Abstract

This paper presents a novel automatic approach to partially integrate FrameNet and WordNet. In that way we expect to extend FrameNet coverage, to enrich WordNet with frame semantic information and possibly to extend FrameNet to languages other than English. The method uses a knowledge-based Word Sense Disambiguation algorithm for matching the FrameNet lexical units to WordNet synsets. Specifically, we exploit a graph-based Word Sense Disambiguation algorithm that uses a large-scale knowledge-base derived from existing semantic resources. We have developed and tested additional versions of this algorithm showing substantial improvements over state-of-the-art results. Finally, we show some examples and figures of the resulting semantic resource.

1. Introduction

Building large and rich predicate models for broad-coverage semantic processing as FrameNet (Baker et al., 1998), VerbNet (Kipper, 2005) or PropBank (Palmer et al., 2005) takes a great deal of expensive manual effort involving large research groups during long periods of development. In fact, the coverage of currently available predicate-argument resources is still unsatisfactory. For example, (Burchardt et al., 2005) or (Shen and Lapata, 2007) indicate the limited coverage of FrameNet as one of the main problems of this resource. Currently, FrameNet1.3 covers around 10,000 lexical-units while for instance, WordNet3.0 contains 206,941 word senses. Furthermore, the same effort should be invested for each different language (Subirats and Petruck, 2003). Following the line of previous works, we empirically study a novel approach to partially integrate FrameNet (Baker et al., 1998) and WordNet (Fellbaum, 1998). The method relies on the use of a knowledge-based Word Sense Disambiguation (WSD) algorithm that uses a large-scale graph of concepts derived from WordNet (Fellbaum, 1998) and eXtented WordNet (Mihalcea and Moldovan, 2001). The WSD algorithm is applied to coherent groupings of words belonging to the same frame. In that way we expect to extend the coverage of FrameNet (by including closely related concepts from WordNet), to enrich WordNet with frame semantic information (by porting frame information to WordNet) and to extend FrameNet to languages other than English (by exploiting local wordnets aligned to the English WordNet).

FrameNet 2 (Baker et al., 1998) is a very rich semantic resource that contains descriptions and corpus annotations of English words following the paradigm of Frame Semantics (Fillmore, 1976). In frame semantics, a Frame corresponds to a scenario that involves the interaction of a set of typical participants, playing a particular role in the scenario. FrameNet groups words or Lexical Units (LUs hereinafter) into coherent semantic classes or frames, and each frame is further characterized by a list of participants or Frame Elements (FEs hereinafter). Different senses for a word are represented in FrameNet by assigning different frames. Currently, FrameNet represents more than 10,000 LUs and 825 frames. More than 6,100 of these LUs also provide linguistically annotated corpus examples. However, only 722 frames have associated a LU. From those, only 9,360 LUs 3 where recognized by WordNet (around 92%) corresponding to only 708 frames. LUs of a frame can be nouns, verbs, adjectives and adverbs representing a coherent and closely related set

1 http://wordnet.princeton.edu/

2 http://framenet.icsi.berkeley.edu/

3 Word-frame pairs
of meanings that can be viewed as a small semantic field. For example, the frame LEADERSHIP contains LUs referring to the leadership activity and their participants. It is evoked by LUs like lead.v, governed.v, led.v, and governed.v, etc. The frame also defines core semantic roles (or FEs) such as GOVERNED or LEADER that are semantic participants of the frame. Note that some FEs also correspond to LUs associated to frame (see example below).

The paper is organized as follows. After this short introduction, in section 2, we present a brief summary of the method used to integrate WordNet and FrameNet and the evaluation made in previous works. Section 3. shows how we build a new multilingual resource that extends the coverage of the Lexical Units of FrameNet, and finally, in section 4., we draw some final conclusions and outline future work.

2. Building WordFrameNet

WordFrameNet (Laparra et al., 2010) is a new resource that combines knowledge from FrameNet and WordNet. In order to connect both resources we used a knowledge-based Word Sense Disambiguation algorithm for assigning appropriate WordNet synsets to the FrameNet lexical units. Specifically, we exploit a graph-based Word Sense Disambiguation algorithm called SSI-Dijkstra+, (Laparra et al., 2010) that is an advanced version of the Structural Semantic Interconnections algorithm (SSI) (Navigli and Velardi, 2005). SSI is a very simple algorithm consisting on an initialization step and a set of iterative steps.

Given W, an ordered list of words to be disambiguated, the SSI algorithm performs as follows. During the initialization step, all monosemous words are included into the set I of already interpreted words, and the polysemous words are included in P (all of them pending to be disambiguated). At each step, the set I is used to disambiguate one word of P, selecting the word sense which is closer to the set I of already disambiguated words. Once a sense is disambiguated, the word sense is removed from P and included into I. The algorithm finishes when no more pending words remain in P.

As SSI-Dijkstra (Cuadros and Rigau, 2008), in order to measure the proximity of one synset (of the word to be disambiguated at each step) to a set of synsets (those word senses already interpreted in I), SSI-Dijkstra+ uses as a knowledge base a very large connected graph with 99,635 nodes (synsets) and 636,077 edges (the set of relations between synsets gathered from WordNet\(^4\) (Fellbaum, 1998) and eXtended WordNet\(^5\) (Mihalcea and Moldovan, 2001). For building this graph we used WordNet version 1.6 and the semantic relations appearing between synsets and disambiguated glosses of WordNet 1.7. To map the relations appearing in eXtended WordNet to WordNet version 1.6 we used the automatic WordNet Mappings\(^6\) (Daudé et al., 2003). SSI-Dijkstra+ uses the Dijkstra algorithm to obtain the shortest path distance between a node and some nodes of the whole graph. The Dijkstra algorithm is a greedy algorithm that computes the shortest path distance between one node and the rest of nodes of a graph. BoostGraph\(^7\) library can be used to compute very efficiently the shortest distance between any two given nodes on very large graphs. On that graph, SSI-Dijkstra computes several times the Dijkstra algorithm.

Initially, the list I of interpreted words should include the senses of the monosemous words in W, or a fixed set of word senses. Note that when disambiguating a Lexical Unit to a particular synset, the list I always includes since the beginning at least the sense of the LU and the rest of monosemous words of W. However, many frames only group polysemous LUs. In fact, a total of 190 frames (around 26%) only have polysemous LUs. Thus, SSI-Dijkstra provides no results when there are no monosemous terms in W. In this case, before applying SSI, the set of the LUs corresponding to a frame (the words included in W) have been ordered by polysemy degree. That is, the less polysemous words in W are processed first.

Obviously, if no monosemous words are found, we need to adapt the SSI algorithm. In order to make an initial guess, we devised four different options trying to initialize the set I with the most probable sense of the less ambiguous word of W. These four different versions of the algorithm are explained in depth in (Laparra and Rigau, 2009) and (Laparra et al., 2010). We have evaluated the performance of the different versions of the SSI-Dijkstra algorithm using the same data set used by (Tonelli and Pianta, 2009). This data set consists of a total of 372 LUs corresponding to 372 different frames from FrameNet1.3 (one LU per frame). Each LU has been manually annotated with the corresponding WordNet 1.6 synset. This Gold Standard includes 9 frames (5 verbs and 4 nouns) with

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\(^4\)http://wordnet.princeton.edu
\(^5\)http://xwn.hlt.utdallas.edu
\(^6\)http://www.lsi.upc.es/~nlp/tools/mapping.html
\(^7\)http://www.boost.org/doc/libs/1_35_0/libs/graph/doc/index.html
only one LU (the one that has been sense annotated). Obviously, for these cases, our approach will produce no results since no context words can be used to help the disambiguation process.\footnote{In fact, FrameNet has 33 frames with only one LU, and 63 with only two.}

As expected, the SSI-Dijkstra algorithms present different performances according to the different POS (Laparra and Rigau, 2009) and (Laparra et al., 2010). Also as expected, verbs seem to be more difficult than nouns and adjectives as reflected by both the results of the baseline and the SSI-Dijkstra algorithms.

As a result of the empirical study presented in (Laparra et al., 2010), we developed SSI-Dijkstra+ a new version of SSI-Dijkstra combining the strategies of the two versions of the algorithm that perform better.

Table 1 presents detailed results per Part-of-Speech (POS) of the performance of the SSI-Dijkstra algorithm on the Gold Standard in terms of Precision (P), Recall (R) and F1 measure (harmonic mean of recall and precision). As baseline, we also include the performance measured on this data set of the most frequent sense according to the WordNet sense ranking (\textit{wn-mfs}). Remember that this baseline is very competitive in WSD tasks, and it is extremely hard to beat upon even slightly (McCarthy et al., 2004). In order to show the improvement over the original SSI-Dijkstra algorithm we also include in this table the results obtained by in the same dataset. Notice that the original SSI-Dijkstra algorithm achieves a higher precision but a lower recall than SSI-Dijkstra+, because of the frames containing only polysemous words.

Table 2 presents detailed results of the performance of the SSI-Dijkstra+ algorithm on the FrameNet–WordNet Verbal mapping (VM) produced by (Shi and Mihalcea, 2005) in terms of Precision (P), Recall (R) and F1 measure. Again, we include on the results obtained by the original SSI-Dijkstra algorithm in this dataset and also the most frequent sense according to the WordNet sense ranking (\textit{wn-mfs}).

On this dataset, the overall results are much higher because this dataset provides several correct verbal senses per LU. Again, the knowledge-based WSD algorithms perform over the most frequent sense baseline.

In fact, we expect much better results performing the disambiguation process including in I, when available, the manually assigned FrameNet–WordNet verbal mappings. Possibly, using this approach very high accuracies for nouns, adjectives and the remaining verbs could be obtained.

|       | P   | R   | F   |
|-------|-----|-----|-----|
| mfs-wn | 0.67| 0.67| 0.67|
| SSI-Dijkstra | 0.79| 0.74| 0.76|
| SSI-Dijkstra+ | 0.79| 0.79| 0.79|

Table 2: Results using FN–WN Verbal mapping from (Shi and Mihalcea, 2005) as gold standard

3. Building eXtended WordFrameNet

After the the integration of WordNet and FrameNet, we have extended WordFrameNet enlarging the coverage of the original FrameNet lexicon and automatically building new local wordframnets for other languages by using the wordnets integrated in the Multilingual Central Repository (MCR)\footnote{Available at http://adimen.si.ehu.es/web/WordFrameNet} (Atserias et al., 2004). We call this new resource eXtended WordFrameNet\footnote{http://adimen.si.ehu.es/web/MCR}.

First, we have extended the coverage of FrameNet. That is, by establishing synset mappings to the FrameNet LUs, we can also add their corresponding synonyms to the frame. For instance, the frame LEADERSHIP only considers \textit{prime minister.n} and \textit{premier.n}, but not \textit{chancellor.n} which is a synonym in WordNet of those LUs. Thus, while the original FrameNet have 9,328 LUs corresponding to 6,565 synsets, eXtended WordFrameNet have 20,587 LUs. That is, more than the double. Table 4 shows the original and new LUs for the LEADERSHIP frame. In this case, 63 of the original LUs have been associated to WN synsets, thus producing 75 new LUs for this frame.

We also automatically have extended WordFrameNet to languages other than English by exploiting local wordnets aligned to the English WordNet. For instance, the Spanish synset aligned to \textit{<prime minister, premier, chancellor>} is \textit{<primer ministro, canciller>} and the Italian one is \textit{<primo ministro>}. We have already generated a WordFrameNet for four different languages: Spanish, Italian, Basque and Catalan. Table 3 shows the volumes of LUs for each one of these resources. Specifically, in Spanish, we obtain a WordFrameNet with 14,106 LUs. In fact, the current version of the Spanish FrameNet consists of 308 frames with 1,047 LUs\footnote{http://gemini.uab.es:9080/SFNsite/sfn-data/current-project-status} (Subirats and Petruck, 2003). For instance, Table 4 presents a partial view of the four versions of WordFrameNet corresponding to the LEADERSHIP...
frame. In this case, 96 Spanish LUs have been associated to this particular frame, while the current version of the Spanish FrameNet does not contain this frame.

|            | nouns   | verbs   | adjectives | all     |
|------------|---------|---------|------------|---------|
|            | P   | R   | F   | P   | R   | F   | P   | R   | F   | P   | R   | F   |
| wn-mfs     | 0.75 | 0.75 | 0.75 | 0.64 | 0.64 | 0.64 | 0.80 | 0.80 | 0.80 | 0.69 | 0.69 | 0.69 |
| SSI-Dijkstra | 0.84 | 0.65 | 0.73 | 0.70 | 0.56 | 0.62 | 0.90 | 0.82 | 0.86 | 0.78 | 0.63 | 0.69 |
| SSI-Dijkstra+ | 0.79 | 0.77 | 0.78 | 0.70 | 0.68 | 0.69 | 0.89 | 0.89 | 0.89 | 0.76 | 0.74 | 0.75 |

Table 1: Results of SSI algorithms on the GS dataset

Furthermore, we have also transported to the disambiguated LUs the knowledge currently available from other semantic resources integrated in the MCR such as SUMO (Niles and Pease, 2001), WordNet Domains (Magnini and Cavaglìa, 2000), etc. For instance, now the LU corresponding to premier.n can also have associated the SUMO label OccupationalRole and its corresponding logical axioms, and the WordNet Domains person and politics. Note that when integrating multiple semantic resources such as FrameNet, WordNet and SUMO, multiple discrepancies may arise. Possibly this process can also help to improve the involved knowledge resources.

4. Conclusions and future work

We have presented an ongoing work aiming to integrate FrameNet and WordNet. The method uses a knowledge based Word Sense Disambiguation (WSD) algorithm called SSI-Dijkstra+ for assigning the appropriate synset of WordNet to the semantically related Lexical Units of a given frame from FrameNet. This algorithm relies on the use of a large knowledge base derived from WordNet and eXtended WordNet. Since the original SSI-Dijkstra requires a set of monosemous or already interpreted words, we have devised, developed and empirically tested different versions of this algorithm to deal with sets having only polysemous words. The resulting new algorithms obtain improved results over state-of-the-art. The integration of FrameNet and WordNet allows to extend the current LUs coverage. In fact, it also allows to locate conceptual areas currently uncovered by FrameNet frames. We also expect to improve the performance of the disambiguation process by using the definitions associated to the LUs. We also plan to disambiguate the Frame Elements and its corresponding definitions of a given frame. Thus, the resulting resource will also integrate the core semantic roles of FrameNet. For example, for the frame LEADERSHIP we will associate the appropriate WordNet synsets to the Frame Elements LEADER or GOVERNED. Finally, we also plan to provide WordFrameNet versions aligned to WordNet3.0 by using also the relations from the semantically annotated "gloss corpus".

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| FrameNet | Synset   | SUMO | WordFrameNet | SpanishWFN | ItalianWFN | BasqueWFN | CatalanWFN |
|----------|----------|------|--------------|------------|------------|-----------|------------|
| lead.v   | 01364494-v | Guiding | lead take direct guide | llevar | portare | carrar | dirigar |
| command.v | 01662860-v | Managing | command control | controlar | governare | murrartu | controlar |
| rule.v   | 01763262-v | Guiding | govern rule | gobernar | governare | gobernara | governar |
| power.n  | 04041746-n | Subjective-Assessment-Attribute | power powerfulness potency | potenza | potenza | potenza | potencia |
| authority.n | 04045518-n | NormalAttribute | authority dominance say-so | autoridad dominio dominación | autorità autorevolezza | autoritate eskumen | autoritad dominio |
| government.n | 06000383-n | Government | government regime authorities | gobierno régimen | gobierno autorità | goberna erregimen | govern régim |
| leader.n | 06950891-n | Human | leader | líder dirigente autoridad | líder | líder | líder |
| prime_minister.n | 07147791-n | OccupationRole | prime_minister premier chancellor | primer_ministro canceller | primo_ministro | lehen_ministro | primer_ministre |
| rector.n | 07196655-n | OccupationRole | rector pastor minister parson curate | rector párroco vicario | rettore curato | errettore ministro | rector curat |
| chief.n | 07311393-n | SocialRole | chief head top dog | responsable cabeza | responsable capo comandante | arduradun erantzule | responsable cap director_d’escola |
| overlord.n | 07451093-n | SocialRole | overlord lord master | amo señor | dominatore capo supremo | nagusi jaun | senyor amo |
| chairman.n | 07496412-n | SocialRole | chairman chairperson chairwoman president chair | presidente moderador | presidente presidentessa | lehendakari buru presidente | president moderador |
| ruler.n | 07539836-n | SocialRole | ruler governor | gobernador gobernante | reggitore governante | gobernataile gobernador | governant gobernador |
| monarch.n | 07593596-n | SocialRole | monarch sovereign crowned_head | monarca soberano | re regnante sovereign sovrano | monarka subirano | monarca sobraria |

Table 4: Partial content of the frame LEADERSHIP in eXtended WordFrameNet

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