Disambiguating prepositional phrase attachment sites with sense information captured in contextualized distributional data

Clayton Greenberg

Department of Computational Linguistics and Phonetics Saarland University



Introduction

Determining the governor of a prepositional phrase (PP) is a well-studied parsing problem:



Classification

We adopt the four step procedure from Zhao and Lin (2004):

- 1. Consider only the training examples for which all four words are equal to those in the test quadruple.
- 2. Consider the *k* highest training examples (same preposition) with highest score: $sim(q_1, q_2) = vn_1 + vn_2 + n_1n_2$
- 3. Same as (2), except using: $sim(q_1, q_2) = v + n_1 + n_2$
- 4. Assign the default class for the preposition, or noun-attach if there is no default class.



We simplify the problem to a binary classification on quadruples of the form (V, N_1 , P, N_2). In cases such as the above example, the senses of the words in the quadruple interact with the proper attachment classification.

Previous systems have implicitly weighted senses by frequency (Zhao and Lin 2004) or performed explicit word sense disambiguation using WordNet (Stetina and Nagao 1997). Both of these approaches are problematic because while sense information is crucial, the task of explicit word sense disambiguation (WSD) has lower accuracy than the original task.

| For the wor | d-word similarities, we test four metrics: |
|------------------------|--|
| abs: | token similarity |
| noctxt: | uncontextualized vectors |
| ctxt _{auad} : | contextualized vectors using quadruple words only |
| ctxt _{sent} : | contextualized vectors using all words from sentence |

Results

| Similarity measure | k value | Accuracy |
|--------------------|---------|----------|
| abs | 3 | 80.2% |
| noctxt | 11 | 86.6% |
| $ctxt_{quad}$ | 10 | 88.4% |
| $ctxt_{sent}$ | 8 | 81.9% |

| Step | Coverage | Coverage % | Accuracy |
|------|----------|------------|----------|
| 1 | 244 | 7.88% | 91.8% |
| 2 | 2849 | 91.99% | 88.1% |
| 3 | 0 | 0.00% | N/A |
| 4 | 4 | 0.13% | 100.0% |

Corpus and model

Ratnaparkhi Reynar and Roukos (1994) extracted 27,937 quadruples from the Penn Treebank.This corpus has become a standard in the PP-attachment disambiguation literature.However, many systems preprocessed or edited the corpus, clouding comparability.For direct comparison with Zhao and Lin (2004), we lemmatize and replace numbers with *@*.

Dinu and Thater (2012) implemented a vector space model based on the GigaWord corpus. We use the "filtered" version, so co-occurrences are linked to target words in dependency parses.

The contextualization function is $v(w,c) = \sum_{w' \in W} \alpha(c, w') f(w, w') \vec{e}_{w'}$

where w is the target word, c is the context, W is the set of words, α is the cosine similarity of c and w', f is a co-occurrence function, and e_w , is a basis vector.



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| Method | Sense handling | Accuracy |
|------------|-------------------|----------|
| BR1994 | All senses equal | 81.8% |
| PL2000 | Global frequency | 84.3% |
| ZL2004 | Global frequency | 86.5% |
| SN1997 | Full WSD | 88.1% |
| Our system | Context weighting | 88.4% |
| G2013 | Full WSD | 89.0% |

Discussion and conclusion

Improvement over uncontextualized system is statistically significant at p < 0.04 level. Using the full sentence as context is harmful, most likely due to data sparsity. This system uses only a task-general knowledge base, whereas the highest performing system (Greenberg 2013) requires task-specific resources and labor intensive modifications to training data.

Implicit handling of sense information seems preferable to using frequencies or full WSD. In future work, we would like to investigate ways to extend the context beyond the quadruple, ideally to whole documents, without losing information as observed here.

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