Improving Word Sense Disambiguation with Linguistic Knowledge from a Sense Annotated Treebank

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Abstract

In this paper we present an approach for the enrichment of WSD knowledge bases with data-driven relations from a gold standard corpus (annotated with word senses, valency information, syntactic analyses, etc.). We focus on Bulgarian as a use case, but our approach is scalable to other languages as well. For the purpose of exploring such methods, the Personalized Page Rank algorithm was used. The reported results show that the addition of new knowledge improves the accuracy of WSD with approximately 10.5%.

1 Introduction

Solutions to WSD-related tasks usually employ lexical databases, such as wordnets and ontolo-However, lexical databases suffer from gies. sparseness in the availability and density of relations. One approach towards remedying this problem is the BabelNet (Navigli and Ponzetto, 2012), which relates several lexical resources - Word-Net¹, DBpedia, Wiktionary, etc. Although such a setting takes into consideration the role of lexical and world knowledge, it does not incorporate contextual knowledge learned from actual texts (such as collocational patterns, for example). This happens because the knowledge sources for WSD systems usually capture only a fraction of the relations between entities in the world. Many important relations are not present in ontological resources but could be learned from texts.

One possible approach to handling this sparseness issue is the incorporation of relations from sense annotated corpora into the lexical databases. We decided to focus on this line of research, by using the Bulgarian sense annotated treebank

¹In this work we used version 3.0 of Princeton WordNet: https://wordnet.princeton.edu/. (Sensed BulTreeBank) in order to extract semantic relations and add them into the lexical resources. The hypothesis that this enrichment would lead to better WSD for Bulgarian was tested in the context of the Personalized PageRank algorithm.

The structure of the papers is as follows: the next section discusses the related work on the topic. Section 3 presents the Bulgarian sense annotated treebank. Section 4 focuses on the Bulgarian Syntactic and Lexical Resources. Section 5 introduces the WSD experiments and results. Section 6 concludes the paper.

2 Related Work

Knowledge-based systems for WSD have proven to be a good alternative to supervised systems, which require large amounts of manually annotated training data. In contrast, knowledge-based systems require only a knowledge base and no additional corpus-dependent information. An especially popular knowledge-based disambiguation approach has been the use of popular graph-based algorithms known under the name of "Random Walk on Graph" (Agirre et al., 2014). Most approaches exploit variants of the PageRank algorithm (Brin and Page, 2012). Agirre and Soroa (2009) apply a variant of the algorithm to Word Sense Disambiguation by translating WordNet into a graph in which the synsets are represented as vertices and the relations between them are represented as edges between the nodes. The resulting graph is called a *knowledge graph* in this paper. Calculating the PageRank vector Pr is accomplished through solving the equation:

$$\mathbf{Pr} = cM\mathbf{Pr} + (1-c)\mathbf{v} \tag{1}$$

where M is an $N \times N$ transition probability matrix (N being the number of vertices in the graph), c is the damping factor and **v** is an $N \times I$ vector. In the traditional, static version of PageRank the val-

ues of **v** are all equal (1/N), which means that in the case of a random jump each vertex is equally likely to be selected. Modifying the values of **v** effectively changes these probabilities and thus makes certain nodes more important. The version of PageRank for which the values in **v** are not uniform is called *Personalized PageRank*.

The words in the text that are to be disambiguated are inserted as nodes in the knowledge graph and are connected to their potential senses via directed edges (by default, a context window of at least 20 words is used for each disambiguation). These newly introduced nodes serve to inject initial probability mass (via the v vector) and thus to make their associated sense nodes especially relevant in the knowledge graph. Applying the Personalized PageRank algorithm iteratively over the resulting graph determines the most appropriate sense for each ambiguous word. The method has been boosted by the addition of new relations and by developing variations and optimizations of the algorithm (Agirre and Soroa, 2009). It has also been applied to the task of Named Entity Disambiguation (Agirre et al., 2015).

Montoyo et al. (2005) present a combination of knowledge-based and supervised systems for WSD, which demonstrates that the two approaches can boost one another, due to the fundamentally different types of knowledge they utilise (paradigmatic vs. syntagmatic). They explore a knowledge-based system that uses heuristics for WSD depending on the position of word potential senses in the WordNet knowledge base. In terms of supervised machine learning based on an annotated corpus, it explores a Maximum Entropy model that takes into account multiple features from the context of the to-be-disambiguated word. This earlier line of research demonstrates that combining paradigmatic and syntagmatic information is a fruitful strategy, but it does so by doing the combination in a postprocessing step, i.e. by merging the output of two separate systems; also, it still relies on manually-annotated data for the supervised disambiguation. Building on the already mentioned work on graph-based approaches, it is possible to combine paradigmatic and syntagmatic information in another way - by incorporating both into the knowledge graph. This approach is described in the current paper.

The success of knowledge-based WSD approaches apparently depends on the quality of the

knowledge graph – whether the knowledge represented in terms of nodes and relations (arcs) between them is sufficient for the algorithm to pick the correct senses of ambiguous words. Several extensions of the knowledge graph constructed on the basis of WordNet have been proposed and implemented. An approach similar to the one presented here is described in Agirre and Martinez (2002), which explores the extraction of syntactically supported semantic relations from manually annotated corpora. In that piece of research, Sem-Cor, a semantically annotated corpus, was processed with the MiniPar dependency parser and the subject-verb and object-verb relations were consequently extracted. The new relations were represented on several levels: as word-to-class and class-to-class relations. The extracted selectional relations were then added to WordNet and used in the WSD task. The chief difference with the presently described approach is that the set of relations used here is bigger (it includes also indirect-object-to-verb relations, noun-to-modifier relations, etc.). Another difference is that the new relations in the present piece of research are not added as selectional relations, but as semantic relations between the corresponding synsets. This means that the specific syntactic role of the participant is not taken into account, but only the connectedness between the participant and the event is registered in the knowledge graph.

3 The Bulgarian Sense Annotated Treebank

The sense annotation process over BulTreeBank (BTB) was organized in three layers: verb valency frames (Osenova et al., 2012); senses of verbs, nouns, adjectives and adverbs; DBpedia URIs over named entities. However, in the experiment presented here, we used mainly the annotated senses of nouns and verbs (together with the valency information), as well as the concept mappings to WordNet. For that reason we do not discuss the DBpedia annotation here. A brief outline can be found in Popov et al. (2014).

The sense annotation was organized as follows: the lemmatized words per part-of-speech (POS) from BTB received all their possible senses from the explanatory dictionary of Bulgarian and from our Core WordNet². When two competing definitions came from both resources, preference was

²Available at http://compling.hss.ntu.edu.sg/omw/

given to the one that was mapped to the WordNet. In the ambiguous cases the correct sense was selected according to the context of usage. For the purposes of the evaluation, some of the files were independently manually checked by two individual annotators. In total, 92,000 running words have been mapped to word senses. Thus, about 43 % of all the treebank tokens have been associated with senses.

The word forms annotated with senses mapped to WordNet synsets are 69,333, consisting of nouns and verbs. From these POS, 12,792 word forms have been used for testing, and the rest have been used for relation extraction. About 20,000 word forms are now in the process of being mapped to WordNet synsets. Most of them are adjectives and adverbs. They will be included in the next round of experiments, which will result in an increase the sense density of the graph.

4 Bulgarian Lexical and Syntactic Resources: BTB-Wordnet and Valency Lexicon

The BTB-Wordnet has been compiled in several steps. Initially, the Core WordNet was created for Bulgarian, which covered 4,999 synsets. Then, nearly the same number of new synsets were added to the WordNet (now we have 9,000 synsets or so). We tried to map the Bulgarian senses to the English ones as faithfully as possible, respecting the Princeton WordNet hierarchy.

Although connectivity was very important for the experiments, we also mapped specific concepts to more general ones in both directions (English to Bulgarian and Bulgarian to English). New definitions for concepts which did not have a counterpart in the Princeton Wordnet have been introduced. In this way, we established a language specific hierarchy for Bulgarian.

The ongoing mapping of word senses in the treebank to the WordNet is thus complicated by the fact that the available resources are not directly comparable. These are: the Treebank, where words were annotated with definitions from an explanatory dictionary of Bulgarian (dictionary entries), and the Princeton WordNet, which contains whole groups of synonyms (synonym sets) unified by common definitions of the concepts. At the same time, such an approach makes it possible to easily structure the resource via the Princeton Wordnet hierarchy, and it also leaves the door

open for developing a language-specific hierarchy.

The valency lexicon consists of around 18,000 verb frames extracted from the BTB. The participants in these frames have ontological constraints. At the moment, the verb senses are mapped to WordNet, but the constraints over arguments are not synchronized with the WordNet concepts in their levels of granularity and specificity. This syncronization is planned as a next step in our work, in order to further enrich the knowledge graph.

5 Experiments

5.1 Description of the WSD tool

The experiments that serve to illustrate the outlined approaches were carried out with the UKB³ tool, which provides graph-based methods for Word Sense Disambiguation and measuring lexical similarity. The tool uses the Personalized PageRank algorithm, described in Agirre and Soroa (2009). It can be and has been used to perform Named Entity Disambiguation as well (Agirre et al., 2015). The tool builds a knowledge graph over a set of relations that can be induced from different types of resources, such as WordNet or DBPedia; then it selects a context window of open class words and runs the algorithm over the graph. There is an additional module called NAF UKB⁴ that can be used to run UKB with input in the NAF format⁵ and to obtain output structured in the same way, only with added word sense information. For compatibility reasons, NAF UKB was used to perform the experiments reported here; the input NAF document contains in its "term" nodes lemma and POS information, which is necessary for the running of UKB. We have used the UKB default settings, i.e. a context window of 20 words that are to be disambiguated together, 30 iterations of the Personalized PageRank algorithm.

The UKB tool requires two resource files to process the input file. One of the resources is a dictionary file with all lemmas that can be possibly linked to a sense identifier. In our case WordNetderived relations were used for our knowledge base; consequently, the sense identifiers are Word-Net IDs. For instance, a line from the dictionary extracted from WordNet looks like this:

³http://ixa2.si.ehu.es/ukb/

⁴https://github.com/asoroa/naf_ukb

⁵http://www.newsreader-project.eu/

files/2013/01/techreport.pdf

predicate 06316813-n:0 06316626-n:0 01017222-v:0 01017001-v:0 00931232-v:0

First comes the lemma associated with the relevant word senses, after the lemma the sense identifiers are listed. Each ID consists of eight digits followed by a hyphen and a label referring to the POS category of the word. Finally, a number following a colon indicates the frequency of the word sense, calculated on the basis of a tagged corpus. When a lemma from the dictionary has occurred in the analysis of the input text, the tool assigns all associated word senses to the word form in the context and attempts to disambiguate its meaning among them. The Bulgarian dictionary comprises of all the lemmas of words annotated with WordNet senses in the BTB. It has 8,491 lemmas mapped to 6,965 unique word senses. Currently we have opted to copy over the frequencies from the English corpus, but they are not actually used in the experiments.

The second resource file required for running the tool is the set of relations that is used to construct the knowledge graph over which Personalized PageRank is run. The distribution of the tool provides data (dictionary and relation files) for WordNet 1.7 and 3.0. Since the BTB has been annotated with word senses from WordNet 3.0, the resource files for version 3.0 were used for our experiments. The distribution of UKB comes with a file containing the standard lexical relations defined in WordNet, such as hypernymy, meronymy, etc., as well as with a file containing relations derived on the basis of common words found in the synset glosses, which have been manually disambiguated. As the Bulgarian lemmas in the generated dictionary are mapped to the English Word-Net and the specific Bulgarian WordNet hierarchy is not exploited in this phase, we have used the same file with the relations for English. Because the generation of gloss-based relations is a timeconsuming task, we have used the relations for the English glosses, on the assumption that they should capture to a significant degree the relatedness between Bulgarian word senses as well. The WordNet ontological relations are 252,392 and the relations from the glosses are 419,387.

5.2 Additional Relations in the Knowledge Graph

In addition to these available relations, we have utilized further resources from WordNet itself and from the annotations in BTB. These additional resources are:

- Inferred hypernymy relations
- Syntactic relations from the golden corpus
- Extended syntactic relations
- Domain relations from WordNet

The phrase "inferred hypernymy relations" means the transitive closure of the hypernymy relation type. That is, if A is a hyponym of B and B is a hyponym of C, it is inferred that A is a hyponym of C. This type of inference has been done for all synset IDs that participate in hypernymy relations in the WordNet hierarchy and are found in the Bulgarian dictionary. 590,272 new relations have been generated in this way.

All relations described up until now are of a lexical nature, therefore essentially paradigmatic and providing information about an idealized model of the world. The work presented here enriches further the knowledge graph by adding syntagmatic information, i.e. contextual knowledge about words and word senses. This has been done by extracting the intersection of the syntactic dependency relations from the BTB corpus and the WordNet sense annotations in the same resource. In this way dependency relations between specific words in the text that also have attached Word-Net identifiers have been transformed into graph relations of the kind described above. The targeted dependency relations are of the types: nsubj, nmod, amod, iobj, dobj; for more information about the Universal Dependencies set of relations that we have used, see the documentation of the UD project⁶, which includes contribution from the BulTreeBank group for the Bulgarian language.

These syntactic relations have been extended in a similar way as the hypernymy relations. For example, in the case of the *nsubj* relation, the hyponyms of the dependent node have been replicated in new relations of the same kind, for all hyponyms of that particular word sense encountered in the golden corpus. Thus, the relation

u:00118523-v v:00510189-n

is derived from an *nsubj* relation, where 00118523-v stands for a sense of the Bulgarian verb "prodalzha" (continue) and is the head

⁶http://universaldependencies.github. io/docs/

node (the predicate in *nsubj*), and 00510189-n, corresponding to a particular word sense of "veselba" (revelry), is the dependent node (the subject). The dependent node has a number of hyponyms in the WordNet hierarchy, therefore all these (and their hyponyms, too) have been added into a relation with the node 00118523-v. For instance, 00510723-n (the synset for particular word senses of the words "binge", "bout" and "tear") has been entered analogously in the same slot as 00510189-n.

The open class word forms in the BTB are all tagged with their respective word senses, but a big portion of those senses are yet to be mapped to WordNet identifiers. Thus, only a part of the dependency relations from the corpus have been extracted for the purpose of these experiments (because both nodes in a relation must have WordNet IDs). More specifically, for 15,675 dependency relations, the numbers for the extracted relations are as follows: 1,844 nsubj, 3,875 nmod, 1,025 amod, 716 iobj, and 1,312 dobj relations. The numbers for the extended relations are: 372,247 nsubj, 1,125,823 nmod (note that there are two cases with nmod: once we extend along the chain of descendants of the dependent element, and once along the chain of those of the head), 377,577 amod, 114,760 *iobj*, and 292,202 *dobj* relations.

Our motivation for using the hyponyms to infer new relations is based on the intuition that these syntactic relations connect an entity to an event⁷ in which the entity participates or connects two participants of an event. We assume that if a class of entities contains possible participants in an event, then the instances of all sub-classes are possible participants in the same kind of event. The original relations are trusted to be valid, because they were annotated manually in the semantically annotated treebank. Another important assumption is that the relations found in the treebank are not the most general ones, which means that there is room for generalization over the participants in these events.

Thus, in addition to the extension of the dependency relations outlined above, we did a further enrichment of the knowledge base by taking the hypernym of the node of interest in the syntactic relation and then taking all nodes beneath it in the hypernym hierarchy, and inserting them in



Figure 1: Traversing the hypernymy hierarchy, an example.

the relevant relation attested in the golden corpus. Returning to the example from above in order to illustrate this strategy, we identify the "revelry" node ("unrestrained merrymaking") as subject of the "continue" node, then we go one level up to its hypernym, which is "merrymaking" ("a boisterous celebration; a merry festivity"), and extend the *nsubj* relation from there downwards the hierarchy. Thus, the hyponym sense "jinks" ("noisy and mischievous merrymaking") is also inserted in the *nsubj* relation with the relevant sense of the verb "continue". This extension leads to an additional significant increase in the size of the knowledge base.

Figure 1 illustrates the described hierarchy as a simple tree. The bolded term ("revelry") is the node we want to use to expand the *nsubj* relation. The expanding procedure finds the hypernym of that node ("merrymaking"), then takes all the nodes below it and inserts them in the same type of relation, in place of "revelry". In this way, multiple relations can be derived from the initial *nsubj* relation.

Finally, we have used information about WordNet domains, e.g. biology, linguistics, time_period, etc. An initial experiment was run whereby all synsets in a given domain were entered in a relation with the domain. Unique WordNet-style IDs were generated for all domains and the relevant synsets were connected to those nodes. This approach yielded poor results, possibly due to the fact that in the PageRank algorithm the contribution of a node weakens the more outgoing edges it has, and the artifical domain nodes have hundreds of outgoing links. Thus, an alternative strategy was adopted of connecting all synsets within a domain to each other. In order to avoid generating many millions of new relations, only the synsets in the Bulgarian dictionary were connected in this fashion. This resulted in 132,596 new relations. The hierarchical relations between

⁷Here we interpret the concept of "event" in a wider sense that also includes states.

domains were also added to the graph, e.g. "grammar" is a hyponym of "linguistics".

5.3 Experimental Setup and Results

Several different versions of the relations graph were used in the experiments with the UKB tool. Those configurations that use relations independently of the corpus (i.e. ontological and definitional) were tested on the full corpus of 40 files. Most of the texts in the corpus are journalistic articles, but there are a number of texts from literary, academic, legal and other sources. Those configurations that include context-dependent relations were tested on a test portion of the corpus comprising of 3 large files with journalistic articles. The syntactic depedency relations and their extensions used in these configurations were extracted and constructed from the development portion of the corpus, i.e. the remaining 37 files.

This is a short description of the different configurations for the graph:

- WN: WordNet relations
- WNG: WordNet relations + relations from the glosses
- WNI: WordNet relations + inferred hypernymy relations
- WNGI: WordNet relations + relations from the glosses + inferred hypernymy relations
- WNGID1: WordNet relations + relations from the glosses + inferred hypernymy relations + domain relations of the kind synsetto-domain and domain hierarchy relations
- WNGID2: WordNet relations + relations from the glosses + inferred hypernymy relations + domain relations of the kind synsetto-synset and domain hierarchy relations
- WNGIS: WordNet relations + relations from the glosses + inferred hypernymy relations + dependency relations from the golden corpus
- WNGISE: WordNet relations + relations from the glosses + inferred hypernymy relations + dependency relations from the golden corpus + extended dependency relations
- WNGISED1: WordNet relations + relations from the glosses + inferred hypernymy relations + dependency relations from the

golden corpus + extended dependency relations + domain relations of the kind synsetto-domain and domain hierarchy relations

- WNGISED2: WordNet relations + relations from the glosses + inferred hypernymy relations + dependency relations from the golden corpus + extended dependency relations + domain relations of the kind synset-to-synset and domain hierarchy relations
- WNGISEUD2: WordNet relations + relations from the glosses + inferred hypernymy relations + dependency relations from the golden corpus + extended dependency relations starting from one level up + domain relations of the kind synset-to-synset and domain hierarchy relations

Table 1 shows the results obtained after running the UKB tool on all texts in the corpus and only with WordNet-induced relations, while table 2 shows the results on the test set and with all relations (WordNet-induced and corpus-induced). The "Recall" column presents results according to the formula:

(CORRECT DECISIONS + INCORRECT DE-CISIONS) / (ALL DECISIONS + FALSE NEGA-TIVES)

As evidenced by the "Recall" column, about 6% of the word forms with gold senses are not tagged at all by the UKB tool (which results in the false negatives). The reasons for this are not completely clear at this moment; possible culprits could be inconsistencies between the lemmatizer and the dictionary or some option of the tool not to output decisions for words that cannot be disambiguated. We are currently working to solve this issue; the solution would possibly lead to a further increase in accuracy (e.g. decision making based on frequency counts can be used as a fall-back disambiguation mechanism).

Config	Accuracy	Recall
WN	0.516	0.942
WNG	0.542	0.942
WNI	0.537	0.942
WNGI	0.549	0.942
WNGID1	0.549	0.942
WNGID2	0.551	0.942

Table 1:	Results on the full corpus	
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Config	Accuracy	Recall
WN	0.517	0.940
WNG	0.538	0.940
WNI	0.535	0.940
WNGI	0.537	0.940
WNGID1	0.538	0.940
WNGID2	0.550	0.940
WNGIS	0.565	0.941
WNGISE	0.616	0.941
WNGISED1	0.617	0.941
WNGISED2	0.624	0.941
WNGISEUD2	0.656	0.941

Table 2: Results on the test portion of the corpus

Several interesting facts can be observed from the two tables. With regards to just the contextindependent configurations, it is evident that the inferred hypernymy relations help increase accuracy when added on top of the WordNet ontological relations alone; however, the relations derived from the glosses are more effective and the two sets of relations do not seem to complement each other, i.e. the addition to inferred hypernymies to the gloss similarity relations does not improve the results.

Secondly, the addition of domain relations does not contribute significantly when all synsets are linked to the domain nodes. Linking all synsets in a domain with each other, however, causes significant improvement, both in the case of contextindependent configurations, and when combined with dependency relations (one such configuration gives the highest accuracy for all experiments).

The last and perhaps most important insight concerns the impact of syntactic information on WSD. Adding the dependency relations extracted from the golden corpus results in close to 3% improvement, while the addition of the downwards extended set adds a further improvement of 5%; extending the set by starting from one level above the original nodes in the dependency relations helps even more. Contextual information accounts for about 10% higher accuracy in the experiment done with the last configuration.

6 Conclusion

The paper demonstrates that the inclusion of additional linguistic knowledge to a graph-based experimental setting increases the accuracy of the WSD module for Bulgarian. The incorporation of additional hypernymy and domain relations from WordNet, as well as syntactic Universal Dependency relations from the BulTreeBank, improves WSD significantly. However, the algorithm performance drops in terms of speed with the addition of links to the graph, and optimization is needed in order to handle the increased space of relations.

The experiments also demonstrate that, given the availability of appropriate language resources, a graph model for one language (in our case English) can be successfully adapted to another language (in our case Bulgarian).

Our future work on WSD for Bulgarian will be focused on: adding more syntactic relations to the setting, adding the information from the mappedto-WordNet adjectives and adverbs, adding more context related features, trying to link WordNet relations with additional resources (e.g. Wikipedia, FrameNet, etc.), experimenting with the fine options of the UKB tool.

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