CONCEPTUAL VECTORS, A COMPLEMENTARY TOOL TO LEXICAL NETWORKS

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Abstract: There is currently much research in natural language processing focusing on lexical networks. Most of them, in particular the most famous, WordNet, lack syntagmatic information and especially thematic information ("*Tennis Problem*"). This article describes conceptual vectors that allows the representation of ideas in any textual segment and offers a continuous vision of related thematics, based on the distances between these thematics. We show the characteristics of conceptual vectors and explain how they complement lexico-semantic networks. We illustrate this purpose by adding conceptual vectors to WordNet by emergence.

Originally resulting from Ross Quillian's work on psycholinguistics (Quillian, 1968), lexical networks are today the subject of much research in Natural Language Processing. They are employed in many tasks (lexical disambiguation (Mihalcea *et al.*, 2004)) or field applications (machine translation with multilingual networks like Papillon (Mangeot-Lerebours *et al.*, 2003) or (Knight & Luk, 1994), information retrieval or text classification (Harabagiu & Chai, 1998)). Most of these networks, including the most famous, WordNet (Fellbaum, 1988), lack syntagmatic information and, in particular, information concerning the domain usage of terms or at least thematically related terms. There is thus no direct relation between terms like ‹*teacher*›-‹*student*› or ‹*boat*›-‹*port*›. This phenomenon is called the "*Tennis Problem*" [(Fellbaum, 1988), p. 10]: ‹*ball*›, ‹*racket*› and ‹*court*› is located at different regions of the hierarchy, and there is no easy way to navigate from one of these terms to the other.

For several years, the TAL team (Natural Language Processing team) from LIRMM (Montpellier Laboratory of Computer Science, Robotics, and Microelectronics) has worked on a formalization of the projection of the linguistic concept of semantic fields in a vector space, namely conceptual vectors. They are used to represent ideas contained in an unspecified textual segment and offers a continuous vision of the related thematics, based on the the finite distances between them.

In this article, we present the conceptual vector model and especially the version built through emergence. We show their characteristics and how they complement lexico-semantic networks. We illustrate our purpose with an experiment done at UTMK (Computer-Aided Translation Unit), Universiti Sains Malaysia, Penang to enrich the WordNet data by conceptual vectors built through emergence.

1 WordNet, an Example Lexico-semantic Network

1.1 Principle

WordNet is a lexical database for English developed under the direction of George Armitage Miller by the Cognitive Science Laboratory of the university of Princeton (New Jersey, USA). It aims to be consistent with the access to the human mental lexicon.

WordNet is organized in sets of synonyms called synsets. Each synset corresponds to a concept. The meaning of a term is described in WordNet by three methods:

- their *definition*

- the *synset* to which the meaning is attached.
- the *lexical relations* which link synsets. There are, among others, hyperonymy, meronymy and antonymy.

WordNet 2.0 contains 152059 terms what constitutes a relatively broad coverage of the English language. In early versions of WordNet, the lexical relations connect only items in the same part-of-speech. There are thus one hierarchy for nouns, one for adjectives, one for verbs and finally one for the adverbs.

1.2 Weakness of WordNet

In (Harabagiu *et al.*, 1999), the authors of WordNet (then at version 1.6) recorded six weaknesses in their network construction:

1. the lack of connections between noun and verb hierarchies;
2. limited number of connections between topically-related words;
3. the lack of morphological relations;
4. the absence of thematic relations and selectional restrictions;
5. some concepts (word senses) and relations are missing;
6. lack of uniformity and consistency in the definitions due to manually-written glosses.

We are interested in items 1, 2 and 4 (constituting the tennis problem) in this article, and will show how conceptual vectors can contribute to resolve them.

1.3 Previous Work on the Tennis Problem

In this article, we will be interested only in WordNet version 2.1 which was the latest available when we carried out our experiments. A new version (3.0) was released in December 2006 but it does not seem to have improvements compared to the previous version for what interests us here.

Since version 2.0, relations such as *derivationally related form* makes it possible to link adjectives to verbs or adjectives to nouns. In the same way, a usage domain can be applied to synsets. However, the number of such data still seem too restricted to be sufficiently relevant. Typical relations as ‹*teacher*›-‹*student*› ‹*boat*›-‹*port*› or ‹*doctor*›-‹*hospital*›, often essential in lexical disambiguation, are still absent and the limited number of thematic indications like domain does not make it possible to compensate this defect. Several solutions were proposed to solve whole or part of this problem.

With Extended WordNet, (Harabagiu *et al.*, 1999) proposed to disambiguate definitions of WordNet in a semi-automatic way. The idea is to perform sense-tagging on the words in the gloss text of each synset. One can then compare two synsets and evaluate their similarity. We will describe how we use this information to manufacture the conceptual vectors in this experiment.

Other researchers chose to add extra information to the synsets. For example, (Agirre *et al.*, 2001) added lexical signatures resulting from tagged corpora or Web documents.

On the other hand, others sought rather to increase the number of existing arcs between synsets. (Stevenson, 2002), for example, combined different metrics to create links between synsets from their definitions and a thesaurus. (Ferret & Zock, 2006) used a co-occurrence network to extract typical relations like those presented in the previous section.

We can see that all these proposals introduce *discrete* information (“hard” links). Our proposal is to introduce a *continuous* representation of related thematic information into the lexical network using conceptual vectors.

2 Conceptual Vectors

2.1 Principle and Thematic Distance

We represent thematic aspects of textual segments (documents, paragraph, phrases, etc) with conceptual vectors. Vectors have long been used in information retrieval (Salton & McGill, 1983) and for meaning representation in the LSI model (Deerwester *et al.*, 1990) from latent semantic analysis (LSA) studies in psycholinguistics. In computational linguistics, (Chauché, 1990) proposed a formalism for the projection of the linguistic notion of semantic field in a vectorial space, from which our model is inspired. From a set of elementary concepts, it is possible to build vectors (conceptual vectors) and to associate them to any linguistic object. This vector approach is based on known mathematical properties. It is thus possible to apply well-founded formal manipulations associated to reasonable linguistic interpretations. Concepts are defined from a thesaurus. In a prototype applied to French, we used the Larousse thesaurus (Larousse, 1992) where 873 concepts are identified, to compare with the thousand defined in the Roget thesaurus (Kirkpatrick, 1987). Let $\mathcal{C}$ be 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 $\mathcal{C}$. For example, the different meanings of ‹*door*› could be projected on the following concepts (the *CONCEPT*⌈*intensity*⌋ are ordered by decreasing values of intensity): V(‹*door*›) = (*OPENING*⌈*0.8*⌋, *BARRIER*⌈*0.7*⌋, *LIMIT*⌈*0.65*⌋, *PROXIMITY*⌈*0.6*⌋, *EXTERIOR*⌈*0.4*⌋, *INTERIOR*⌈*0.39*⌋, ...

2.2 Operations on Vectors

2.2.1 Angular Distance

Comparison between conceptual vectors is done using angular distance. For two conceptual vectors A and B,

$$\begin{array}{l} Sim(X,Y) = \cos(\widehat{X,Y}) = \frac{X \cdot Y}{\|X\| \times \|Y\|} \\ D_A(A,B) = arccos(Sim(A,B)) \end{array} \quad (1)$$

Intuitively, this function constitutes an evaluation of the *thematic proximity* and measures the angle between the two vectors. We would generally consider that, for a distance $D_A(A,B)$:

- if $\leq \frac{\pi}{4}$ (45°), A and B are thematically close and share many concepts;
- if $D_A(A,B) \geq \frac{\pi}{4}$, the thematic proximity between A and B would be considered as loose;
- around $\frac{\pi}{2}$, they are not related.

D_A is a real distance function. It has the properties of reflexivity, symmetry and triangular inequality. We have, for example, the following angles (values are in radian and degrees).

D_A(V(‹*tit*›), V(‹*tit*›))=0 (0°)
D_A(V(‹*tit*›), V(‹*bird*›))=0.55 (31°)
D_A(V(‹*tit*›), V(‹*sparrow*›))=0.35 (20°)
D_A(V(‹*tit*›), V(‹*train*›))=1.28 (73°)
D_A(V(‹*tit*›), V(‹*insect*›))=0.57 (32°)

The first one has a straightforward interpretation, as a ‹*tit*› cannot be closer to anything else than itself. The second and the third are not very surprising since a ‹*tit*› is a kind of ‹*sparrow*› which is a kind of ‹*bird*›. A ‹*tit*› has not much in common with a ‹*train*›, which explains the large angle between them. One may wonder why ‹*tit*› and ‹*insect*› are rather close with only 32° between them. If we scrutinise the definition of ‹*tit*› from which its vector is computed (*Insectivourous passerine bird with colorful feather*) perhaps the interpretation of these values would seem clearer. In effect, the thematic proximity is by no way an ontological or is-a distance.

2.3 Neighbourhood: a Continuous Vision of Thematic Aspects

2.3.1 Principle

The thematic neighbourhood function $\mathcal{V}$ is the function which returns the n closest LEXICAL OBJECTS[1] to a lexical object x according to the angular distance:

$$\begin{array}{l} \sigma \times \mathbb{N} \rightarrow \sigma^k : \\ X,k \rightarrow E = \mathcal{V}(D_A,X,k) \end{array} \quad (2)$$

where $\mathcal{F}$ is the set of evaluation lexical functions and σ the set of LEXICAL OBJECTS. The function $\mathcal{V}$ is defined by :

$$\begin{array}{l} |\mathcal{V}(D_A,Z,k)| = k \\ \forall X \in \mathcal{V}(D_A,Z,k), \quad \forall Y \notin \mathcal{V}(D_A,Z,k), \\ D_A(\mathrm{X, Y}) \leq D_A(\mathrm{Y, Z}) \end{array} \quad (3)$$

The thematic neighborhood function can be used for a learning process to check the overall relevance of the semantic base or to find a more appropriate word to use for a statement. Thus, they give new tools to access words through a proximity notion to those described in (Zock, 2002) and issued from psycholinguistic considerations like form and part-of-speech. They also allow navigation of a huge associate network in a continuous way instead of a discrete way as is commonly done in semantic networks.

2.3.2 Examples

For example, we can have :

$\mathcal{V}$(D_A, ‹*life*›, 7)=(‹*life*› 0.4) (‹*to born*› 0.449) (‹*alive*› 0.467) (‹*to live*› 0.471) (‹*existence*› 0.471) (‹*mind*› 0.484) (‹*to live*› 0.486)

$\mathcal{V}$(D_A, ‹*death*›, 7)=(‹*death*› 0) (‹*murdered*› 0.367) (‹*killer*› 0.377) (‹*age of life*› 0.481) (‹*tyrannicide*› 0.516) (‹*to kill*› 0.579) (‹*dead*› 0.582)

2.3.3 Vectorial Sum

If X and Y are two vectors, their *normalised vectorial sum* V is defined as :

$$\vartheta^2 \rightarrow \vartheta \ : V = X \oplus Y \quad | \quad V_i = \frac{X_i + Y_i}{\|X+Y\|} \quad (4)$$

where ϑ is the set of the conceptual vectors, V_i (resp. X_i, Y_i) is the i-th component of the vector V (resp. X, Y).

[1] We define LEXICAL OBJECT to be any object in the lexicon which meaning can be described. For WordNet, they are the unique strings (called in this article lexical items) and synsets.

The normalized vectorial sum of two vectors gives a vector bisecting the angle between the two operand vectors. It is in fact an average of the operand vectors. As an operation on the conceptual vectors, one can thus see the normalized vectorial sum as the union of the ideas contained in the terms.

2.3.4 Normalised Term to Term Product

If X and Y are two vectors, their *normalised term to term product* V is defined as :

$$\vartheta^2 \rightarrow \vartheta \ : V = X \otimes Y \quad | \quad v_i = \sqrt{x_i y_i} \qquad (5)$$

The $\otimes$ operator can be interpreted as an operator of intersection between vectors. If the intersection between two vectors is the null vector, then they do not have anything in common. From the point of view of the conceptual vectors, this operation thus makes it possible to select the ideas common to the terms involved.

2.4 Construction of Vectors by Emergence

The emergence approach does not use any thesaurus, nor does it use base concept vectors as was done in (**insert ref?**). Only d, the vector size, is fixed *a priori*. The construction method of the vectors is identical to the traditional model with the difference that if one of the vectors needed to compute the sum is non-existent, because it has yet to be computed, then this vector is drawn randomly. The computing process is reiterated until convergence of each vector is achieved.

As (Lafourcade, 2006) showed in more detail, there are certain advantages to using this model. The first of them is to be able to freely choose the quantity of resources which one wishes to use by choosing the size of the vectors in a suitable way. To give an idea of the importance of this choice, a base of 500000 vectors of dimension 1000 is approximately 2GB, of dimension 2000, 4GB, and so on. As it would not be then reasonable nor easy to define a concept set of the chosen size, it is easier to seek an approach which enable us to avoid this necessity. Moreover, what initially seems like a makeshift or at least a compromise proves to be an advantage because the lexical density in the space of the words calculated by emergence is much more consistent than in a space where concepts are pre-defined. Indeed, the resources (dimensions of space) tends to be harmoniously distributed according to the lexical richness (number of terms).

3 Hybrid Modeling of Meaning: Conceptual Vectors and Lexical Networks

3.1 Contribution of Lexical Networks to Conceptual Vectors

As shown in (Besançon, 2001), distances computed on vectors are influenced by shared components and/or distinct components. Angular distance is a good tool for our aims because of its mathematical characteristics; its simplicity to be understood and to be linguistically interpreted; and its effectiveness for computational processes. Whatever the type of the chosen distance used for such of vectors (representing ideas instead of term occurences), the lower the distance is, the closer the lexical objects are in the same semantic field (called isotopy by Rastier (Rastier, 1985)).

In the framework of semantic analysis as the one which interests us, we use angular distance to benefit from mutual information carried by conceptual vectors to perform lexical disambiguation on words whose meanings are in close semantic fields. Thus, "*Zidane scored a goal.*" can be disambiguated thanks to common ideas about sport while "*The lawyer pleads at the court.*" can be disambiguated thanks to those of justice. Furthermore, for prepositional attachments, vectors will help in analysing "*He saw the girl with the telescope.*" to attach "*with a telescope*" to the verb "*saw*" due to ideas about vision.

On the contrary, conceptual vectors cannot be used to disambiguate terms which are in different semantic fields. We can even note that an analysis only based on them can lead to misinterpretation. For example, the French noun ‹*avocat*› has two meanings. It is the equivalent of ‹*lawyer*› and the equivalent of ‹*avocado*›. In the French sentence "*L'avocat a mangé un fruit.*", "*The lawyer has eaten a fruit*", ‹*to eat*› and ‹*fruit*› both carry the idea of ‹*food*›. The acception computed by conceptual vectors for ‹*avocat*› would then be ‹*avocado*›. It would have been necessary that the knowledge "*a lawyer is a human*" and "*a human eats*" be identified, something that is not possible with only conceptual vectors. Alone, they are not sufficient to exploit lexical functions instanciations in the texts. This is where lexical network can contribute to correct these shortcomings. These limitations were demonstracted in experiments for semantic analysis using ant algorithms in (Lafourcade, 2006).

3.2 Contribution of Conceptual Vectors to Lexical Networks

While lexical networks offer unquestionable precision, their recall is poor. It is difficult to represent all possible relations between all terms. Indeed, how can we represent the fact that two terms are in the same semantic field? They may be absent from the network because they are not connected by "traditional" arcs. Introducing arcs of the type "semantic field" is also problematic for us because of two reasons implicated by the fuzzy and flexible of this relation:

- the first one is related to the database creator's understanding on this relation: when are two synsets considered to be in the same semantic field? In an unfavourable case there would be very few arcs, while in the extreme opposite case we could have a combinative explosion in the number of arcs;
- the second and more fundamental problem is related to the representation itself. How could a fuzzy relation, the essence of which is a continuous field, be represented with discrete elements?

Thus, the continuous domain offered by conceptual vectors gives flexibilities that the discrete domain offered by the networks cannot. They are able to bring closer words which share ideas, including less common ones. A network, on the other hand, cannot do so, however common the ideas are. The conceptual vectors and the operation of thematic distance can correct the weak recall inherent of the lexical networks. This, then, is why conceptual vectors and lexical networks are complementary tools to each other: the defects of one are mitigated by qualities of the other.

4 Experience on WordNet: Usage of Data

4.1 Use of Definitions

EXtended WordNet (Mihalcea & Moldovan, 2001) is a project carried out by *Southern Methodist University* of Dallas (Texas, USA) with two aims:

- to disambiguate terms used in the definitions of the synsets i.e. to indicate other synsets invoked in the definition of a synset;
- to transform these definitions into a logical form, allowing easier computations.

These data were built semi-automatically using information from the network. For example, if the genus of the definition (following Aristotelian logic) has a meaning which is also an hypernym of the defined synset, it is taken that the meaning of the genus is this hypernym. Other information, such as the distances between definitions or domain information, was also used. The data in *EXtended WordNet* are partly verified manually and the rate of precision is more than 90%.

For the conceptual vectors construction, we used these data in their logical forms because they make it possible to locate the most important elements of the definition text, in particular the genus. Computation is done thus on a constructed dependency tree. The definition text was pre-processed to remove the metalanguage not easily exploitable for a thematic analysis. To illustrate, we will use the logical form of the definition of ‹*ant*› as an example.

$$\begin{aligned} ant:NN(x1) \ \rightarrow\ & social:JJ(x1)\ insect:NN(x1) \\ & live:VB(e1,x1,x3)\ in:IN(e1,x2) \\ & organized:JJ(x2)\ colony:NN(x2) \end{aligned}$$

There are 3 sets : $x1$ = {*social*, *insect*}, $x2$ = {*organised*, *colony*} and $e1$ = {*live*}. $e1$ in *live* and *in* allows us to organise the sets as a hierarchy (Figure 1). The vector of each of these sets is calculated; they then make up the vectorial sum of the item ‹*ant*›. Sets of type verbs (VB) and nouns (NN) are assumed to be carrying most of the meaning and thus have weight 1 for their vectors, while those of the dependents (adverbs, RB; adjectives, JJ) are assigned a weight of $\frac{1}{2}$. The global vector is then computed by weighted vectorial sum of the various sets in the tree starting with the leaf sets. This mode of calculation makes it possible to consider in a dominating way the genus on the other terms of the definitions and in a more general ways the heads on their syntactic dependent. Figure 1 shows this calculation. ($x3$ is the "null" predicate here, therefore it does not appear in the figure.)

4.2 Use of Relations

The relations are used on two levels: (1) for the vector construction, they build in a different method, complementary to the approach using the definitions in a synset; (2) to avoid phenomenon of regrouping of distinct sets.

4.2.1 Vector Construction

A conceptual vector is constructed for each node of the lexical network by simple weighted normalised sum of the vectors of the linked nodes. If N is a node linked to k nodes $N_1 \ldots N_k$, the vector of N is

$$V(N) = p_1V(N_1) + p_2V(N_2) + \ldots + p_kV(N_k) \quad (6)$$

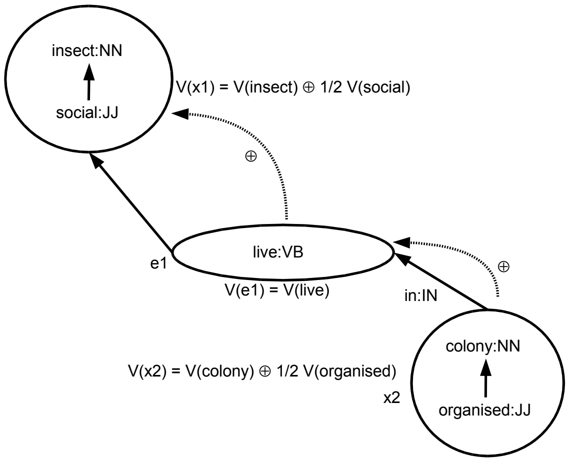

Figure 1: Construction of a conceptual vector from a definition : example of ant

This approach naturally involves an agglomeration of the vectors. It is thus necessary to increase the contrast of one vector following its computation. With this intention, one calculates the coefficient of variation[2] of V. If the coefficient of variation is not around 10% of a (pre-computed) average value, the vector undergoes a nonlinear operation of amplification (exponentiation of each component followed by normalisation). This is repeated until the coefficient of variation falls in an acceptable range, which is predetermined based on the chosen vector dimension.

4.2.2 Regrouping of Distinct Sets

A last potential problem is that the vectors of two distinct sets (at the same time for the lexical network and for thematic) of terms might occupy the same area in the vectorial space. This may happen by accident, as computation is done by activation and vectors are randomly drawn up when needed. It is thus necessary to "separate" the vectors that are near to each other, but corresponds to very different parts of the lexical network and thematic fields.

The phenomenon can be detected by examining the neighbourhood of a conceptual vector. If among the N first neighbors, the density of words with no correlation with the target word is significant, then a separation process must be undertaken.

This action of separation is analogous to plunging the whole network into the field from which the nodes needs to be pushed back. With an inpiration from physics, a force of repulsion, $1/d^2$, is calculated iteratively between nodes. For a given node, one can thus calculate a vector displacement which will move it away from uncomfortably near nodes. Nodes not brought closer by thematic neighbourhood (at the time of the first phase of calculation cf. section 4.1) but being close "accidentally" end thus end up separating naturally.

[2]given by the formula $\frac{EC(V)}{\mu(V)}$, where $EC(V)$ = the standard deviation of the vector V and $\mu(V)$ = the arithmetic mean of the components of V.

5 Conclusion

In this article, we presented how conceptual vectors can be built by emergence and their uses. We showed how they can help to solve the "tennis problem" courtesy of their characteristics complementary to the lexico-semantic networks, WordNet being the most famous example in current research. Recall of networks are usually weak and do not make it easy to represent semantic fields. In contrast, conceptual vectors handle semantic fields well, but are not sufficient to represent relations like hyperonymy or meronymy.

Our proposal is to benefit from this complementary situation and enrich WordNet with conceptual vectors, built from the definitions and relations available in WordNet. The method suggested here subscribes to the notion of a continuous field contrary to most methods in the literature, which uses discrete features (addition of arcs for the relations, symbols about the domain, etc).

We are aware that this method can only help to solve part of the tennis problem. The conceptual vectors certainly cannot represent non-thematic collocational relations between lexical items. Such relations are primarily thosed modelled by Igor Mel'čuk with his syntagmatic lexical functions (Mel'čuk *et al.*, 1995), such as intensification ("*great fear*"; *Magn* (‹*fear*›) = ‹*great*›)), centre (or core) ("*crux of the problem*"; *Centr* (‹*problem*›) = ‹*crux*›) or even the confirmator("*legitimate excuse*"; *Ver* (‹*excuse*›) = ‹*legitimate*›). As noted by (Ferret & Zock, 2006), these relations belong to a family which is probably compulsary to have in a lexical base. We agree with this point of view. Some avenues were explored in (Schwab, 2005) and continue to be followed in our current work.

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