

# Incorporating Word Sense Disambiguation in Neural Language Models

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## Abstract

We present two supervised (pre-)training methods that incorporate gloss definitions from lexical resources to leverage Word Sense Disambiguation (WSD) capabilities in neural language models. Our training focuses on WSD but keeps its capabilities when transferred to other tasks while adding almost no additional parameters. We evaluate our technique on 15 downstream tasks, e.g., sentence pair classification and WSD. We show that our methods exceed comparable state-of-the-art techniques on the SemEval and Senseval datasets as well as increase the performance of its baseline on the GLUE benchmark.

are trained on large unlabeled corpora and often ignore relevant information of word senses in LKB (e.g., gloss<sup>1</sup>). As our experiments support, there is a positive correlation between the LM’s ability to disambiguate words and NLP tasks performance.

We propose a set of general supervised methods that integrate WordNet knowledge for WSD in LM during the pre-training phase and validate the improved semantic representations on other tasks (e.g., text-similarity). Our technique surpasses comparable methods in WSD by 0.5% F1 and improves language understanding in several tasks by 1.1% on average. The repository for all experiments is publicly available<sup>2</sup>.

## 1 Introduction

WSD tries to determine the meaning of words given a context and is arguably one of the oldest challenges in natural language processing (NLP) (Weaver, 1955; Navigli, 2009). In knowledge-based methods (Camacho-Collados et al., 2015), lexical knowledge databases (LKB) (e.g., WordNet (Miller, 1995; Fellbaum, 1998)) illustrate the relation between words and their meaning. Supervised techniques (Pasini and Navigli, 2020) rely on annotated data to perform disambiguation while unsupervised ones (Chaplot and Salakhutdinov, 2018) explore other aspects, e.g., larger contexts, topic modeling.

Recently, supervised methods (Huang et al., 2019; Bevilacqua and Navigli, 2020) rely on word representations from BERT (Devlin et al., 2019), although advances in bidirectional transformers have been proposed (Yang et al., 2019; Clark et al., 2020). We compare these novel models and validate which ones are most suitable for the WSD task. Thus, we define an end-to-end approach capable of being applied to any language model (LM).

Further, pre-trained word representations have become crucial for LMs and almost any NLP task (Mikolov et al., 2013a; Radford et al., 2018). LMs

## 2 Related Work

The same way word2vec (Mikolov et al., 2013b) inspired many models in NLP (Bojanowski et al., 2017; Ruas et al., 2020), BERT (Devlin et al., 2019) echoed in the literature with recent models as well (Yang et al., 2019; Clark et al., 2020). These novel models achieve higher performance in several NLP tasks but are mostly neglected in the WSD domain (Wiedemann et al., 2019) with a few exceptions (Loureiro et al., 2020).

Based on the Transformer (Vaswani et al., 2017) architecture, BERT (Devlin et al., 2019) proposes two pre-training tasks to capture general aspects of the language, i.e., *Masked Language Model* (MLM) and *Next Sentence Prediction* (NSP). AIBERT (Lan et al., 2019), DistilBERT (Sanh et al., 2019), and RoBERTa (Liu et al., 2019) either boost BERT’s performance through parameter adjustments, increased training volume, or make it more efficient. XLNet (Yang et al., 2019) focuses on improving the training objective, while ELECTRA (Clark et al., 2020) and BART (Lewis et al., 2020) propose a discriminative denoising method to distinguish real

<sup>1</sup>Brief definition of a synonym set (synset) (Miller, 1995).

<sup>2</sup>[https://github.com/jpelhaW/incorporating\\_wsd\\_into\\_nlm](https://github.com/jpelhaW/incorporating_wsd_into_nlm)

and plausible artificial generated input tokens.

Directly related to our work, GlossBERT (Huang et al., 2019) uses WordNet’s glosses to fine-tune BERT in the WSD task. GlossBERT classifies a marked word in a sentence into one of its possible definitions. KnowBERT (KBERT) (Peters et al., 2019) incorporates LKB into BERT with a knowledge attention and recontextualization mechanism. Peters et al. (2019) best-performing model, i.e., KBERT-W+W, surpasses BERT<sub>BASE</sub> at the cost of  $\approx 400\text{M}$  parameters and 32% more training time. Our methods do not require embeddings adjustments from the LKB or use word-piece attention, resulting in a cheaper alternative. Even though recent contributions in WSD such as LMMS (Loureiro and Jorge, 2019), BEM (Blevins and Zettlemoyer, 2020), GLU (Hadiwinoto et al., 2019), and EWISER (Bevilacqua and Navigli, 2020) enhance the semantic representation via context or external knowledge, they do not explore their generalization to other NLP tasks.

### 3 Methods

Current methods (Huang et al., 2019; Du et al., 2019; Peters et al., 2019; Levine et al., 2019) modify the WSD task into a text classification problem, leveraging BERT’s semantic information through WordNet’s resources. Although BERT is a strong baseline, studies show the model does not converge to its full capacity, and its training scheme still presents opportunities for development (Liu et al., 2019; Yang et al., 2019).

We define a general method to perform WSD in arbitrary LMs and discuss possible architectural alternatives for its improvements (Section 3.1). We assume WSD is a suitable task to complement MLM as we often find polysemous words in natural text. We introduce a second variation in our method (Section 3.2) that keeps previous LM capabilities while improving polysemy understanding.

#### 3.1 Language Model Gloss Classification

With Language Model Gloss Classification (LMGC), we propose a general end-to-end WSD approach to classify ambiguous words from sentences into one of WordNet’s glosses. This approach allows us to evaluate different LMs at WSD.

LMGC builds on the final representations of its underlying transformer with a classification approach closely related to (Huang et al., 2019). Each input sequence starts with an aggregate token (e.g.,

the “[CLS]” token in BERT), i.e., an annotated sentence containing the ambiguous word, followed by a candidate gloss definition from a lexical resource, such as WordNet, for that specific word.

Sentence and gloss are concatenated with a separator token and pre-processed with the respective model’s tokenizer. We modify the input sequence with two supervision signals: (1) highlighting the ambiguous tokens with two special tokens and (2) adding the polysemous word before the gloss.

Considering Du et al. (2019) and Huang et al. (2019) findings, we apply a linear layer to the aggregate representation of the sequence to perform classification rather than using token embeddings. In contrast, we suggest modifying the prediction step from sequential binary classification to a parallel multi-classification construct, similar to Kågebäck and Salomonsson (2016). Therefore, we stack the  $k$  candidate sentence-gloss pairs at the batch dimension and classify them using softmax.

We retrieve WordNet’s gloss definitions of polysemous words corresponding to the annotated synsets to create sentence-gloss inputs. To accelerate training time by approximately a factor of three, compared to (Huang et al., 2019), we reduced the sequence length of all models from 512 to 160<sup>3</sup> as the computational cost of transformers is quadratic concerning the sequence length.

#### 3.2 LMGC with Masked Language Modeling

Comparable WSD systems (Huang et al., 2019; Bevilacqua and Navigli, 2020; Blevins and Zettlemoyer, 2020) and LMGC focus on improving the performance in WSD rather than leveraging it with lexical resources for language understanding. We assume the transfer learning between LM and WSD increases the likelihood of grasping polysemous words in co-related tasks. Thus, we employ LMGC as an additional supervised training objective into MLM (LMGC-M) to incorporate lexical knowledge into our pre-training.

LMGC-M performs a forward pass with annotated examples from our corpus with words masked at a certain probability. Moreover, LMGC-M uses LMGC as a second objective, similar to NSP in BERT. To prevent underfitting, due to task difficulty, we only mask words in the context of the polysemous word. Before inference, we fine-tune LMGC without masks.

<sup>3</sup>99.8% of the data set can be represented with 160 tokens; we truncate remaining sequences to this limit.

## 4 Experiments

We evaluate our proposed methods in two benchmarks, namely SemCor (3.0) (Miller et al., 1993; Raganato et al., 2017) and GLUE (Wang et al., 2019b). The English all-words WSD benchmark SemCor, detailed in Table 1, is popular in the WSD literature (Huang et al., 2019; Peters et al., 2019) and one of the largest manually annotated datasets with approximately 226k word sense annotations from WordNet (Miller, 1995). GLUE (Wang et al., 2019b) is a collection of nine language understanding tasks widely used (Devlin et al., 2019; Lan et al., 2019) to validate the generalization of LMs in different linguistic phenomena. All GLUE tasks are single sentence or sentence pair classification, except STS-B, which is a regression task.

Dataset	POS Tags					Class dist.	
	Noun	Verb	Adj.	Adv.	Total	Pos.	Neg.
SemCor	87k	88.3k	31.7k	18.9k	226k	226.5k	1.79m
SE2	1k	517	445	254	2.3k	2.4k	14.2k
SE3	900	588	350	12	1.8k	1.8k	15.3k
SE7	159	296	0	0	455	459	4.5k
SE13	1.6k	0	0	0	1.6k	1.6k	9.7k
SE15	531	251	160	80	1k	1.2k	6.5k

Table 1: SemCor training corpus details: general statistics (left) and class distribution for LMGC (right).

### 4.1 Setup

All models were initialized using the base configuration of its underlying transformer (e.g., BERT<sub>BASE</sub>, L=12, H=768, A=12). Both of our methods have  $2 * H + 2$  more parameters compared to their baseline (e.g., LMGC (BERT) has  $\approx 110$ M parameters). We increased the hidden dropout probability to 0.2 as we observed overfitting for most models. Further, we explicitly treated the class imbalance of positive and negative examples (Table 1) in LMGC with focal loss (Lin et al., 2017) ( $\gamma = 2$ ,  $\alpha = 0.25$ ). Following Devlin et al. (2019), we used a batch size of 32 sequences, the AdamW optimizer ( $\alpha = 2e-5$ ), trained three epochs, and choose the best model by validation loss. We applied the same hyperparameter configuration for all models used in both SemCor and GLUE benchmarks. The training was performed on 1 NVIDIA Tesla V100 GPU for  $\approx 3$  hours per epoch.

For all GLUE tasks, except for STS-B, we transformed the aggregate embedding into a classification vector applying a new weight matrix  $W \in \mathbb{R}^{K \times H}$ ; where  $K$  is the number of labels. For STS-

System	SE7	SE2	SE3	SE13	SE15	All
BERT 2019	71.9	77.8	74.6	76.5	79.7	76.6
RoBERTa 2019	69.2	77.5	73.8	77.2	79.7	76.3
DistilBERT 2019	66.2	74.9	70.7	74.6	77.1	73.5
AlBERT (2019)	71.4	75.9	73.9	76.8	78.7	75.7
BART (2020)	67.2	77.6	73.1	77.5	79.7	76.1
XLNet (2019)	<b>72.5</b>	<b>78.5</b>	<b>75.6</b>	<b>79.1</b>	<b>80.1</b>	<b>77.2</b>
ELECTRA (2020)	62.0	71.5	67.0	73.9	76.0	70.9

Table 2: SemCor test results of LMGC for base transformer models. **Bold** font indicates the best results.

System	SE7	SE2	SE3	SE13	SE15	All
GAS (2018b)	-	72.2	70.5	67.2	72.6	70.6
CAN (2018a)	-	72.2	70.2	69.1	72.2	70.9
HCAN (2018a)	-	72.8	70.3	68.5	72.8	71.1
LMMS <sub>BERT</sub> (2019)	68.1	76.3	75.6	75.1	77.0	75.4
GLU (2019)	68.1	75.5	73.6	71.1	76.2	74.1
GlossBERT (2019)	72.5	77.7	75.2	76.1	80.4	77.0
BERT <sub>WSD</sub> (2019)	-	76.4	74.9	76.3	78.3	76.3
KBERT-W+W (2019)	-	-	-	-	-	75.1
LMGC (BERT)	71.9	77.8	74.6	76.5	79.7	76.6
LMGC-M (BERT)	72.9	78.2	75.5	76.3	79.5	77.0
LMGC (XLNet)	72.5	78.5	75.6	79.1	80.1	77.2
LMGC-M (XLNet)	<b>73.0</b>	<b>79.1</b>	<b>75.9</b>	<b>79.0</b>	<b>80.3</b>	<b>77.5</b>

Table 3: SemCor test results compared to state-of-the-art techniques. **Bold** font indicates the best results.

B, we applied a new weight matrix  $V \in \mathbb{R}^{1 \times H}$  transforming the aggregate into a single value.

### 4.2 Results & Discussion

Table 2 reports the results of applying LMGC to different transformer models. Our rationale for choosing models was two-fold. First, we explore models closely related or based on BERT, either by improving it through additional training time and data (RoBERTa), or compressing the architecture with minimal performance loss (DistilBERT, AlBERT). Second, models that significantly change the training objective (XLNet), or employ a discriminative learning approach (ELECTRA, BART). In Table 3, we compare our techniques to other contributions in WSD. All results of SemCor are reported according to Raganato et al. (2017).

RoBERTa shows inferior F1 when compared to BERT although it uses more data and training time. As expected, DistilBERT and AlBERT perform worse than BERT, but AlBERT keeps reasonable performance with only  $\approx 10\%$  of BERT’s parameters. ELECTRA and BART results show their denoising approach is not suitable for our WSD setup. Besides, BART presents similar performance to BERT, but with 26% more parameters. XLNet constantly performs better than BERT on all evalu-

System	Classification		Semantic Similarity			Natural Language Inference			Average
	CoLA (mc)	SST-2 (acc)	MRPC (F1)	STS-B (sc)	QQP (acc)	MNLI m/mm(acc)	QNLI (acc)	RTE (acc)	- -
BERT <sub>BASE</sub>	52.1	93.5	<b>88.9</b>	85.8	89.3	84.6/83.4	<b>90.5</b>	66.4	81.4
GlossBERT	32.8	90.4	75.2	90.4	68.5	81.3/80	83.6	47.3	70.7
LMGC (BERT)	31.1	89.2	81.9	89.2	87.4	81.4/80.3	85.4	60.2	74.5
LMGC-M (BERT)	<b>55.0</b>	<b>94.2</b>	87.1	<b>88.1</b>	<b>90.8</b>	<b>85.3/84.2</b>	90.1	<b>69.7</b>	<b>82.5</b>

Table 4: GLUE test results. As in BERT, we exclude the problematic WNLI set. We report F1-score for MRPC, Spearman correlations (sc) for STS-B, Matthews correlations (mc) for CoLA, and accuracy (acc) for the other tasks (with matched/mismatched accuracy for MNLI). **Bold** font indicates the best results.

ation sets with no additional parameters, justifying its choice for our models’ variations.

We see an overall improvement when comparing LMGC to the other approaches in Table 3. LMGC (BERT) generally outperforms the baseline BERT<sub>WSD</sub> approach, and KBERT-W+W which has four times the number of parameters. We show by using an optimal transformer (XLNet) and adjustments in the training procedure, we can outperform GlossBERT in all test sets. We exclude EWISER (Bevilacqua and Navigli, 2020) which explores additional knowledge other than gloss definition (e.g. knowledge graph). We leave for future work the investigation of BEM (Blevins and Zettlemoyer, 2020), a recently published bi-encoder architecture with two encoders (i.e., context and gloss) that are learned simultaneously.

LMGC-M often outperforms LMGC, which we assume is due to the similarity to discriminated fine-tuning (Howard and Ruder, 2018). We combine LMGC and MLM in one pass, achieving higher accuracy in WSD and improving generalization. Considering large models, preliminary experiments<sup>2</sup> showed a difference of 0.08% in F1 between BERT<sub>BASE</sub> and BERT<sub>LARGE</sub> for the SemCor datasets which is in line with Blevins and Zettlemoyer (2020). Thus, we judged the base configuration sufficient for our experiments.

To show that WSD training allows language models to achieve higher generalization, we fine-tune the weights from our approaches in the GLUE (Wang et al., 2019b) datasets. Our results in Tables 3 and 4 show LMGC-M outperforms the state-of-the-art in the WSD task and successfully transfer the acquired knowledge to general language understanding datasets. We exclude XLNet from the comparison to show that the additional performance can be contributed mainly to our method; not to the improvement of XLNet over BERT. The number of polysemous words in the

GLUE benchmark is high in general, supporting the training design of our method. We provide more details about polysemy in GLUE in our repository<sup>2</sup>.

We evaluated our proposed methods against the best performing model in WSD (Table 3) on the GLUE datasets (Table 4). Comparing LMGC-M with the official BERT<sub>BASE</sub> model, we achieve a 1.1% increase in performance on average. In this work, we did not compare LMGC-M to the other WSD methods performing worse than Huang et al. (2019) in the WSD task (Table 3) because of computational requirements (i.e., KBERT-W+W is 32% slower). Unsurprisingly, LMGC and GlossBERT perform well in WSD, but cannot maintain performance on other GLUE tasks. LMGC-M outperforms the underlying baseline (BERT) on most tasks and is comparable to the others. Therefore, incorporating MLM to our WSD architecture leverages LMGC semantic representation and improves its natural language understanding capabilities.

## 5 Conclusions and Future Work

In this paper, we proposed a set of methods (LMGC, LMGC-M) that allows for (pre-)training WSD, which is essential for many NLP tasks (e.g., text-similarity). Our techniques perform WSD combining neural language models with lexical resources from WordNet. We exceeded state-of-the-art of WSD methods (+0.5%) and improved the performance over BERT in general language understanding tasks (+1.1%). Future work will include testing generalization on the WiC (Pilehvar and Camacho-Collados, 2019), and SuperGLUE (Wang et al., 2019a) datasets. Besides, we want to test discriminative fine-tuning against our parallel approach (Howard and Ruder, 2018), and perform an ablation study to investigate which components of our methods lead to the most benefits. We also leave for future work to incorporate knowledge from other sources (e.g., Wikidata, Wikipedia).



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