

Don't Neglect the Obvious: On the Role of Unambiguous Words in Word Sense Disambiguation

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Abstract

State-of-the-art methods for Word Sense Disambiguation (WSD) combine two different features: the power of pre-trained language models and a propagation method to extend the coverage of such models. This propagation is needed as current sense-annotated corpora lack coverage of many instances in the underlying sense inventory (usually WordNet). At the same time, unambiguous words make for a large portion of all words in WordNet, while being poorly covered in existing sense-annotated corpora. In this paper we propose a simple method to provide annotations for most unambiguous words in a large corpus. We introduce the UWA (Unambiguous Word Annotations) dataset and show how a state-of-the-art propagation-based model can use it to extend the coverage and quality of its word sense embeddings by a significant margin, improving on its original results on WSD.

1 Introduction

There has been a lot of progress in word sense disambiguation (WSD) recently. This progress has been driven by two factors: (1) the introduction of large pre-trained transformer-based language models and (2) propagation algorithms that extends the coverage of existing training sets. The gains due to pre-trained Neural Language Models (NLMs) such as BERT (Devlin et al., 2019) have been outstanding, helping reach levels close to human performance when training data is available. These models are generally based on a nearest neighbours strategy, where each sense is represented by a vector, exploiting the contextualized embeddings of these NLMs (Melamud et al., 2016; Peters et al., 2018; Loureiro and Jorge, 2019). However, training data for WSD is hard to obtain, and the most widely used training set nowadays, based on WordNet, dates back from the 90's (Miller et al., 1993,

SemCor). This lack of curated data produces the so-called knowledge-acquisition bottleneck (Gale et al., 1992; Navigli, 2009).

To overcome this issue, in this paper we propose a very simple approach that has not been explored in the literature. There is a key source of information that has been neglected so far in existing sense-annotated corpora and propagation methods, which is the presence of unambiguous words from the underlying knowledge resource. Strikingly, WordNet, which is known to be a comprehensive resource, is mostly composed of unambiguous entries (30k lemmas are ambiguous, compared to 116k unambiguous). While the lack of unambiguous annotations does not have a direct effect in WSD, the fact that these unambiguous words are part of the same semantic network means they can have an effect on ambiguous words via standard propagation algorithms. These propagation algorithms start from a seed of senses occurring in the training data (and therefore their embeddings can be directly computed) and then propagate to the whole sense inventory via the semantic network (Vial et al., 2018; Loureiro and Jorge, 2019). Consequently, computing sense embeddings for unambiguous words can increase the number of seeds and improve the whole process.

Covering these unambiguous words, however, is not an arduous task, as unlabelled corpora may suffice. We explore this hypothesis by labeling a large amount of unambiguous words in corpora extracted from the web, using WordNet as our reference sense inventory. While we can certainly find other usages of a word which are not covered by WordNet, we found that our approach is comprehensive enough to get accurate occurrences with simple heuristics.

In general, the contribution of this paper is twofold. First, we devise a simple methodology to construct UWA (Unambiguous Word Annota-

tions), a large and, most importantly, diverse sense-annotated corpus that focuses on WordNet unambiguous words. Second, we show that by leveraging UWA, we can attain important improvements in a state-of-the-art WSD model.

2 Related Work

Constructing sense-annotated corpora, either automatically or semi-automatically, is the most common way of addressing the knowledge-acquisition bottleneck. One of the earlier examples of such approaches is *One Million Sense-Tagged Instances* (Taghipour and Ng, 2015, OMSTI). This corpus was constructed by exploiting the alignments of an English-Chinese parallel corpus. Similarly, Delli Bovi et al. (2017) presented EuroSense, a multilingual sense-annotated corpus constructed by using the Europarl parallel corpus for 21 languages as reference. The main issue with these approaches is their reliance on parallel corpora for two or more languages. In contrast, our proposed method is flexible and can be applied to any kind of unlabeled monolingual corpora.

Recent works propose other automatic methods that exploit knowledge from Wikipedia such as NASARI vectors (Camacho-Collados et al., 2016) for providing sense annotations for concepts and entities (Scarlini et al., 2019; Pasini and Navigli, 2019). In the case of Scarlini et al. (2019), and similarly to Raganato et al. (2016), their method further requires a Wikipedia corpus, including its hyperlinks and category information, hence making it not extensible to other kinds of corpora.¹ As our model exploits unambiguous senses, we are not constrained to only nouns, knowledge from Wikipedia or a specific corpus.

Moreover, as we will show, our methodology is aimed at significantly extending the coverage of existing manually sense-annotated corpora such as SemCor (Miller et al., 1993). This is not the main focus of these approaches, which mainly provide a higher average of examples of those word senses already available in SemCor, without significantly extending its coverage.

3 Methodology

In this section we first explain our method to construct a corpus with unambiguous word annotations (Section 3.1). Then, we explain current models

¹Pasini and Camacho-Collados (2020) provide a more detailed overview of existing sense-annotated corpora.

based on Neural Language Models (NLMs) to perform WSD by exploiting sense annotations, both ambiguous and non-ambiguous (Section 3.2). Finally, we present a propagation method employed to infer additional OOV sense representations (Section 3.3).

3.1 Unambiguous Word Annotations (UWA)

In order to properly test our hypothesis, we first require a sizable compilation of unambiguous words in context, particularly words that correspond to lemmas covered by WordNet. The extensiveness of WordNet means that most of its lemmas occur very rarely, and thus require processing proportionately large volumes of texts to achieve a high coverage. As such, in this work we develop the Unambiguous Word Annotations (UWA) corpus based on OpenWebText (Gokaslan and Cohen, 2019) and English Wikipedia (November 2019), processing over 53GB of texts from the web.

Each text is automatically annotated for lemmas and part-of-speech using the state-of-the-art Stanford CoreNLP toolkit (Manning et al., 2014). The annotations are filtered so that we only consider lemma/part-of-speech pairs that are present in WordNet, and correspond to a single sense (hence unambiguous), e.g., ‘keypad/noun’. Naturally, some lemma/part-of-speech pairs may have additional meanings not covered in WordNet. For example, in “*Inception* was a box-office hit.”, *Inception* makes reference to a movie and not to the unambiguous word *inception* from WordNet. To mitigate this issue, we also applied Named Entity Recognition (NER) tagging, using spaCy (Honnibal and Montani, 2017), to filter out lemmas that are recognized as entities but do not correspond to an entity in their WordNet sense. To this end, we leverage the entity annotations of WordNet synsets available in BabelNet (Navigli and Ponzetto, 2012). Due to the Zipfian nature of word distributions, a minority of lemmas occurs much more often than the rest. To keep the corpus at a reasonable size, we cutoff the maximum number of associated sentences (examples henceforth) per sense at 100.

Release. The full version of UWA, including WordNet sense embeddings, is freely available at <http://danlou.github.io/uwa>

Statistics. UWA covers a total of 98,494 senses, where 56.7% have 100 examples, and 81.2% have at least 10 examples. In Table 1 we show that UWA covers most senses for unambiguous words and,

Corpus	# Instances		Avg # Exs	Coverage (w/ SC)		
	Amb	Unamb		Amb	Unamb	Total
SemCor	198,153	27,883	6.8	26.2	7.4	16.1
OMSTI	909,830	1,304	244.7	26.8	7.4	16.4
T-o-M	719,888	114,580	152.4	28.5	7.5	17.2
UWA(1)	0	98,494	1.0	26.2	82.9	56.7
UWA(10)	0	804,861	8.8	26.2	82.9	56.7
UWA(all)	0	6,111,453	54.1	26.2	82.9	56.7

Table 1: Number of instances, average number of examples per word sense, and coverage percentage (including SemCor) of various sense-annotated corpora.

combined with SemCor, includes most senses in WordNet. This contrasts with other automatically-constructed datasets such as OMSTI (Taghipour and Ng, 2015) or T-o-M (Pasini and Navigli, 2019). These sense-annotated corpora, not aimed specifically at unambiguous words, have limited coverage in this respect, as they are mainly composed of annotations for senses already available in SemCor.

3.2 Neural Language Models for WSD

Recent NLMs, such as ELMo (Peters et al., 2018) and BERT (Devlin et al., 2019), have been used with a high degree of success on WSD. They have been used differently depending on the nature of the disambiguation task: as feature providers for other neural architectures (Vial et al., 2019), simple classifiers after fine-tuning (Wang et al., 2019), or as generators of contextual embeddings to be matched through nearest neighbours (Melamud et al., 2016; Peters et al., 2018; Loureiro and Jorge, 2019; Reif et al., 2019, 1NN). Our experiments in this paper will focus on improving the latter type of approach. In particular, we will investigate the state-of-the-art LMMS model (Loureiro and Jorge, 2019). This model learns sense embeddings which are based on BERT states, and propagated using WordNet’s ontology to infer additional senses, effectively providing a full coverage of the underlying resource. While Loureiro and Jorge (2019) proposed variants of LMMS that combined propagation with gloss embeddings, or static embeddings, this paper is only concerned with the propagation method.

In our case, we essentially follow LMMS’s layer pooling method to generate contextual embeddings for each sense occurrence in context (from a training set), and derive sense embeddings from the average of all corresponding contextual embeddings.

3.3 Network Propagation for Full-Coverage

The propagation method used in LMMS exploits the WordNet ontology to obtain a full coverage of sense embeddings from an initial set of embeddings based on a manually sense-annotated corpus like SemCor. This method explores different abstraction levels represented in WordNet: sets of synonyms (synsets), Is-A relations (hypernyms) and categorical groupings (lexnames²).

Initial sense embeddings are first used to compute synset embeddings as the average of all corresponding senses (analogously to how sense embeddings are computed from contextual embeddings). From that point, missing senses are represented by their corresponding synset embeddings. The remaining unrepresented senses are inferred from their hypernyms and lexname embeddings, computed by averaging their neighbour synset embeddings. Note that this propagation process does not follow transitive relations in WordNet, i.e., a single synset’s hypernym is considered, while the subsequent hypernyms along the path to a root node are ignored.

Since lexname embeddings can always be computed, this process can reach a full-coverage of WordNet starting with just the initial set of embeddings produced using SemCor. However, the set of SemCor embeddings only covers 16.1% of WordNet, so many of the inferred representations are redundant and therefore not entirely meaningful. In Section 5.3 we provide more details on this underlying issue.

4 Evaluation

For our experiments we are interested in verifying the impact of using UWA to improve WSD performance. In particular, in this section we test the unambiguous annotations of UWA as a complement of existing sense-annotated training data to perform WSD. To this end, as explained in Section 3, we make use of the state-of-the-art WSD model LMMS (Loureiro and Jorge, 2019). In addition to the original version using BERT, we also provide results with RoBERTa (Liu et al., 2019) for completeness. We use the 24-layer models for both BERT and RoBERTa (commonly referred to as *large* models).

Table 2 shows the WSD results on the standard evaluation framework of Raganato et al. (2017) for

²Lexnames are also known as supersenses in the literature (Flekova and Gurevych, 2016; Pilehvar et al., 2017).

	Corpus	SE-2	SE-3	SE07	SE13	SE15	ALL
LMMS-BERT	SC-noP.	70.2	71.1	64.7	65.5	70.2	69.0
	SC-only	75.5	74.2	66.8	72.9	75.3	74.0
	OMSTI	73.7	68.8	63.5	73.2	74.8	71.9
	T-o-M	69.9	66.1	62.4	64.8	74.2	67.9
	UWA (1)	77.0	74.2	66.2	73.1	75.4	74.5
	UWA (10)	77.3	74.1	66.2	72.7	75.7	74.5
LMMS-RoBERTa	SC-noP.	70.7	70.6	66.7	65.1	70.5	69.2
	SC-only	76.0	73.6	69.2	72.3	75.9	74.1
	OMSTI	73.4	70.1	66.6	71.5	74.6	71.9
	T-o-M	70.3	65.9	64.8	65.8	74.0	68.4
	UWA (1)	77.8	73.6	68.8	72.0	75.3	74.5
	UWA (10)	77.6	73.7	68.8	72.7	75.3	74.6
SOTA	SC [†] _{LMMS+}	76.3	75.6	68.1	75.1	77.0	75.4
	SC [†] _{Vial et al.}	76.6	76.9	69.0	73.8	75.4	75.4
	SC ^{††} _{EWISE}	73.8	71.1	67.3*	69.4	74.5	71.8
	SC ^{††} _{GlossBERT}	77.7	75.2	72.5*	76.1	80.4	77.0

Table 2: F1 performance on the WSD evaluation framework of Raganato et al. (2017). All corpora marked are concatenated with SemCor (SC). SOTAs reported for reference but not directly comparable due to use of definitions ([†]) or not using a 1NN approach (^{††}). All reported SOTAs are based on BERT trained on SC. Results in datasets that were used as development are marked with *.

the LMMS trained on the concatenation of SemCor and automatically-constructed corpora. In the table we include UWA with two different maximum number of examples per unambiguous word, i.e., 1 and 10. For comparison, we also include the results of EWise (Kumar et al., 2019) and GlossBERT (Huang et al., 2019), which attempt to overcome the limited coverage of SemCor by exploiting textual definitions. As can be observed, the concatenation of our UWA corpus and SemCor provides the best overall results, regardless of the number of examples cut-off. Perhaps surprisingly, our corpus is the only one that provides improvements over the baseline (SemCor-only). This can be explained by the fact that our corpus is the only one that significantly extends the coverage of SemCor, as explained in Section 3.1.

5 Analysis

In this section we attempt to answer three questions: 1) How many examples of unambiguous words are required to see improvements in WSD?; 2) How much is this improvement when we’re not restricting candidate senses?; and finally 3) Can we see a significant difference in the embedding space using UWA?

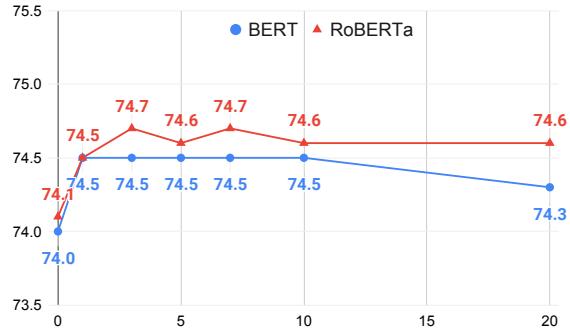


Figure 1: WSD performance (F1 on the unified framework) with different numbers of UWA examples.

5.1 Number of Examples

When compiling examples for learning sense representations, a natural question that arises is: how many examples are required to learn effective representations? The answer to this question can not only guide collection efforts, but also help clarify the requirements for learning effective representations in the simplest setting. To that end, we analyse the impact of using different number of examples from UWA on LMMS’s WSD performance. In Figure 1, we show the performance trend by using different number of examples per sense. As can be seen, performance improves substantially with only one example, and then stops improving after just two examples.

5.2 Uninformed Sense Matching

We test the capabilities of the LMMS model in a WSD setting without external help. In standard WSD benchmarks, models are given the advantage of knowing the pre-defined set of possible senses before-hand. This is because gold PoS tags and lemmas are provided in these datasets. However, to better understand how robust a 1NN WSD model is, we can test it in an uninformed setting, i.e., where PoS tags and lemmas are not given and the model does not have access to the list of candidate senses. Instead, the model has to select senses from the whole sense inventory, unconstrained. Therefore, in this setting we can use additional information retrieval ranking metrics with the predictions of the model (i.e. MRR or P@K) in addition to the standard F1.

Table 3 shows the results in this uninformed setting of LMMS using SemCor and UWA with different maximum numbers of examples. As can be observed, low number of examples, such as 2,

Corpus	BERT			RoBERTa		
	F1	P@5	MRR	F1	P@5	MRR
SC	52.5	67.1	59.2	58.0	72.8	64.7
UWA(1)	55.1	74.1	63.5	61.3	79.8	69.5
UWA(2)	55.5	74.6	64.0	61.8	80.3	70.0
UWA(3)	55.4	74.5	63.9	61.9	80.3	70.0
UWA(5)	55.4	74.4	63.8	62.1	80.3	70.1
UWA(7)	55.2	74.1	63.7	61.9	80.3	70.0
UWA(10)	54.9	74.1	63.5	62.1	80.2	70.1
UWA(20)	54.9	73.7	63.3	62.1	79.9	70.0

Table 3: Uninformed WSD results of the LMMS model using SemCor (SC) and UWA with different example thresholds. Models tested on the concatenation of all WSD datasets of Raganato et al. (2017). As before, UWA is concatenated with SC in this experiment.

already achieves the best overall results. More generally, in this setting the differences with respect to SemCor are more marked. This is expected as the propagation algorithm has a stronger effect in this setting where all sense embeddings are considered.

5.3 Visualization of the Embedding Space

The propagation method used in LMMS is designed to backoff to increasingly abstract representation levels, from synsets, to hypernyms, to supersenses (see Section 3.3). This naturally leads to a clustering effect, where many senses are represented with very similar, or equal, embeddings. In fact, we find that only 22% of sense embeddings learned from SemCor, and propagated following LMMS, are actually unique (remaining are shared by two or more senses). The addition of UWA increases this percentage to 68%.

To better understand this clustering effect, we used T-SNE (Maaten and Hinton, 2008) to visualize the WordNet synset embedding space. In Figure 2 we show synset embeddings learned from the SemCor+UWA(10) dataset, and learned from SemCor alone, both based on RoBERTa. While the same number of synset embeddings are learned in both cases, Semcor+UWA embeddings are better distributed across the vector space. This, in turn, causes a substantial reduction of high-density clusters.

6 Conclusion

Unambiguous words are a surprisingly large portion of existing knowledge resources like WordNet. At the same time, their coverage in existing sense-annotated corpora is very limited. In this

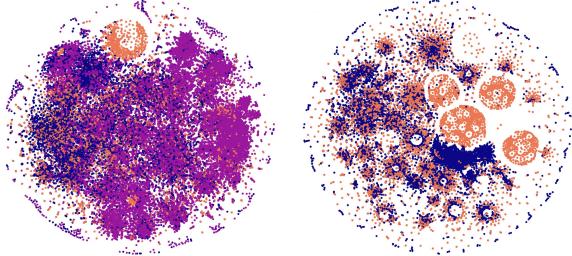


Figure 2: T-SNE comparison of synset embeddings for whole WordNet learned from SC+UWA10 (left), or just SC (right). Colors represent source of annotations for embeddings (● SC ● UWA ● Propagation).

paper we proposed a simple method which exploits sense annotations of unambiguous words from unlabeled corpora, thereby effectively extending existing sense-annotated corpora with low-effort. By leveraging a state-of-the-art BERT-based WSD system that propagates sense embeddings across WordNet, we have shown that these unambiguous words provide an excellent bridge to reach a wider range of OOV senses. This translates, in turn, into improving results for WSD. For future work it would be interesting to test these sense embeddings in a wider range of applications outside WSD. The embedding space is clearly more diversified, as shown in Figure 2, which may lead to improvements in other downstream tasks.

Moreover, one of the most surprising findings from this paper is that a single occurrence of OOV unambiguous words is enough to improve the performance of WSD models. This is relevant as not in all cases a large number of unambiguous words may be retrieved, and in this case this also allows for a cheaper manual verification, if it were required. Finally, as part of our contribution we openly release UWA, a large corpus based on Wikipedia and OpenWebText annotated with unambiguous words.

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