (like in ‹*dog*› `agent` ‹*bark*›). Again, all these relations are found mostly in texts (as opposed to dictionaries).

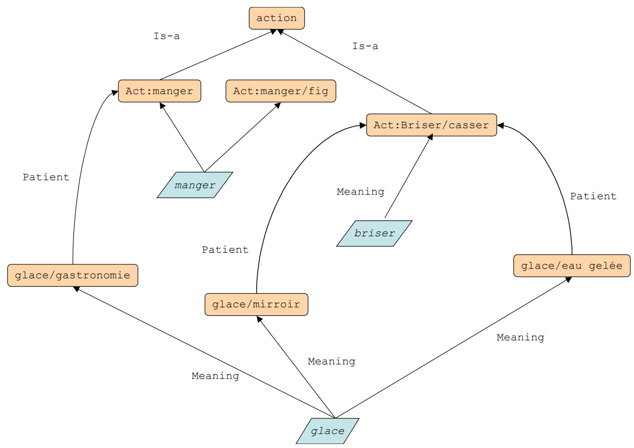

Fig. 2. Example of `Patient` relation. The vocable ‹*glace*› has three meanings, two of them sharing the same relation with ‹*briser*›. Conceptual vectors, through mutual-information can confirm such relations, or take advantage of these relations to adjust the activation values.

Fuzzy Templates. To extract some relations we do use very classical templates. Thereafter, we detail some typical templates and the relations(s) they are inducing. Templates can have several syntactic forms, especially when applied to dictionary definitions (with D subscript) of to texts (with T subscript). The relations induced are written at the right of the → with a weight w.

$[\mathtt{GN}_1\ \mathtt{:\ Type\ de\ GN}_2]_D, [\mathtt{GN}_1\ \mathtt{:\ Sorte\ de\ GN}_2]_D, [\mathtt{GN}_1\ \mathtt{:\ Genre\ de\ GN}_2]_D, \ldots$
$\rightarrow 1 : \mathrm{GN}_1$ `is-a` GN_2

$[\mathtt{GN}_1\ \mathtt{:\ est\ un\ type\ de\ GN}_2]_T, [\mathtt{GN}_1\ \mathtt{est\ une\ sorte\ de\ GN}_2]_T, \ldots$
$\rightarrow 0.7 : \mathrm{GN}_1$ `is-a` GN_2

These templates related to `is-a` are very classical and do not pose much problem, except in free texts where $[\mathtt{GN}_1\ \mathtt{est\ une\ sorte\ de\ GN}_2]_T$ can hold some metaphoric contents. If the metaphor is recurrent, the weight would add up eventually splitting some meaning. If the metaphoric meaning already exists, then conceptual vectors and constraints would select it.

$[\mathtt{GN}_1\ \mathtt{:\ groupe\ de\ GN}_2]_D$, $[\mathtt{GN}_1\ \mathtt{:\ ensemble\ de\ GN}_2]_D$, ...
$\rightarrow 1 : \mathrm{GN}_2$ `member-of` $\mathrm{GN}_1 + 1 : \mathrm{GN}_1$ `is-a` ‹*groupe*›

The meanings selected for GN_1 should be a group. If it is not already the case, then the vocable GN_1 is related to ‹*group*›, then selection of the proper meaning being postponed until more clues are available.

$[\mathtt{GN}_1\ \mathtt{:\ Partie\ \{GA\}\ de\ GN}_2]_D$, $[\mathtt{GN}_1\ \mathtt{:\ Élément\ \{GA\}\ de\ GN}_2]_D$
$\rightarrow 1 : \mathrm{GN}_2$ `part-of` GN_1

$[\mathtt{GN}_1\ \mathtt{est\ une\ partie\ \{GA\}\ de\ GN}_2]_T$, $[\mathtt{GN}_1\ \mathtt{est\ un\ élément\ \{GA\}\ de\ GN}_2]_T$
$\rightarrow 0.7 : \mathrm{GN}_2$ `part-of` GN_1

These templates are typical of the `part-of` relation. However, again if free texts (not dictionaries) they could be metaphoric or metonymic, or both adding difficulties to the proper meanings selection.

[$\texttt{GN}_1$ `fait partie de` $\texttt{GN}_2$]$_T$ ...
$\rightarrow$ 0.5 : GN_1 `part-of` GN_2 & 0.5 : GN_1 `member-of` GN_2 + GN_1 `is-a` ‹*groupe*›

This template is typically ambiguous as we do not know if it refers to a `part-of` or `member-of` relation.

Temporary Relation Selection. When a template is instantiated, a temporary relation is created between both vocables A and B. With the help of sense selection (with conceptual vectors) and constraints activation (through network relations), the relation is transfered to some senses A_i and B_i. We enumerate all possible paths between all meanings of A, all meanings of B and all possible relations induced by the template. The question is now to select one of these relations. The process for selecting the relations to be kept is based on the approach proposed by [*Dorigo et al.*, 1997]. In effect, we consider the task at hand as being equivalent of the Traveling Salesman Problem, a shortest and most activated path to be found for a relation at stake between two meanings.

The rational for adopting *ant algorithms* take its roots in some properties of the problem at hand. First, it is highly combinatorial with uncertain and evolving information. Second, the constructed structures need to be dynamic and adaptative both in time and toward application or domain. Multi-agent approaches are of practical value for such kind of tasks which relates fundamentally to learning and game theory [*Vidal*, 2003].

Example 1. Let's start with an unambiguous template, but where proper word meanings have to be selected. For example *une frégate est un navire* (Eng: a frigate is a ship). The only problem here is to select to proper meaning, which can be done here efficiently with conceptual vector and the angular distance: D_A(frégate/ship, ship) $= 0,24$) and D_A(frégate/bird, ship) $= 1,15$)

Example 2. Now, consider a text containing the following sentence (fig 3): *un soldat fait partie d'une division* (Eng: a soldier belongs to a division). Both terms ($A =$ soldat and $B =$ division) are polysemous: ‹*division*› may (at least) be the (a_1) mathematical operation, (a_2) sharing, (a_3) discord or the (a_4) military structure ; ‹*soldat*› may be the (b_1) military personnel or (b_2) insect caste. At first, two relations (`part-of` and `member-of`) between the vocable ‹*soldat*› and the vocable ‹*division*› are created. Then, other temporary relations between all meanings of A and all meanings of B are proposed. Thus, for `member-of` we have created $(1 + 6) = 7$ temporary relations (same thing for `part-of`).

Then, each meaning produces a fixed set of ants (20 in our experiments) that move pseudo-randomly. The score S of neighbor vertex y for a ant (created by the vertex z) being at vertex x, is a function of several parameters: the activation value *beta* on the relation between x and y, the type of this relation r (for example: `member-of`), the angular distance between the vector of x and the vector of z (vector carried by the ant). If an ant is at node x with p neighbors $x_i (i = 1 \cdots p)$, the probability for the ant to choose node y is computed as follows:

$$\alpha(y) = \cot(D_A(V(y), V(z)) \quad \text{and} \quad S(y) = (1 + \beta(y)) \times \alpha(y) \times F(z, r)$$
$$P(y) = \mathrm{S}(y) / \sum_{1 \leq i \leq p} \mathrm{S}(x_i) \tag{3}$$

The function $F(z, r)$ returns a value corresponding to a fitness between the relation type and the z node. The closer this value is to 1 the better. For instance, if x `is-a` ‹*group*› > 0 then $F(x,$ `member-of`$) = 1$ and x `is-a` ‹*group*› $= 0$ then $F(x,$`member-of`$) = 1/10$ (this value has been empirically determined and seems to give a good balance between precision and recall).

Each time an ant is moving from one node to another, the concerned edge activation is incerased by a small amount $\epsilon = 0.1$. At each cycle of the simulation, a small decay factor simulates deactivation of edges. If an edge is taken by many ants, it is able to maintain a high level of activation, and attract other ants. On the other hand, if ants are somehow detracted from an edge, its activation will slowly decrease toward 0. Below a small threshold, the edge is deleted.

At the end of the process which generally converges (but not always), we retain only the most activated relation among the temporary relations. To ensure some precision, we keep the most activated relation only if it is activated twice as much as the second activated one. This heuristic aims at not creating too uncertain relations in the network.

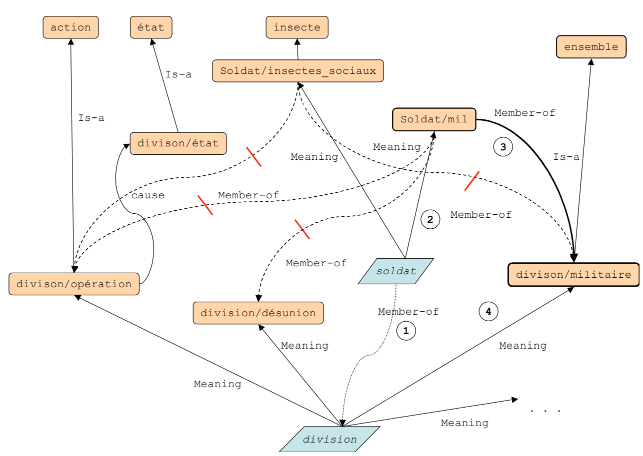

Fig. 3. Examples of potential relation selection through path activation. We have here found a template instantiation inducing either a `part-of` or a `member-of` relation. After activation and iteration only one path emerges inducing only one relation to be kept (here relation (3)).

4 Conclusion

This paper has presented an approach mixing conceptual vectors and fuzzy templates for hierarchy construction. Our model combines vocables (terms) and meanings as vertices and once a template has been instantiated, an iterated propagation process permits to the proper word meanings and relation emerge. The propagation is directly inspired from *ant algorithm* and is formally identical to the Traveling Salesman Problem. The information exploited for the ant propagation are the topology of the network and the mutual information between the conceptual vectors used for meaning representation.

We have defined some underlying principles to our approach. First, it is interesting to combine dictionaries and free texts. A dictionary gives support to almost certain templates and as such leads to very precise relations. Texts give more distributional information, which are most of the time absent from dictionaries, but are nevertheless very needed both for NLP application of domain modeling. Another idea is that hierarchy construction should rely also on existing relations established so far, and as such it can be viewed as an iterated and non-ending process. At early stages of the construction mostly dictionaries are exploited to produce solid relations, later one more subtle and difficult information can be extracted from encyclopedia and texts. Finally, uncertainty should be tackled explicitly and not avoided. If we consider how vocables and knowledge are processed psycholinguistically, we have definitive advantages to mix vocable vertices and meaning vertices. This last aspect is very instrumental for the selection process.

Our strategies have been prototyped and tested on French dictionaries. The obtained network used for Word Sense Disambiguation, with very promising results. It is also used for comforting vector calculation and detecting inconsistencies either in thematic association or in relations between vocables. As the overall process is iterative and incremental, the construction will never be totally completed. We have tested the model on domain descriptive texts (from encyclopedia) and got very precise relations between specialized terms (that are quite low in the hierarchy) even in difficult and ambiguous cases which are most of the time solved through the the use of instrumental relations `agent`, `cause`, etc.). Beside NLP, our approach can be directly used for domain modeling by extracting only the main relation like `is-a` and `part-of` from the network. We really believe that domain modeling cannot be done in isolation from common sense reasoning, which itself can be approximated thanks to such lexical network and quite simple swarm of reactive agents.

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