Word Sense Disambiguation with LSTM: Do We Really Need 100 Billion Words?

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Abstract

Recently, Yuan et al. (2016) have shown the effectiveness of using Long Short-Term Memory (LSTM) for performing Word Sense Disambiguation (WSD). Their proposed technique outperformed the previous state-of-the-art with several benchmarks, but neither the training data nor the source code was released. This paper presents the results of a reproduction study of this technique using only openly available datasets (GigaWord, SemCore, OMSTI) and software (TensorFlow). From them, it emerged that state-of-the-art results can be obtained with much less data than hinted by Yuan et al. All code and trained models are made freely available.

1 Introduction

Word Sense Disambiguation (WSD) is a long-established task in the NLP community (Navigli, 2009). Many approaches have been proposed – the more popular ones include the usage of Support Vector Machine (SVM) (Zhong and Ng, 2010), combined with unsupervisedly-trained embeddings (Iacobacci et al., 2016; Rothe and Schütze, 2015), and graph-based approaches (Agirre et al., 2014), which can also be combined with embeddings (Tripodi and Pelillo, 2016).

Recently, Yuan et al. (2016) coupled a Long short-term memory (LSTM) language model (Hochreiter and Schmidhuber, 1997) trained on 100B words with small sense-annotated corpora to achieve state-of-the-art performance in all words WSD. This method was designed to address, in a distant supervision fashion, what is believed to be one central problem in WSD, that is “lack of sufficient labeled training data” (Yuan et al. (2016), first page). This method addresses this problem by training a language model with an LSTM network and a huge unlabeled textual corpus of 100B words, and then construct sense embeddings using a much smaller labeled dataset.

Even though the results obtained by Yuan et al. outperform the previous state-of-the-art, this work has two important limitations: First, neither the datasets nor the models are available to the community and, to the best of our knowledge, there is no other publicly available dataset which comes close to the size of the one used in the work. This is unfortunate because this unavailability makes the re-application of this technique in other contexts a non-trivial process, especially because the input size was indicated as one of the main reason behind the excellent performance. Second, it is unclear which are the problems that prevent even higher accuracies. These problems could be algorithmic, relate to the input (either size or quality), or both. Identifying the nature of these problems is crucial in order to limit the search space for further improvements.

To address these two issues, we reimplemented Yuan et al.’s method with the goal of reproducing and make available the results. While a full replication is not possible due to the unavailability of the original data, our work allowed us to perform a deeper investigation on the actual performance of this technique. This allows us to provide a first, preliminary, answer to the following two questions:

- How sensitive to the amount of training data is a WSD process driven by a large-scale statistical model? In other words, do we really need very large training sets to achieve state-of-the-art performance?
- Are there some limitations that cannot be overcome by using larger training sets?
The contribution of this paper is thus two-fold: On the one side, we present a reproducibility study whose results are publicly available and hence can be freely used by the community. Notice that the lack of available models has been explicitly mentioned, in a recent work, as the cause for the missing comparison of this technique with other competitors (Raganato et al., 2017, footnote 10). On the other side, we investigate on the effective role played by the training set, and report our conclusions to shed more light into the value of this and similar methods.

We anticipate one interesting conclusion that emerged from our analysis, which is that we were able to replicate the same performance as reported in Yuan et al. (2016), but using only a corpus of 1.8B words (GigaWords), which is less than 2% of the data used in the original study.

In the remaining, we proceed as follows: First, we describe the original work in Section 2. Then, we report the methodology for our reproduction study and other technical details in Section 3. The results and related analysis are reported in Section 4. Section 5 concludes the paper.

2 WSD with Language Models

Broadly speaking, the method proposed by Yuan et al. performs WSD by: 1) constructing a language model from a large textual corpus; 2) extracting sense embeddings from this model using a much smaller annotated corpus; 3) rely on the sense embeddings to make predictions in unseen sentences. Each operation is described below.

2.1 Constructing the language model

The first operation consists of constructing a language model that produces embeddings for phrases using a Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997). LSTM is a celebrated recurrent neural network architecture that has proven effective in many natural language processing tasks (Sutskever et al., 2014; Dyer et al., 2015; He et al., 2017, among others). Different from previous networks, LSTM is equipped with trainable gates that control the flow of information, allowing the neural networks to learn both short- and long-range dependencies (we refer the interested reader to the textbook by Goodfellow et al. and (Hochreiter and Schmidhuber, 1997) for more details on this network).

In Yuan et al. (2016), an LSTM neural network is used to capture the meaning of words in context. Given a sentence $s = (w_1, w_2, \ldots, w_n)$, they replace word $w_k$ ($1 \leq k \leq n$) by a special token $\$$. The model takes this new sentence as input and produces a context vector $c$ of dimensionality $p$ (see Figure 1).

![Figure 1: The LSTM model used to perform language modeling and compute context embeddings.](Image)

Each word $w$ in the vocabulary $\mathcal{V}$ is associated with an (output) embedding $\phi_o(w)$ of the same dimensionality.\(^2\) The model is trained to predict the omitted word, minimizing the softmax loss $\ell$ over a big collection of sentences $D$:

$$
\ell = - \sum_{s \in D} \sum_{k=1}^{s} \log \frac{\exp(c \cdot \phi_o(w_k))}{\sum_{w' \in \mathcal{V}} \exp(c \cdot \phi_o(w'))}
$$

After the model is trained, we can use it to extract context embeddings, i.e., latent numerical representations of the sentence surrounding a given word.

2.2 Calculating the sense embeddings

The model produced by the LSTM network is meant to capture the “meaning” of words in the context they are mentioned. In order to perform the sense disambiguation, we need to extract from it a suitable representation for word senses. To this purpose, the method relies on another corpus where each word is annotated with the corresponding sense.

The main intuition is that words intended with the same sense are mentioned in contexts which are very similar to each other. This suggests a simple way to calculate sense embeddings. First, the

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\(^1\)As usual, vectors are indicated with boldface to distinguish them to scalar and other symbols.

\(^2\)Notice that each word has one more vector used as input to the neural network. Those vectors are separate from the output embeddings.
LSTM model is invoked to compute the context vector for each occurrence of one sense in the annotated dataset. Once all context vectors are computed, the sense embedding is defined as the average of all vectors. Let us assume, for instance, that the sense horse\textsubscript{2n} (that is, the second sense of horse as a noun) appears in the two sentences:

1. The move of the horse\textsubscript{2n} to the corner forced the checkmate.
2. Karjakin makes up for his lost bishop a few moves later, trading rooks and winning black’s horse\textsubscript{2n}.

In this case, the method will replace the sense by $\$\$ in the sentences and feed them to the trained LSTM model to calculate two context vectors $c_1$ and $c_2$. The sense embedding $s_{\text{horse}_{2n}}$ is then computed as:

$$s_{\text{horse}_{2n}} = \frac{c_1 + c_2}{2}$$

This procedure is computed for any sense that appears in the annotated corpus.

### 2.3 Predicting the senses

After all sense embeddings are computed, the method is ready to disambiguate target words. This procedure proceeds as follows:

1. Given an input sentence and a target word, it replaces the occurrence of the target word by $\$\$ and uses the LSTM model to predict a context vector $c_t$.
2. The lemma of the target word is used to retrieve from Wordnet the candidate synsets $s_1, \ldots, s_n$ where $n$ is the number of synsets. Then, the procedure looks up the corresponding sense embeddings $s_1, \ldots, s_n$ computed in Section 2.2.
3. The procedure invokes a subroutine to choose one of the $n$ senses for the context vector $c_t$. The paper proposes two implementations for this subroutine:
   - (a) The procedure selects the sense whose vector is closest to $c_t$ using the cosine similarity as distance function;
   - (b) The procedure invokes a label propagation algorithm to perform a more sophisticated classification where also non annotated sentences which contain the target word (picked from the large textual corpus), are taken into account.

In our study, we attempted at implementing the procedure 3(b) but we encountered technical difficulties we did not solved yet. Thus, we will limit to evaluate procedure 3(a) for the sense prediction, and leave 3(b) as future work.

### 3 Reproduction Study: Methodology

Before we report the results of our experiments, we describe the datasets we used and give some details regarding our implementation.

**Training data.** For the training of the LSTM model, we make use of the English Gigaword Fifth Edition\textsuperscript{3}. The corpus consists of 1.8 billion tokens in 4.1 million documents, originated from four major news agencies. We leave the study of bigger corpora for future work.

For the training of the sense embeddings, we use the same corpora used by Yuan et al.:

1. *SemCor* (Miller et al., 1993) is a corpus containing approximately 240,000 sense annotated words. The tagged documents originate from the Brown corpus (Francis and Kucera, 1979) and cover various genres.
2. *OMSTI* (Taghipour and Ng, 2015) contains one million sense annotations automatically tagged by exploiting an the English-Chinese part of the parallel MultiUN corpus.

**Implementation.** We used the BeautifulSoup HTML parser to extract the text from Gigawords. Then, we used the English models\textsuperscript{4} of Spacy 1.8.2 for sentence boundary detection and tokenization.

The LSTM model is implemented using TensorFlow 1.2.1 (Abadi et al., 2015). We chose TensorFlow because of its industrial-grade quality and because it comes with vital functionalities for training large-scale models.

The main bottleneck of Yuan et al.’s approach is the training of the LSTM model. Although we do not use a 100-billion word corpus, training the model on Gigaword can already take years if not optimized properly.

To reduce training time, we assumed that all (padded) sentences in the batch have the same

\textsuperscript{3}Linguistic Data Consortium (LDC) catalog number LDC2011T07

\textsuperscript{4}en\_core\_web\_md-1.2.1
length. This optimization increases the speed by 17%. Second, following Yuan et al., we use sampled softmax loss (Jean et al., 2014). Third, we grouped sentences of similar length together while varying the number of sentences in a batch to fully utilize GPU memory. Together, these heuristics increased training speed by 42 times.

**Evaluation framework.** For evaluating the WSD predictions, we selected two test sets: one from Senseval 2 (Palmer et al., 2001), which tests the disambiguation of nouns, verbs, adjectives and adverbs, and one from SemEval 2013 (Navigli et al., 2013), which focuses only on nouns.

The test test from Senseval 2 is the English All-Words Task; senseval2 henceforth. This dataset contains 2387 annotations from three articles from the Wall Street Journal. Most of the annotations are nominal, but the competition also contains annotations for verbs, adjectives, and adverbs. About 67% of all tokens are annotated with the most frequent sense (MFS). This means that the simple and well-known heuristic would score 67% of accuracy on this dataset.

The test set from SemEval 2013 is the one taken from the task 12: Multilingual Word Sense Disambiguation; sem2013-aw henceforth. This task consists of two disambiguation tasks: Entity Linking and Word Sense Disambiguation for English, German, French, Italian, and Spanish. We restricted ourselves to the WSD part using WordNet as a sense repository. The test set contains 13 articles obtained from previous editions of the workshop on Statistical Machine Translation. The articles cover different domains, ranging from sports to financial news. With respect to the English WSD part, there are 1,644 test instances in total, all nouns. The sense repository used to tag these instances is WordNet version 3.0. Based on this sense repository, we computed the number of instances annotated with the MFS, and the number of instances annotated with one of the least frequent sense (LFS). Out of the 1,644 test instances, the MFS applies in 1,035 cases, while one of the LFS applies in the rest of 609 cases. This gives a baseline of 62.96% for the MFS heuristic.

| Vocab. | p  | h  | #params |
|--------|----|----|---------|
| 1M     | 10 | 100| 20M     |
| 1M     | 64 | 256| 128M    |
| 1M     | 128| 512| 258M    |
| 1M     | 512| 2048| 1050M   |

Table 1: LSTM models used in our paper. $h$ is the number of LSTM units and $p$ is embedding dimensionality.

nVIDIA GeForce GTX 1080 Ti with 12GB of RAM. We trained the network with different parameters (Table 1). Despite the optimizations described before and the relatively recent hardware, our implementation still requires about a day to finish an epoch with $h = 2048$ hidden units and $p = 512$ embedding dimensions (henceforth called the “Google” setting). At the time this paper is written, the training is still ongoing and has reached the 180th epoch, which means the program is running for about 4.5 months.

In the following, we will first look at the WSD predictions produced by our model and compare with the original work and other state-of-the-art models (Section 4.1). Then, we report other experiments where we varied the amount of training data (Section 4.2) and other parameters of the language model (Section 4.3). Finally, we perform stability check to make sure that the conclusions hold when models are retrained (Section 4.4).

### 4.1 WSD predictions

Since our goal is to reproduce the results presented in the original work, we intended to use with the “Google” setting which was reported as leading to the best performance. However, since the training is still ongoing, we started to perform WSD using a model trained with less iterations. To our surprise, already after the 65th iteration we did not observe any improvement in the downstream WSD task. This does not mean that the training did not produce better models. Indeed, after this iteration the training algorithm returned new models with a lower negative log likelihood in language modeling. However, none of these models yielded better performance for WSD, thus we will be using the model produced at the 65th iteration to compare our results to the original work.

Table 2 presents the results. Notice that we report the accuracy when either SemCor or OMSTI was used for creating the sense embeddings. For each experiment, we report the results with and
Table 2: Performance of our implementation compared to already published results. A star (*) at the end of a model name indicates that the results are copied from the respective paper.

| Model | MFS back-off | senseval2 | sem2013-aw |
|-------|--------------|-----------|------------|
|       | P   | R   | F1  | R_mfs | R_lfs | P   | R   | F1  | R_mfs | R_lfs |
| Our implementation (T: SemCor) | No | 0.700 | 0.671 | 0.685 | 0.808 | 0.392 | 0.675 | 0.641 | 0.658 | 0.825 | 0.327 |
|       | Yes | 0.700 | 0.700 | 0.700 | 0.850 | 0.392 | 0.666 | 0.666 | 0.866 | 0.327 |
| Our implementation (T: OMSTI) | No | 0.694 | 0.455 | 0.549 | 0.541 | 0.278 | 0.696 | 0.489 | 0.574 | 0.614 | 0.278 |
|       | Yes | 0.674 | 0.674 | 0.674 | 0.867 | 0.278 | 0.655 | 0.655 | 0.876 | 0.278 |
| Our impl. (T: SemCor+OMSTI) | No | 0.682 | 0.653 | 0.667 | 0.781 | 0.392 | 0.677 | 0.642 | 0.659 | 0.798 | 0.378 |
|       | Yes | 0.682 | 0.682 | 0.682 | 0.823 | 0.392 | 0.668 | 0.668 | 0.839 | 0.378 |

Table 3: Effect of training set size on language modeling perplexity

| Data size (%) | Perplexity |
|---------------|------------|
| 1             | 286.3      |
| 10            | 50.4       |
| 25            | 31.8       |

Kuchaiev and Ginsburg (2017) 28.1

6Yuan et al. did not report if they use a MFS back-off strategy or not.
7See Navigli (2009) for the definitions of the metrics.
Yuan et al. used a 100-billion-word corpus only reinforces this intuition. In this section, we empirically evaluate the effectiveness of data by varying the size of data used to train LSTM models and measure corresponding WSD performance.

We use a separate development set of 20K sentences and select random sentences from the rest of GigaWord to create a training set. The size of the training set was set at 1%, 10%, 25% and 100% of the corpus. For language modeling task, we use our second-largest model ($h=512, p=128$) and for WSD, we evaluate on SemEval13 with MFS fallback.

Table 3 reports the change of perplexity as more data is added. To put the results in perspective, we compare to the reported result of Kuchaiev and Ginsburg (2017) which is among the state-of-the-art in language modeling. The results verify that adding training data improves the quality of the language model.

Figure 2 shows the effect of unannotated data on WSD performance. The data points at 100 billion words correspond to Yuan et al.’s reported results. As can be expected, a bigger corpus leads to more meaningful context vectors and therefore higher performance on WSD. However, the amount of added data for 1% of improvement in F1 grows exponentially fast (notice that the horizontal axis is in log scale). Extrapolating from this graph, to get a performance of 0.8 F1 by adding more unannotated data, one would need a corpus of $10^{12}$ words.

### 4.3 Effect of Language Model Capacity

One might suspect that the models in Section 4.2 are not big enough to absorb the added data. We argue that this is not the case.

![Figure 3: The effect of LSTM model capacity on WSD performance. Notice that the horizontal axis is in log scale.](image)

| Parameters | Mean F1 | Std. |
|------------|---------|------|
| $h=100$, $p=10$ (T: SemCor) | 0.559 | 0.008 |
| $h=100$, $p=10$ (T: OMSTI) | 0.604 | 0.005 |
| $h=256$, $p=64$ (T: SemCor) | 0.636 | 0.005 |
| $h=256$, $p=64$ (T: OMSTI) | 0.640 | 0.003 |

Table 4: Performance of our models on SemEval13 when trained with different random seeds.

Figure 3 plots WSD performance against number of parameters in the LSTM model. We train our LSTM models on 100% of GigaWord corpus and evaluate it against SemEval13 with MFS fallback. It is clear that increasing capacity brings only negligible improvement (notice that the number of parameters is plotted in log scale). To improve WSD performance further, one should consider qualitatively different models instead of adding more data and computing power.

### 4.4 Stability

Reimers and Gurevych (2017) reported the performance of LSTM models on five NLP tasks. Their results show that it is crucial to report the distribution of test scores instead of only one score as they might lead to opposite conclusions. As pointed out in the beginning of Section 4, our biggest models take months to train, making training multiple versions of them impractical. However, we report results of smaller models as a way to gauge the extent of random variation (Table 4). When trained with different random seeds, the models show slight difference in performance but it does not affect our conclusions.
5 Conclusions

In the current research, we do not aim at reproducing the same results reported in Yuan et al. (2016) because we do not have access to the amount of data and computational power that Google researchers do. Instead, we hope to build a software package that can be deployed to the computing facilities of common research universities and publish a set of high-quality models to facilitate WSD research.

The analysis of our reimplemented model reveals the dependence of the model on a most-frequent-sense back-off strategy on one hand and relatively good performance in less-frequent-sense test instances on the other hand. We publish our models and source code so that researchers can perform further analysis.

We make a rather surprising observation that we do not need a huge unannotated corpus to achieve state-of-the-art WSD performance. We train our LSTM language model on GigaWord which is two orders of magnitude smaller than Yuan et al.’s corpus and got performance higher than many state-of-the-art systems on Senseval2 and SemEval13. Deeper analysis reveals that adding more words is subject to diminishing returns and increasing model capacity is not a viable solution.

We publish our code with detailed replication instructions at: https://github.com/cltl/wsd-dynamic-sense-vector and our trained models at: http://kyoto.let.vu.nl/~minh/wsd/.

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