The Usefulness of Conceptual Representation for the Identification of Semantic Variability Expressions

Zornitsa Kozareva, Sonia Vázquez and Andrés Montoyo

Departamento de Lenguajes y Sistemas Informáticos
Universidad de Alicante
{zkozareva,svazquez,montoyo}@dlsi.ua.es

Abstract. The need of the current Natural Language Processing applications to identify text segments that express the same meaning in different ways, evolved into the identification of semantic variability expressions. Most of the developed approaches focus on the text structure, such as the word overlaps, the distance between phrases or syntactic trees, word to word similarity, logic representation among others. However, current research did not identify how the global conceptual representation of a sentences can contribute to the resolution of this problem. In this paper, we present an approach where the meaning of a sentence is represented with the associated relevant domains. In order to determine the semantic relatedness among text segments, Latent Semantic Analysis is used. We demonstrate, evaluate and analyze the contribution of our conceptual representation approach in an evaluation with the paraphrase task.

1 Introduction

The identification of text snippets that express the same semantic meaning in different surface forms became an inseparable module for current NLP systems such as Question Answering, Text Summarization, Information Extraction among others. A major component for the semantic variability expressions are paraphrases. Given two text snippets, the paraphrase rules identify words such as the synonyms “car” and “vehicle”, complex phrases “X married Y” and “Y is the husband of X”, or even whole sentence, which can replace each other but still transmit the same meaning of the text.

Most of the developed approaches focus on the automatic collection of paraphrase rules [1], [11], [2]. Others identify whether two sentences are paraphrases of each other or not by measuring the ratio of the overlapping words [9], or the word-to-word semantic similarity [3]. [18] captured paraphrase rules by a probabilistic projection of the texts and information from the web. [2] aligned text segments to determine whether they are equivalent or not, [8] estimated the edit distance of the syntactic trees between two texts.

However, all these approaches suffer from global conceptual representation, and fail to understand the meaning of the text. In this paper, we present a hypothesis according to which the determination of relevant domain labels among the different word syntactic categories can provide a powerful way to establish the semantic relations among text segments. Since the domains are related to text coherence, this means that words occurring in coherent texts maximize the domain similarity of the texts. Imagine a text segment where the verb "eat" and the noun "cake" appear, both of them are conceptually related to food and the domain alimentation.

Previously, the usage of domain information was successfully applied to Word Sense Disambiguation [13], Information Extraction [17], Definite Description [14] and Information Retrieval [7]. For our approximation, we demonstrate how conceptual representation can function during the identification of semantically equivalent expressions. We have evaluated the performance of our approach with paraphrases corpus, but of course this approach can be applied with no restrain to the resolution of answer validation or textual entailment.

The paper is structured as follows. Section 2 presents the extraction of Relevant Domains [19] and Latent Semantic Analysis. Section 3 shows a walk–through example for paraphrases identification by global conceptual representation. Section 4 reports the obtained results with the Microsoft Paraphrase data and finally we conclude in Section 5.

2 Conceptual Representation Space with Latent Semantic Analysis

The Latent Semantic Analysis (LSA) [4] [10] corpus-based approach has been previously applied to various NLP tasks such as Information Retrieval, Information Extraction, Question Answering, Text Summarization among others. Although the systems can obtain good results in a specific domain, the problems arise when we want to acquire knowledge for a general domain. To surmount this obstacle, we present a conceptual representation approach with LSA. Instead of the traditional term-document matrix, we construct a term-conceptual matrix from two lexical resources: WordNet Domains and WordNet alignment with SUMO.

2.1 WordNet Domains

The semantic domains provide a natural way to establish the semantic relations among words. They can be used to describe texts and to assign a specific domain from previously established domain hierarchy.

Based on this idea, a new resource called WordNet Domains (WND) [12] has been developed. This resource uses information from WordNet [6] and labels each word sense with semantic domains from a set of 200 domain labels. These labels are obtained from the Dewey Decimal Classification and are hierarchically organized. This information is complementary to WordNet and is useful to obtain new relations among the words.

In order to obtain the WND resource, each word of WordNet is annotated with one or more domain labels. One of the most important characteristic of WND is that each domain label can be associated to different syntactic categories. This is an interesting feature because we can relate words of different syntactic categories with the same domain and obtain new relations that previously does not exist in WordNet.

For example, the domain 'Economy' is associated with the nouns (bank, money, account, banker, etc), the verbs (absorb, amortize, discount, pay, etc) and the adjectives (accumulated, additional, economic, etc). Moreover, these domain labels have been associated to different senses of the same word and thus we can distinguish the meaning of each word using the domains. The word "plant" has three different domain senses: 'Industry, Botany, Theatre' and in order to establish its word sense, we can use the domain information of other words that are seen in the context of "plant" ("it is an industrial plant to manufacture automobiles", "a plant is a living organism laking the power of locomotion").

Taking advantage of the properties of this resource, we formulate the following hypothesis: the conceptual representation of a text can be obtained when the contextual information provided by its words is used.

In WordNet, each word sense has a definition[1] like in a dictionary and the words in the gloss are used to obtain the specific context for the sense. Respectively, the word sense has a domain label which contains the global concept for this sense. Our assumption is that words that form part of the gloss are highly probable to be associated to the same concept of the word. For instance, "plant#1" [2] is associated to the domain 'Industry'. It gloss contains: 'buildings for carrying on industrial labor; "they built a large plant to manufacture automobiles"'. From the gloss, the words "building", "carry", "industrial", "labor", "plant", "manufacture" and "automobile" are semantically related to the domain 'Industry' and thus they can help us to understand the concept of the definition word.

Taking into account this principle, we extracted from WordNet a list with all words and their associated domains. Then, we used the information provided by the context to build the conceptual representation space of LSA.

2.2 WordNet Alignment with SUMO

The Suggested Upper Merged Ontology (SUMO) [15] is an ontology that is obtained from the merging of publicly available ontological content into a single, comprehensive, and cohesive structure with around 800 terms. In our approximation these terms are used as relevant domains. The SUMO ontology is aligned with the WordNet lexical database on the basis of the synonymy, hypernymy

[1] gloss
[2] plant with sense one

and instantiation relations. So each WordNet synset is associated to a SUMO concept.

The information added by the SUMO ontology into WordNet is useful to the WND resource, because we establish the global concept of the words using the concepts of SUMO. The final relevant domain resource is a list of words tagged with the concepts of SUMO. The main idea for the usage of the WND and SUMO resources is that we want to study the effect of the usage of two different types of ontologies: a coarse-grained (WND) and a fine-grained (SUMO). In our experimental work we determine the effect of the ontological specification over the final textual conceptual representation.

In order to see the differences between SUMO and WND we extract the SUMO concepts for the same three senses of "plant": "Stationary_Artifact", "Plant", "Social_Role". We observe the pairs WND-SUMO concepts: "Industry"–"Stationary_Artifact", "Plant"–"Botany", "Social_Role"–"Theatre" and we realize that the SUMO ontology is fine-grained in comparison with the WND.

Figure 1 shows a part of the SUMO and WordNet ontologies so that the different degree of specialization of the hierarchies can be seen.

- Entity
  - Physical
    - Object
      - SelfConnectedObject
        - Region
        - Substance
        - CorpuscularObject
      - Collection
    - Process
  - Abstract
    - Class
      - Set
    - Relation
    - Proposition
    - Quantity
      - Number

Part of the SUMO hierarchy

- doctrines
  - archaeology
  - astrology
  - history
    - heraldry
  - linguistics
    - grammar
  - literature
    - philology
  - philosophy
  - psychology
    - psychoanalysis
  - art
    - dance
    - drawing
      - painting

Part of the WND hierarchy

Fig. 1. SUMO and WND hierarchies

2.3 Latent Semantic Analysis

The traditional usage of LSA is based on a text corpus represented as a $M \times N$ co-occurrence matrix, where the rows M are words and the columns N are documents, phrases, sentences or paragraphs. Each cell in this matrix contains the number of times that a word occurs in the context of a column.

Once the matrix is obtained, it is decomposed using Singular Value Decomposition (SVD). In this way the initial dimensions are reduced into a new distribution which is based on similar contexts. This reduction makes the similarity among the words and the contexts to become more apparent.

Our approach is based on the idea that semantically related words appear in the same contexts. However, the contexts we use are not a specific corpus divided in documents or paragraphs, but words related to a specific concept (e.g. domain) that belongs to a predefined hierarchy. In our case, the domains are derived from WND and SUMO and with this information we construct the conceptual matrix of LSA.

However, we want to rank the words not only on the basis of their meaning, but also on the basis of their co-occurrences with other words. Therefore, we applied the Mutual Information (MI) 1 and Association Ratio (AR) 2 measures which can relate the words with the domains.

$$MI(w_1, w_2) = log_2 \frac{P(w_1|w_2)}{P(w_1)P(w_2)} \tag{1}$$

$$AR(w, Dom) = Pr(w|Dom)\, log_2 \frac{Pr(w|Dom)}{Pr(w)} \tag{2}$$

MI provides information about the pairwise probability of two words w_1 and w_2 compared to their individual probabilities. When there is a real association between two words w_1 and w_2, their joint probability $P(w_1, w_2)$ is much larger than $P(w_1)P(w_2)$, and $MI(w_1, w_2) \gg 0$. For the cases where w_1 and w_2 are not related, $P(w_1, w_2) \approx P(w_1)P(w_2)$, therefore $MI(w_1, w_2) \approx 0$. When w_1 and w_2 are in complementary distribution, then $P(w_1, w_2)$ is less than $P(w_1)P(w_2)$, and $MI(w_1, w_2) \ll 0$.

Adapting this notion to our approach, we used w_1 in the aspect of a word we are observing and w_2 in the aspect of a domain D from the WND that corresponds to the word w_1. The values are normalized with the number of word–domain pairs N in the WND. Once the relation between the words and the domains is obtained, AR is applied and the conceptual space of LSA is constructed.

3 A Walk-Through example

We illustrate the application of the relevant domains and LSA with a paraphrase example. Given two text segments, we want to obtain their conceptual spaces and then determine a score that reflects the semantic similarity relatedness of the texts. According to this text cohesion score and an empirically derived threshold, the segments are considered as paraphrases of each other or not.

First, the two texts segments as shown in Figure 2 are lemmatized with TreeTagger [16] part-of-speech tagger. This is done because the LSA conceptual matrix is build from the lemmatized words in WordNet. The relevant domains for these segments are obtained only for the nouns, the verbs, the adverbs and the adjectives of the two text segments. The underlined words in Figure 2 are those whose relevant domains are going to be considered during the generation of the text conceptual representation.

Text Segment 1: <u>Women</u> who <u>eat</u> <u>potatoes</u> and other <u>tuberous</u> <u>vegetables</u> during <u>pregnancy</u> may be at <u>risk</u> of <u>triggering</u> <u>type</u> 1 <u>diabetes</u> in their <u>children</u>, Melbourne <u>researchers</u> <u>believe</u>.

Text Segment 2: Australian <u>researchers</u> <u>believe</u> they have <u>found</u> a <u>trigger</u> of <u>type</u> 1 <u>diabetes</u> in <u>children</u> - their <u>mothers</u> <u>eating</u> <u>potatoes</u> and other <u>tuberous</u> <u>vegetables</u> during <u>pregnancy</u>.

Fig. 2. Text segments number 1634 from the paraphrase corpus

Starting with each of the two text segments and for each of the previously selected word categories, we determine the corresponding relevant domains from WordNet and SUMO. Figure 3 shows the set of WordNet relevant domains that correspond to each one of the words and their associated probabilities to the relevant domains according to the association ratio measure.

Once the words are associated to the domains, then the overlapping domains between the two text segments are determined. For this step, we use LSA, which returns a list of the most common relevant domains for Text Segment 1 and Text Segment 2. In the experiment, we consider the first twenty most relevant domains, but in our example in Table 1 we list only the first nine relevant domains.

LSA domains in segment 1		LSA domains in segment 2	
`Domain`	Similarity	`Domain`	Similarity
`applied_science`	0.770537	`applied_science`	0.793825
`pharmacy`	0.740445	`pharmacy`	0.777943
`philology`	0.717400	`ecology`	0.713885
`publishing`	0.716576	`transport`	0.709478
`theology`	0.714463	`biology`	0.705481
`pedagogy`	0.705165	`botany`	0.701570
`telecommunication`	0.700763	`university`	0.694129
`university`	0.698827	`publishing`	0.693940
`psychoanalysis`	0.697876	`chemistry`	0.693747

Table 1. LSA list of the nine most relevant domains for the two text segments

Text Segment 1:

woman={sexuality 0.236904, fashion 0.074808, person 0.072525, athletics 0.048517, jewellery 0.042176}
eat={gastronomy 0.168685, ecology 0.034430, folklore 0.026185, physiology 0.017776, anthropology 0.012501}
potato={agriculture 0.056402, gastronomy 0.009348, entomology 0.004056, racing 0.003743, medicine 0.002409}
tuberous={agriculture 0.000782, biology 0.000284, botany 0.003115, botany 0.003115, gastronomy 0.002218}
vegetable={gastronomy 0.040430, zootechnics 0.023290, agriculture 0.022609, earth 0.009891, body_care 0.009335}
pregnancy={surgery 0.027848, physiology 0.025092, medicine 0.005344, anatomy 0.002291, color 0.001075}
risk={insurance 0.049295, exchange 0.015876, enterprise 0.013756, industry 0.001393, commerce 0.001289}
trigger={commerce 0.002437, computer_science 0.001999, factotum 0.000088 }
type={zoology 0.052495, philology 0.048450, bowling 0.043687, publishing 0.023217, biology 0.018311}
diabetes={pharmacy 0.006108, medicine 0.005782, alimentation 0.000724, time_period 0.000290, factotum 0.000020...}
child={ethnology 0.008168, acoustics 0.006704, color 0.002306, body_care 0.001732, economy 0.001036}
researcher={person 0.000636, factotum 0.000010}
believe={doctrines 0.195175, theology 0.155574, pure_science 0.137293, folklore 0.079765, religion 0.067227}

Text Segment 2:

researcher={person 0.000636, factotum 0.000010}
believe={doctrines 0.195175, theology 0.155574, pure_science 0.137293, folklore 0.079765, religion 0.067227}
find={zoology 0.102364, chemistry 0.072100, statistics 0.045846, geology 0.043141, astrology 0.042836}
trigger={commerce 0.002437, computer_science 0.001999, factotum 0.000088 }
type={zoology 0.052495, philology 0.048450, bowling 0.043687, publishing 0.023217, biology 0.018311}
diabetes={pharmacy 0.006108, medicine 0.005782, alimentation 0.000724, time_period 0.000290, factotum 0.000020}
child={ethnology 0.008168, acoustics 0.006704, color 0.002306, body_care 0.001732, economy 0.001036}
mother={archaeology 0.014541, anthropology 0.003027, computer_science 0.000241, administration 0.000241, biology 0.000239}
eat={gastronomy 0.168685, ecology 0.034430, folklore 0.026185, physiology 0.017776, anthropology 0.012501}
potato={agriculture 0.056402, gastronomy 0.009348, entomology 0.004056, racing 0.003743, medicine 0.002409}
tuberous={agriculture 0.000782, biology 0.000284, botany 0.003115, botany 0.003115, gastronomy 0.002218}
vegetable={gastronomy 0.040430, zootechnics 0.023290, agriculture 0.022609, earth 0.009891, body_care 0.009335}
pregnancy={surgery 0.027848, physiology 0.025092, medicine 0.005344, anatomy 0.002291, color 0.001075}

Fig. 3. The first five relevant domains per word according to the association ratio measure

Finally, a ranking function calculates the average value of the coinciding domains and determines only one candidate domain according to which the two texts are strongly or weakly semantically related. This candidate domain contains the global conceptual representation of the texts. To determine this domain, we compare each of the domains listed in Table 1 from Text Segment 1 to those of Text Segment 2. The most relevant domain for the two text segments is determined by the highest probability domain relevance value. The final result of the ranking function contains the global representation domain for the two text segments. For our example, the most relevant domain is `applied_science`. It includes the subdomains `agriculture`, `alimentation`, `gastronomy`.

4 Evaluation

In order to estimate the effectiveness of the developed conceptual representation approach, we carried out an experimental evaluation with a paraphrasing corpus[3]. The evaluation task consists in given two text segments, the system has to determine whether the text are paraphrases of each other or not.

4.1 Microsoft Paraphrase Corpus

The paraphrase corpus [5] we worked with has been automatically collected from the web. The number of train instances is 4076, and the number of test instances is 1725.

Each paraphrase pair consists of two text segments for which the semantic variability has to be determined. An example of a paraphrase pair is "Inhibited children tend to be timid with new people, objects, and situations, while uninhibited children spontaneously approach them." and " Simply put, shy individuals tend to be more timid with new people and situations."

4.2 Evaluation Measures

The performance of our conceptual representation model for the resolution of paraphrases is evaluated with the following measures.

$$Precision = \frac{number\,of\,correct\,answers\,found\,by\,the\,system}{number\,of\,answers\,given\,by\,the\,system} \tag{3}$$

$$Recall = \frac{number\,of\,correct\,answers\,found\,by\,the\,system}{total\,number\,of\,correct\,answers\,in\,the\,corpus} \tag{4}$$

$$F_{\beta=1} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5}$$

$$Accuracy = \frac{number\,of\,answers\,given\,by\,the\,system}{total\,number\,of\,correct\,answers\,in\,the\,corpus} \tag{6}$$

[3] http://research.microsoft.com/nlp/msr_paraphrase.htm

4.3 Results

We have conducted two types of experiments. In the first one, we study how to represent the concept of two texts using the WordNet and SUMO domains, while in the second experiment we examine whether the usage of a fine-grained or coarse-grained ontology is better. This observations are made when WordNet is annotated with the SUMO ontology. The results from the carried out experiments are shown in Table 2.

In this table we show the performance of the system during its development and test stage. We have examined several empirical thresholds, in order to determine the most significant one. A threshold value of 0.8 corresponds to a high assurance that two text are paraphrases of each other, because the probability of LSA domain determination is above 0.8. In the experiments we found out that all thresholds below 0.4 perform the same. This observation is made with the WordNet and SUMO domains. Therefore, we consider the 0.4 threshold as a robust one.

	Data Set	Thresh	Acc	Prec	Rec	F
WordNet Domains	Train	0.8	80.29	72.97	70.83	71.89
		0.6	97.35	68.91	96.07	80.26
		0.4	**98.52**	68.36	97.82	**80.48**
	Test	0.8	80.34	72.08	70.44	71.25
		0.6	97.10	67.50	95.64	79.14
		0.4	**98.26**	66.84	97.38	**79.27**
WordNet Annotated with SUMO	Train	0.8	38.59	81.69	09.08	16.34
		0.6	94.28	69.44	91.53	78.97
		0.4	**96.27**	68.93	94.47	**79.71**
	Test	0.8	40.05	81.29	09.85	17.57
		0.6	93.50	68.67	90.23	77.99
		0.4	**95.18**	68.11	92.76	**78.55**
text similarity approach	Test	–	68.80	74.10	81.70	77.70

Table 2. Conceptual representation for paraphrase identification

For the paraphrase resolution task, our approach transmits not only the meaning of the text but also the global concept. During the train and test phase, WordNet and SUMO performed alike however, the coarse-grained hierarchy of WordNet domains gave more precise results. The only differences among the two experiments are observed when we worked with high threshold values. WordNet domains had a variation of 10% across the thresholds, while SUMO's performance ranged from 16 to 79%. This is due to assurance score established from the relevant domains. While in WordNet the domain overlap is always with high probability, in SUMO the domains are more specialized and the probability to find an overlaps among them is lower. Of course this does not mean that fine-grained domains hamper the conceptual representation, it only indicated that a lower probability threshold is needed.

During the error analysis, we found out sentences which have no common domains at all and where determined as non-paraphrase. However, these texts had common sub-domains. One interesting approximation in the future is to study how the sub-domains affect the global conceptual representation and estimate the semantic variability.

In Table 2, we show a comparative study with the text similarity approach of [3], which is also evaluated with the same paraphrase data. It can be seen that our global conceptual representation approach performs better. Establishing word-to-word similarity or text-to-text similarity does not explain the meaning of the text, therefore our approach is better not only from the point of view of the coverage of the correctly established paraphrase examples, but also from the point of view that we measure similarity among different syntactic categories of words on behalf of the same concept. In this way we have a reasonable explanation how and to what extend the two text segments are semantically related.

4.4 Discussion

Some limitations for the development of the conceptual representation are due to the FACTOTUM domain. This domain groups words with no specific domain. Therefore, when a text segment has many words belonging to the FACTOTUM domain, we cannot obtain the global concept of the sentence.

The precision in our approach can be improved when we establish correctly the senses of the words in the gloss. Because in this approximation, the words in the gloss were not disambiguated and we were assuming that they belong to the domain of the defined word. To resolve this problem and to improve the performance, the ExtendedWordNet resource is going to be used. In this way, we will have a better mapping between the words in the gloss and their corresponding domains.

Regarding SUMO's experiments, we saw that considering only the first twenty relevant domains is not representative enough for the modelling of the conceptual space. This is due to SUMO's fine-grained ontology. In the future we will expand the number of SUMO's relevant domains.

In conclusion we can say that the identification of semantically variable expression with conceptual representation is possible and obtains better results than text-to-text similarity approaches. We used the paraphrase data to demonstrate the applicability and the usefulness of the conceptual representation approach. Of course, this approach can be used to identify semantic variability expressions for other task such as textual entailment, answer validation or to find similar sentences related to different semantic categories of Named Entities.

5 Conclusions

We have described an approach for global conceptual representation of text segments using relevant domains. Our hypothesis is that domains constitute a fundamental feature of text coherence, therefore words occurring in coherent portion of texts maximize the domain similarity.

To build the conceptual space of the text, LSA is employed. In this study we observe the effect of fine-grained and coarse-grained ontologies from which the relevant domain resources are extracted. To demonstrate the usefulness of our conceptual approach, we have evaluated it with the paraphrase resolution task.

The results show that the conceptual representation approach we propose is reliable and performs better than the already developed lexical overlap, or text-to-text similarity approaches. One advantage of this method is the ability to extract the global meaning of the texts and give reasonable explanation why two texts are considered semantically equivalent.

In the future, we will use this approximation to develop a repository of Named Entity context examples which are representatives of various semantic categories, such as Person_Politics, Person_Sport, Person_Musician among others.

Acknowledgements

This research has been funded by the Spanish Government under project CICyT number TIC2003-07158-C04-01 and PROFIT number FIT-340100-2004-14.

References

1. Regina Barzilay and Kathleen McKeown. Extracting paraphrases from a parallel corpus. In *ACL, 2001.*, pages 50–57.
2. Regina Barzilay and Kathleen McKeown. Learning to paraphrase: An unsupervised approach using multiple-sequence alignment. In *HTLT-NAACL, 2003.*, pages 16–23.
3. Courtney Corley and Rada Mihalcea. Measures of text semantic similarity. In *Proceedings of the ACL workshop on Empirical Modeling of Semantic Equivalence.*, 2005.
4. Scott Deerwester, Susan T. Dumais, George W. Furnas, Thomas K. Landauer, and Richard Harshman. Indexing by latent semantic indexing. In *Journal of the American Society for Information Science.*, volume 41, pages 321–407, 1990.
5. Bill Dolan, Chris Quirk, and Chris Brockett. Unsupervised construction of large paraphrase corpora: Exploiting massively parallel news sources. In *Proceedings of the 20th International Conference on Computational Linguistics, Geneva, Switzerland.*, 2004.
6. Christiane FellBaum. *WordNet, an electronic lexical database.* MIT Press, 1998.
7. Julio Gonzalo, Felisa Verdejo, Carol Peters, and Nicoletta Calzolari. Applying eurowordnet to cross-language text retrieval. pages 113–135, 1998.
8. Milen Kouylekov and Bernardo Magnini. Tree edit distance for recognizing textual entailment: Estimating the cost of insertion. In *Proceedings of the PASCAL Challenges Workshop on Recognising Textual Entailment, 2006.*, pages 17–20.
9. Zornitsa Kozareva and Andrés Montoyo. Paraphrase identification on the basis of supervised machine learning techniques. In *FinTAL*, pages 524–533, 2006.
10. Thomas Landauer and Susan Dumais. A solution to plato's problem: The latent semantic analysis theory of acquisition. In *Psychological Review*, pages 211–240, 1997.

11. Dekang Lin and Patrik Pantel. Discovery of inference rules for question answering. *Natural Language Engineering, 4(7)*, pages 343–360.
12. Bernardo Magnini and Gabriela Cavaglia. Integrating Subject Field Codes into WordNet. In M. Gavrilidou, G. Crayannis, S. Markantonatu, S. Piperidis, and G. Stainhaouer, editors, *Proceedings of LREC-2000, Second International Conference on Language Resources and Evaluation*, pages 1413–1418, Athens, Greece, 2000.
13. Bernardo Magnini, Carlo Strapparava, Giovanni Pezzulo, and Alfo Gliozzo. Using domain information for word sense disambiguation. In *SENSEVAL-2, 2001.*
14. Rafael Muñoz and Andrés Montoyo. Definite description resolution enrichment with wordnet domain labels. In *IBERAMIA*, pages 645–654, 2002.
15. I. Niles and A. Pease. Linking lexicons and ontologies: Mapping wordnet to the suggested upper merged ontology. *Proceedings of the 2003 International Conference on Information and Knowledge Engineering (IKE 03). Las Vegas, Nevada*, 2003.
16. Helmut Schmid. Probabilistic part-of-speech tagging using decision trees. In *International Conference on New Methods in Language Processing, Manchester, UK, 1994.*
17. Mark Stevenson and Mark A. Greenwood. Learning information extraction patterns using wordnet. In *Proceedings of the 3rd International Conference of the Global WordNet Association (GWA'06)*, 2006.
18. Idan Szpektor, Hristo Tanev, Ido Dagan, and Bonaventura Coppola. Scaling web-based acquisition of entailment relations. In *Proceedings of Empirical Methods in Natural Language Processing*, 2004.
19. Sonia Vázquez, Andrés Montoyo, and German Rigau. Using relevant domains resource for word sense disambiguation. In *IC-AI*, pages 784–789, 2004.