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Evaluating the impact of some linguistic information on the performances of a similarity-based and translation-oriented Word-Sense disambiguation method

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Abstract
In this article, we present an experiment of linguistic parameter tuning in the representation of the semantic space of polysemous words. We evaluate quantitatively the influence of some basic linguistic knowledge (lemmas, multi-word expressions, grammatical tags and syntactic relations) on the performances of a similarity-based Word-Sense disambiguation method. The question we try to answer, by this experiment, is which kinds of linguistic knowledge are most useful for the semantic disambiguation of polysemous words, in a multilingual framework. The experiment is about 20 French polysemous words (16 nouns and 4 verbs) and we make use of the French-English part of the sentence-aligned EuroParl Corpus for training and testing. Our results show a strong correlation between the system accuracy and the degree of precision of the linguistic features used, particularly the syntactic dependency relations. Furthermore, the lemma-based approach absolutely outperforms the word form-based approach. The best accuracy achieved by our system amounts to 90%.

1. Introduction
In word sense disambiguation (WSD) task, multiple experiments of parameter tuning in the representation of the semantic spaces have been carried out (Pancado-Rodguez & al., 2005; Crestan & al., 2003). In this paper, we present the results of a similar experiment, looking, among all the cooccurrents of a polysemous word, for the best candidates to be employed as dimensions of its semantic space: those which are discriminative enough to give a WSD method the ability for distinguishing its different senses. For this purpose, we varied the combinations of some basic linguistic knowledge in the semantic spaces (lemmas, multi-word expressions, grammatical tags and syntactic relations).

The semantic spaces, built from pre-classified instances of the ambiguous words in their occurring contexts, are used in examplar-based classification methods like k Nearest Neighbors algorithm (kNN) (Veenstra & al., 2000), Support Vector Machines (SVM, Keok Lee & al., 2004), Semantic Classification Trees (SCT, Loupy & al., 2000) and other methods that use context-similarity measures (Apidianaki, 2009). The classes associated with the training instances in the semantic space of a word can be its senses as they are defined in traditional lexical resources (dictionaries, thesauri) (Gale & al., 1993). In a multilingual framework, the classes can also be its translation equivalents in one (Kaji & Morimoto, 2002) or more (Crego & al., 2009) other languages. For our experiment, we chose the machine translation (MT) oriented and similarity-based method described in (Apidianaki, 2009).

Our corpus for training and testing was the French (SL) and English (TL) aligned version of the sentence-aligned EuroParl corpus (Koehn, 2003), and we evaluated the performances of our WSD method for the disambiguation of 20 polysemous words (16 nouns and 4 verbs). In the first section of this article, we give a description of the WSD method we used for this experiment. The second section is our definition of the semantic spaces. And in the third section, we propose an analysis for the results of our experiment.

2. Description of our WSD method
We used for this experiment the MT oriented method described in (Apidianaki, 2009). The training instances, for a given word, are the vectors of cooccurrences representing the SL segments (SL_segment) of the aligned corpus in which this word occurs. The classes are its translation equivalents (EQV) in the corresponding TL parts. (Apidianaki, 2009) takes things in two steps. First, the EQVs of the word are grouped into clusters representing its various senses, and the new instance is assigned the most suitable cluster. And secondly, the most probable EQV is chosen among those in this cluster. We evaluated the first step of this method.

Clustering the EQVS. First, every EQV is associated with a unique vector (EQV_segment) which contains the union of the components of all the SL_segments with which it is associated. Every cooccurrence (j) is assigned as many relative weights (rw_i,j) as classes (i) with which it is associated. The value of rw_i,j is the discriminating potential of j between EQV i and the other EQVs of the word (see Apidianaki, 2009). We then build a similarity matrix of EQVs using the weighted Jaccard coefficient (WJ, Grefenstette, 1994). While all the cooccurrences are taken into account when computing the relative weights, the computation of EQVs similarity can be made either taking into account all the cooccurrences or only the syntactic cooccurrences and the neighbors (parameter sim, described in section 3).

Clusters of semantically similar EQVs are built, in which the similarity between all EQVs is equal or higher than the average of all the similarities in the matrix. Every cluster is represented by a vector containing all the cooccurrences that appear in all the EQV_segment of its components at once.
The decision function used for determining the cluster of the new instance \( w_{\text{new}} \) is defined as follows:

- The similarity between the context vector of \( w_{\text{new}} \) and the vector of every cluster is calculated on the basis of their intersection: it is the ratio between, on one hand, the sum of the relative weights of the cooccurrences that appear in both vectors, and, on the other hand, the product of the sizes of the two vectors.
- And the most similar cluster is assigned to \( w_{\text{new}} \).

### 3. Our definition of the semantic space(s)

Representing the dimensions of the semantic spaces have been done using various kinds of linguistic knowledge. Table 1 describes the corresponding parameters and their modalities.

The linguistic preprocessing of every vector corresponding to a SL_segment was done in three steps:

- **step 1**: *type* and *comp* parameters are applied to the whole vector.
- **step 2**: *ctxt_type* parameter is applied. The output of this step is a vector in which the components that belong to the same kind of context (thematic, neighbours or syntactic cooccurrences) are assigned the same absolute weight \( (aw=1) \). Three kinds of vectors are obtained, corresponding to the three combinations of contexts we have tested:
  - a *neighbours and thematic* vector is a vector in which two kinds of contexts are represented: the neighbours of the ambiguous word and the other (thematic) cooccurrences of the word. The first ones are distinguished by a strong absolute weight \( (aw=2) \) while \( aw \) is 1 for the other (thematic) cooccurrences;
  - a *syntactic and thematic* vector is a vector in which the direct syntactic cooccurrences are distinguished from the other cooccurrences by the same weighting procedure as in the preceding kind of vector;
  - a *thematic vector* is a vector in which all the (thematic) components of the original vector are assigned the same absolute weight \( (aw=1) \).
- **step 3**: *ctxt_component* is applied differently to every kind of context represented in the vector. For a given cooccurrence \( j \), all its absolute weights in the context vectors that are associated with a given EQV \( i \) are summed. Its weight relatively to this EQV \( (rw_{ij}, \text{section 2}) \) is then multiplied by this sum. Thus, the neighbours and the syntactic cooccurrences are favoured when computing EQVs similarity.

We give in table 2 below an example, using, as a context of the word ‘article’, the SL sentence: “Selon l’article 22 du règlement, vous voulez que les membres dressez un compte-rendu détaillé de leurs activités”. This example illustrates the ‘neighbour (in bold) and thematic’ context. In the ‘vectorial representation’ row, we put in brackets the value of \( aw \) for each cooccurrence.

**NLP tools.** The NLP tools we used for preprocessing the corpus are Unitex (Paumier, 2008), for multi-word expressions extraction, TreeTagger (Schmidt, 1995), for lemmatization and grammatical tagging, and the Xip parser online demo (Xerox Incremental Parser, Aït-Mokhtar & al., 2002), for the detection of syntactic relations.

### 4. Evaluation

We evaluate the parameter combinations defined in section 2 above, in order to find the more relevant one for our WSD method, in terms of representativeness for the different senses of a word. We use for that the French-English part of the sentence-aligned EuroParl corpus, which consists of about one million sentences, that is 30 million words for each language version.

We evaluate the disambiguation of 20 French polysemous words, 16 of which are nouns (article,
The ambiguous word: article

SL_segment:
Selon l'article 22 du règlement, vous voulez que les members dressent un compte rendu détaillé de leurs activités

TL_segment:
Under rule 22 of the rules of procedure, you want us, as members, to give you an exact account of what we do, at what time.

Parameters combination:
- Step 1: type=norm#tag; comp=yes
- Step 2: ctxt_type = neighbours and thematic
- Step 3: ctxt=1+3 (1 for neighbours; 3 for thematic cooccurrents)

Vectorial representation:
article#nom(4) - #det:art(2) – #card:22 – selon #prp(1) – du #prp(1) – règlement#nom(1) – vous #pro:per(1) – vouloir#ver:pres(1) – que #kon(1) – le #det:art(1) – membre#nom(1) – dresser#ver:pres(1) – un #det:art(1) – compte-rendu#nom(1) – détailler#ver:pper(1) – de #prp(1) – leur #det:pos(1) – activité#nom(1)

Table 2: An illustration for the neighbours and thematic context.

barrage, cadre, compte, conclusion, culture, matière, passage, produit, rapport, reserve, société, traitement et vol) while 4 are verbs (lever, monter, porter and saisir).

4.1 Training and testing data

We first manually built a bilingual lexicon in which each SL word is associated with its various TL translations (EQV) in the aligned corpus. Then, for every word, we extracted a corpus, consisting of sub-corpora for its EQVs: one sub-corpora consists of the SL part (SL_segment) of all the aligned segments in the corpus in which the word is translated by the EQV concerned. Every sub-corpora contains around one thousand SL_segments, 80% of which are used for training and 20% for testing.

Table 3 describes the words of our task: it summarizes the mean polysemy from monolingual and multilingual points of view (the number of usages of the words according to the French (Larousse, 2009) dictionary and the number of TL EQVs in our corpus, respectively), the size of the training and testing sets for each word and the size of the sub-corpora for each EQV (minimal and maximal size).

In the bilingual lexicon, each word is associated with all the TL EQVs that are used to translate it the aligned corpus. Table 4 gives the lexicon entries for the word compte and their part-of-speech (POS). Figure 1 is an illustration of the extraction of the semantic space for the word article.

4.2 Evaluation metrics

The metrics used for the evaluation are:
- recall: the ratio between the number of correct predictions and the number of reference instances
- enriched precision: the ratio between the number of correct predictions and the number of predictions
- f-score: \((2 \times \text{recall} \times \text{precision}) / (\text{recall} + \text{precision})\)

A prediction is considered as correct if the selected cluster for \(w_{new}\) contains the EQV used as its reference translation in the aligned segment of the SL part which contains \(w_{new}\).

| NOUNS | VERBS |
|-------|-------|
| mean polysemy | #usages in SL | #TL EQVs |
| 4.5 | 9.5 | 8 |
| #train (for each word) | 72 to 2471 | 21 to 942 |
| #test (for each word) | 50 to 691 | 14 to 178 |
| #examples for each EQV | 1 to 1000 | 1 to 514 |

Table 3: Description of the words and their sub-corpora
4.3 Best scores obtained
The best score obtained for our WSD method amounts to 90.5%. This score is equally obtained with the ‘neighbours and thematic’ context or with the ‘syntactic and thematic’ context, both defined with the following parameters combination: type is form#tag, comp is yes, ctxt is 3 for the thematic cooccurrents and any value for the neighbours or the syntactic cooccurrents, and sim is strong.

4.4 Parameters evaluation

4.4.1. Quantitative evaluation
Due to lack of space, we cannot show in this extended abstract all the results we have obtained. The diagrams in figure 1 represent the evolution of the f-score depending on ctxt parameter, when type is form#tag and comp is yes. For parameters type and comp, we give the most significant scores only.

4.4.2. Global tendencies
In this sub-section, we propose several conclusions concerning the linguistic parameters we have drawn from the results of the experiment. Table 5 illustrates quantitatively the interaction between the linguistic informations. Each cell of the table contains the highest score obtained with all the parameter combinations in which both the row entry and the column entry modalities of the two parameters concerned are activated. Concerning ctxt_comp parameter, only its application to the thematic context is represented, since we found that it have no influence for the neighbors and the syntactic cooccurrents. We can draw, from this table, the global tendency for every parameter. For example, in the row and column that represent type parameter, the values in the form#tag (in dark gray in the table) part are always higher than the ones in the form part (in light gray), whatever the parameter with which type is combined.

4.4.3. Our findings
In this sub-section, we propose several conclusions concerning the linguistic parameters we have drawn from the results of the experiment.

Parameter sim. The best score (90.5%) falls to 73.9% when sim is all: the similarity between two EQVs is computed using all their cooccurrents. Representing the different usages of a polysemous word is then more precise when using ‘syntactic patterns’. However, the thematic context cannot be ignored, since the best score fell to 74% when only the syntactic cooccurrents and the neighbors were considered in the computation of the relative weights of the cooccurrents (rwj).

Parameter ctxt_type. We observe that the f-scores are higher when neighbors and syntactic cooccurrents are used in the semantic spaces.

Parameter type. The representation of the semantic spaces was more precise with form#tag value for this parameter. With the optimal combination, we observed a strong decrease when type is form (81.4%). Then, we can say that the morpho-syntactic component plays a significant role in the representation of the linguistic context of the words.

Parameter comp. The f-scores were better when multi-word expressions were considered as single units: the best-score falls to 81.8% when comp is no. This is explained by the fact that the sense, for this kind of expressions, cannot be induced by a semantically compositional process.

| Linguistic parameters and their modalities | sim     | type   | comp   | ctxt_comp (1 vs 3) |
|------------------------------------------|---------|--------|--------|-------------------|
|                                          | all     | strong | form#tag| no     | yes    | words | lemmas |
| type                                     |         |        |        |        |        |       |
|                                          | 81.6    | 81.6   | 90.5   |        |        |       |
| comp                                     |         |        |        |        |        |       |
|                                          | 81.3    | 81.4   | 90.5   |        |        |       |
| ctxt_comp (1 vs 3)                       |         |        |        |        |        |       |
|                                          | 81.6    | 82.7   | 80.8   | 80.9   | 82.7   |       |
|                                          | 81.3    | 90.5   | 81.4   | 81.1   | 90.5   |       |
| ctxt_comp (2 vs 4)                       |         |        |        |        |        |       |
|                                          | 80.1    | 84.6   | 75.9   | 76     | 84.5   | 75.8  | 84.5  |
|                                          | 81.6    | 90.5   | 81.6   | 85.7   | 90.5   | 82.7  | 90.5  |

Table 5: Global tendencies of the linguistic parameters and their interaction with each other.
So, inserting the sense of the lexical units composing them in the semantic space of a word is literally incorrect. **Parameter ctxt_comp.** This parameter was very influential for the performances of our WSD method. The grammatical filtering was absolutely bad. And the influence of the lemmatization varies depending on the kind of context. It was good for the thematic context, but had no influence for the neighbors and for the syntactic cooccurrences.

**Conclusion.** Making use of distributional hypothesis in order to describe the semantic space of the words cannot be done by considering all the co-textual elements in a homogenous way. Then, each word can be characterized by a multifaceted representation of its local and global contexts of usage in which each kind of co-textual element (neighbors as left and right lexical and grammatical context, syntactic cooccurrences, first and second order thematic cooccurrences, predicates and arguments, semantic roles, and so on) has to be taken into account. Moreover, each kind of co-textual element has then to be favoured depending on the goal of the task. For example, (Baroni & Bisi, 2004) used narrow windows of size 2 and 5 (immediate lexical neighbors) to discover synonymy relations.

### 4.4.4. Analysis of the evolution of the scores

Figure 1 is a diagram representation of the evolution of the scores following ctxt_comp parameter. The evolution of the labels of the Y-axis shows us consistent relation between the scores and ctxt_comp parameter. In fact, in the two first diagrams, the scores are formed of four groups, corresponding to the fours modalities of ctxt_comp applied to the thematic context (a part in the a+b labels). This four groups are in the following ascending order: [2 1 4 3], which provides two rankings in the scores:

- a first order in terms of words and lemmas: (2,1) < (4,3), so words < lemmas;
- and a second order in terms of grammatical filtering: 2×1 and 4×3, so filtering < no filtering.

In the first diagram, within this first ranking, a second ranking is observed that follows the modality of ctxt_comp applied to the syntactic cooccurrences (a part in the a+b labels). This second ranking is a corroboration of the order we observed in the first ranking, relating to the grammatical filtering: in the four groups, we effectively observe that (4,2) < (3,1). And in the second diagram, we observe an identical second ranking relating to the lemmatization and that corroborate the fact that lemmas are better than words: 3<1 in the four groups.

The third diagram represents the scores obtained when no distinction is made between the neighbors and syntactic cooccurrences on one hand, and the other (thematic) cooccurrences. Once again, we observe the same ranking concerning the grammatical filtering: (2,4)<(1,3). But the lemmas are better than words (80 vs. 77.7%, respectively) when this filtering is applied, while the words are (slightly) better than lemmas (81.6 vs. 81.3%) when no grammatical filtering is applied.

### 5. Conclusion and future work

We have evaluated the impact of some linguistic knowledge on WSD performances using a classification method based on the kNN algorithm. The best scores were obtained with five different parameter combinations, what corroborate (Habert & al., 1997)'s conclusion according to which the best linguistic model does not exist, theoretically. Every kind of linguistic knowledge has fluctuating effects depending particularly on the other kind of linguistic knowledge it is combined with and on the NLP application for which the WSD method concerned will be a sub-task.

Various improving factors should be considered, like combining both neighbors and syntactic cooccurrences, or using neighbors from windows of size higher than 1 and second order cooccurrences from every kind of context. Besides, we could define the semantic spaces differently according to the grammatical tag of the ambiguous word as suggested by (Habert & al., 1997) (adjectival and adverbal cooccurrences are certainly more semantically informative for nouns than for verbs, for example). We could also extend the training corpora and define more fine-grained entries in the bilingual lexicon by using more than one TL.
Finally, we should do the same experiment using WSD methods based on other learning techniques, like SVM and SCT, and complete our evaluation with a comparative one, both in monolingual and multilingual frames.

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