Abstract
We propose to take on the problem of Word Sense Disambiguation (WSD). In language, words of the same form can take different meanings depending on context. While humans easily infer the meaning or gloss of such words by their context, machines stumble on this task. As such, we intend to replicated and expand upon the results of Huang et al.’s GlossBERT, a model which they design to disambiguate these words (Huang et al., 2019). Specifically, we propose the following augmentations: data-set tweaking (α hyper-parameter), ensemble methods, and replacement of BERT with BART and ALBERT. The following GitHub repository contains all code used in this report, which extends on the code made available by Huang et al.: https://github.com/nkhp-glossBERT. Additionally, the following links to a short presentation: https://youtu.be/X2OxgcF7lsM.

1 Introduction
Take the following two sentences: The dog’s bark was loud, and The tree’s bark was dark. In each case, the word bark appears with a different sense: the sound a dog makes, and the rough covering of a tree trunk respectively. Note, without context, the disambiguation of bark would be impossible; however, with context it becomes trivial for a human, and possible for a computer (the surrounding words dog and tree would be clues). One can easily see WSD lies at the foundation of many NLP tasks, and therefore has many traditional NLP applications: e.g. machine translation, information extraction, and sentiment analysis (Tang et al., 2018; Chai and Biermann, 1999; Hung and Chen, 2016). As such, we consider steady improvement in this domain as of great importance, and choose it as our area of focus.

To formally define the WSD task, let us reference Huang et al. They define a sentence $S$ as a series of words $\{w_0, \ldots, w_m\}$, and wish to disambiguate some words $w \in S' \subseteq S$; then, each $w_i \in S'$ has some candidate senses, of which the task definition dictates the model select the most appropriate given the context (Huang et al., 2019).

There are several possible approaches to consider in WSD. In his survey of WSD,Navigli describes three main classes of WSD methods: supervised, where the model generalizes gloss mappings from labeled data; unsupervised, which learn from non-labeled data, and try to disambiguate based on patterns in the training set; and knowledge-based methods, which leverage lexi-
cal resources (e.g. dictionaries) to disambiguate words (Navigli, 2009). He further states that supervised systems outperform the other methods (Navigli, 2009). As such, we will focus our efforts specifically in the domain of supervised-WSD.

Now, let us introduce the work on which we wish to focus our project. Huang et al. propose GlossBERT (a supervised model) for WSD; they feed context-gloss pairs (context being the input sentence, and the glosses coming from WordNet) into a BERT-based binary classifier for the disambiguation task, where the model will determine whether the context fits the gloss (Huang et al., 2019). Specifically, for each ambiguous word $w$ in a sentence, the authors create $N$ context-gloss pairs with different senses of $w$ and a label corresponding with each pair (positive if the gloss matches, negative if not) (Huang et al., 2019). Further, the authors propose three variations of GlossBERT: Token-CLS, Sent-CLS, and Sent-CLS-WS (Huang et al., 2019).

 Principally, we propose to replicate and expand on GlossBERT (Huang et al., 2019). Initially, after replication of results, we will tweak hyper-parameters to either justify or contradict the authors’ choices. Lastly, we intend to conduct a more invasive series of tests involving GlossBERT’s classification architecture—e.g. attempting ensemble methods, and replacing BERT with BART and ALBERT.

2 Methods and Experiments

2.1 Data-sets

Training Dataset: We choose the smallest dataset, Senseval-2, among all test sets used in the Senseval and SemEval context for training, merely due to its size (Edmonds and Cotton, 2001). Initially, we tried training on SemCor, as did Huang et al., however we were unable to accommodate such a large training set with memory and time constraints. Therefore, we train all our models on Senseval-2 (SE2).

Evaluation Dataset: For comparable results we use the benchmark datasets proposed in GlossBERT (Huang et al., 2019), employing the standard all-words fine-grained WSD datasets from the Senseval and SemEval competition namely:

- **Senseval-3** (SE3) (Mihalcea et al., 2004)
- **SemEval-2007** (SE07) Task 17 (Pradhan et al., 2007)
- **SemEval-2013** (SE13) Task 12 (Navigli et al., 2013)
- **SemEval-2015** (SE15) Task 13 (Moro and Navigli, 2015)

Dataset Statistics: The statistics of the WSD datasets are presented in GlossBERT (Huang et al., 2019) in Table 1.

| Data-set  | Total | Noun | Verb | Adj | Adv |
|-----------|-------|------|------|-----|-----|
| SemCor    | 226036| 87002| 88334| 31753| 18947|
| SE2       | 2282  | 1066 | 517  | 445 | 254 |
| SE3       | 1850  | 900  | 588  | 350 | 12  |
| SE07      | 455   | 159  | 296  | 0   | 0   |
| SE13      | 1644  | 1644 | 0    | 0   | 0   |
| SE15      | 1022  | 531  | 251  | 160 | 80  |

Table 1: Part of speech tags in WSD dataset (table from Huang et al.) (Huang et al., 2019)

• **SemEval-2013** (SE13) Task 12 (Navigli et al., 2013)
• **SemEval-2015** (SE15) Task 13 (Moro and Navigli, 2015)

2.2 Trials
Base: Technical limitations disallowed complete replication of Huang et al.’s results. However, we compromised and trained on a smaller data-set (Senseval-2) with a smaller batch-size (10). Obviously, this led to worse performance than that from the original paper. However training the original models in this manner gave us a baseline to which we could compare augmentations.

Making an $\alpha$ hyper-parameter: Intuitively, the more possible labels of an instance, the longer (or more iterations) it will take to learn; conversely, the less labels, the shorter. We draw from this intuition to reform the data-set to embody this idea—i.e. ambiguous words with more glosses will appear in the data-set disproportionately more. More formally, let $N$ be the number of glosses of an ambiguous word and $\alpha$ be some hyper-parameter. Then, we randomly sample $N^{\alpha} - 1$ data-points from the $N$ data-points described by Huang et al. (binary classification points for context-gloss pairs, with a positive label for the correct pair), and add the positive pair to ensure it appears at least once in the training-set (Huang et al., 2019). As such, given a word $w$, its set of glosses $G_w$, and a hyper-parameter $\alpha$, we use Algorithm 1 to construct some data-points to append to our training-set.

Ensemble Methods: Ensemble methods allow for combination of various models in the hopes of improving performance; they have proven themselves quite effective in myriad scenarios and forms (e.g. random forests). As such, we in-
Algorithm 1 Constructs array of data-points append when constructing train-set (note ‘+’ means concatenation of two arrays)

\[
\text{procedure } \text{TRAIN-GLOSS}(w, \alpha) \\
G_w \leftarrow \text{Set of glosses of } w \text{ from WordNet} \\
G_w' \leftarrow \text{Empty array} \\
g \leftarrow x \text{ s.t. } x \in G_w \text{ labeled positive} \\
\text{for } 0 \to \lceil |G_w|/\alpha \rceil \text{ do} \\
x \overset{R}{\leftarrow} G_w \text{ s.t. } x \text{ is a uniformly sampled gloss from } G_w \\
G''_w \leftarrow G'_w + \text{array}(x) \triangleright \text{Add newly sampled point to } G''_w \\
\text{end for} \\
G''_w \leftarrow G''_w + \text{array}(g) \triangleright \text{Ensure at least one positive labeled point in } G''_w \\
\text{end procedure}
\]

Figure 1: Demonstrates how number of points for ambiguous word (with \(N\) possible glosses) changes with different \(\alpha\) and \(N\) values

investigated whether an ensemble of WSD models could improve performance. In the proceeding trials, we used a heterogeneous combination of model types—taking our trained models from the base-case, and with various \(\alpha\) values, and combining them in a manner demonstrated in Figure 2. Unfortunately, the BERT(Token-CLS) model had a different tensor output shape than the other three models, so we did not include it in any ensemble trials; specifically, we conducted ensemble trials with a combination of GlossBERT(Sent-CLS-WS), GlossBERT(Token-CLS), and GlossBERT(Sent-CLS). Essentially, we take their outputs before the final softmax, add them, and pass the resulting tensor through softmax activation.

Replacing BERT with ALBERT: Another intuitive approach to improve the existing approach is to replace the BERT model with a better version of it, ALBERT. After studying multiple existing researches on BERT, we found that ALBERT is a much better version of BERT, as it reduces the memory consumption of the model and simultaneously increasing the speed by significant amount.

Per the huggingface documentation, the key idea behind this improvement is

- (i) “splitting the embedding matrix into two smaller matrices” (huggingface, a)
- (ii) “repeating layers split among groups” (huggingface, a)

ALBERT model is computationally the same as BERT model as it iterates through same number of layers and repeating layers result in smaller memory consumption (huggingface, a). Our approach is to replace BERT model with ALBERT model. The following are the conclusions and challenges faced:

- **Similar class design architecture:** AlbertConfig :: BertConfig, AlbertForPreTrained :: BertForZreTrained.
- **Different input parameters, output values and class methods:** Authors of GlossBERT
rewrite large amounts of code to build GlossBERT.

Replacing BERT with BART: Another intuitive approach to improve the existing approach is to replace the BERT model with BART. We chose BART as the model that can change the learning approach to discriminative. In the paper [Lewis et al., 2019] the author mentions that on experimenting with BART, the model does not work well on WSD. On trying techniques to replace BERT completely with BART we confirmed that the findings of author of [Lewis et al., 2019] that existing trained BART model is not suitable for word sense disambiguation tasks. Even after adding parameters required for BART, which are more than BERT, the findings are similar and we found that classes and functions given in the [huggingface, BART and BERT are very different and hence make BART not compatible for changes in the GlossBERT. In the [Lewis et al., 2019], the author has provided with following results:

| System   | SE7  | SE2  | SE3  | SE13 | SE15 |
|----------|------|------|------|------|------|
| BERT(2019) | 71.99| 77.8 | 74.6 | 76.5 | 79.7 |
| BART(2020) | 67.2 | 77.6 | 73.1 | 77.5 | 79.7 |
| Albert(2020) | 71.4 | 75.9 | 73.9 | 76.8 | 78.8 |

Table 2: SemCor test results of LMGc for base trained former models (table from [Lewis et al., 2019])

showing that BERT is at par with the latest models such as BART.

3 Results and Discussion

Table 3 shows the performance of Huang et al.’s models [Huang et al., 2019] in comparison to ours. We were able to get the following results by setting the hyper-parameters outlined in Figure 3 unless otherwise denoted. Of note, Sent-CLS-WS, Token-CLS, and Sent-CLS models performed better over Base BERT Token-CLS model. A proportionately similar trend was observed from the results of previously published work [Huang et al., 2019]. Accommodating the batch in GPU memory for training presented as a major challenge, which caused us to limit ourselves to a batch size of 10 in comparison to 64 used in the original paper [Huang et al., 2019]. We encountered over-fitting as another major obstacle. We tried experimenting with different optimizers and learning rates, but were unable to solve this problem due to GPU memory limits (16 GB on Google Colab Pro). To further optimize our results with these limitations, we employed gradient accumulation—set to 3—to help prevent over-fitting, resulting in slight improvement in comparison to updating gradients on every batch.

We ran two experiments varying the aforementioned α hyper-parameter. In the first experiment, we set α to 0.8 in hopes of mitigating over-fitting. In the second, we set α to 1.2 to reinforce the learning based in the number of glosses of a word in WordNet. While our attempt to avoid over-fitting didn’t turn out to be effective, it helped in improving overall accuracy marginally across other development data sets, which can be seen in Table 3.

Unfortunately, the ensemble methods under-performed, unable to defeat each of their components (though defeating some of them). For improvement, in future work, we would like to investigate homogeneous combinations of ensemble methods with popular ensemble techniques—e.g. bagging; we would also like to experiment with various voting schemes, rather than just combining output as done here; and lastly, we would like to increase the number of models in the ensemble (here we only have three).

| Variables              | Value |
|------------------------|-------|
| max_seq_length         | 512   |
| train_batch_size       | 10    |
| learning_rate          | 2e-6  |
| num_train_epochs       | 6.0   |
| Training set           | SE02  |

Figure 3: Hyper-parameters and other variables used for results in Figure 3 from us and Huang et al. with differences bolded (*note Huang et al. tested on more data-sets, but we used their results from SE13 for comparison) [Huang et al., 2019]

4 Conclusion

In this paper, we investigated Huang et al.’s GlossBERT and attempted to expand on their work. We saw some success against our baseline with our α hyper-parameter. However, the ensemble methods could not outperform all of their components. We listed possible future work with more ensemble techniques, and also we could try to follow through with the BART and ALBERT directions.
Lastly, we would be curious to see whether these results hold up when training on SemCor with higher compute power.

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