Connect-the-Dots: Bridging Semantics between Words and Definitions via Aligning Word Sense Inventories

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Abstract

Word Sense Disambiguation (WSD) aims to automatically identify the exact meaning of one word according to its context. Existing supervised models struggle to make correct predictions on rare word senses due to limited training data and can only select the best definition sentence from one predefined word sense inventory (e.g., WordNet). To address the data sparsity problem and generalize the model to be independent of one predefined inventory, we propose a gloss alignment algorithm that can align definition sentences (glosses) with the same meaning from different sense inventories to collect rich lexical knowledge. We then train a model to identify semantic equivalence between a target word in context and one of its glosses using these aligned inventories, which exhibits strong transfer capability to many WSD tasks. Experiments on benchmark datasets show that the proposed method improves predictions on both frequent and rare word senses, outperforming prior work by 1.2% on the All-Words WSD Task and 4.3% on the Low-Shot WSD Task. Evaluation on WiC Task also indicates that our method can better capture word meanings in context.

1 Introduction

Human language is inherently ambiguous since words can have various meanings in different contexts. Word Sense Disambiguation (WSD) aims to automatically identify the correct sense (meaning) of the target word within a context sentence, which is essential to many downstream tasks such as machine translation and information extraction. Recently, many approaches have achieved state-of-the-art performance on WSD by fine-tuning language models pretrained with massive text data on task-specific datasets (Blevins and Zettlemoyer, 2020; Yap et al., 2020).

However, fine-tuning a WSD model using task-specific resources could limit its applicability and may cause two major problems. First, the performance of models decreases significantly when predicting on rare and zero-shot word senses (Kumar et al., 2019; Choubey and Huang, 2020; Blevins et al., 2021) because there are no sufficient supporting examples in training data. Second, the trained models are often inventory-dependent which can only select the best definition from one predefined word sense inventory (mainly WordNet) that human annotations are based upon.

In this paper, we overcome these limitations by leveraging abundant lexical knowledge from various word sense inventories. As we know, dictionaries that are compiled by experts contain rich sense knowledge of words. Moreover, a dictionary usually provides several example sentences for each word sense to illustrate its usage, which can be viewed as context sentences of that word sense. Since a word’s sense (meaning) can be determined by its context, the word itself in a given context and the definition sentence corresponding to the correct sense are merely two surrogates of the same meaning (semantically equivalent). Furthermore, we observe that different dictionaries normally summarize meanings of a word to a close number of word senses, where definition sentences (glosses) from different dictionaries are different expressions of the same bunch of meanings. For example, Figure 1 lists glosses retrieved from three dictionaries for verb word search. We can see that glosses with the same color have the same meaning and can be aligned across different dictionaries.

Based on this observation, we propose a gloss alignment algorithm to leverage abundant lexical knowledge from various word sense inventories. We convert the problem of aligning two groups of glosses according to meanings to an optimization problem and find the optimal solution through iterative optimization.

1Models and code are available at https://github.com/wenlinyao/EMNLP21-ConnectTheDots. We will also release the checkpoint of the pretrained model for reproducibility.
problem – Maximum Weighted Graph Matching – to find the best matching that maximizes the overall textual similarity. In this way, we can gather general semantic equivalence knowledge from various dictionaries as a whole for all word senses, especially for rare senses that are less frequently seen in human-annotated data.

To make use of the derived semantic equivalence knowledge, we adopt a transfer learning approach that first pretrains a general semantic equivalence recognizer by contrasting the word representations in example sentences with the sentence representations of positive glosses or negative glosses. The general model can be directly applied to downstream WSD tasks or further fine-tuned on the task-specific dataset to get an expert model. We test our two-stage transfer learning scheme on two WSD benchmark tasks, i.e., the standard task (Raganato et al., 2017b) that focuses on all-words WSD and FEWS (Blevins et al., 2021) task that emphasizes low-shot (including few-shot and zero-shot) WSD. Experimental results show that the general model (without fine-tuning) surpasses the supervised baseline by 13.1% on zero-shot word senses. After further fine-tuning with build-in training data, the expert model outperforms the previous state-of-the-art model by 1.2% on all-words WSD tasks and 4.3% on low-shot WSD tasks. Adding semantic equivalence knowledge to the Word-in-Context (WiC) task (Pilehvar and Camacho-Collados, 2019) also improves the accuracy of RoBERTa_large (Liu et al., 2019) by 6%, which even outperforms the 9X larger T5 model (Raffel et al., 2020).

Overall, the major contributions of our work are two-fold. 1) We propose a gloss alignment algorithm that can integrate lexical knowledge from different word sense inventories to train a general semantic equivalence recognizer. 2) Without using task-specific training data, the general model not only performs well on overall word senses but demonstrates strong applicability to low-shot senses. The general model can turn into an expert model to achieve new state-of-the-art performance after further fine-tuning.

2 Related Work

Supervised WSD Approaches. Most existing WSD models are learned in a supervised manner and depend on human-annotated data. For example, Raganato et al. (2017a) regarded WSD as a sequence labeling task and trained a BiLSTM model with self-attention using multiple auxiliary losses. Luo et al. (2018a) introduced a hierarchical co-attention mechanism to generate gloss and context representations that can attend to each other. More recently, several BERT-based models have achieved new state-of-the-art performance on WSD by fine-tuning a pretrained language model. GlossBERT (Huang et al., 2019) appends each gloss to a given context sentence to create pseudo sentences and predicts them as either positive or negative depending on whether the sense corresponds to the correct sense or not. Bi-Encoder Model (BEM) (Blevins and Zettlemoyer, 2020) represents the target words and senses in the same embedding space using a context encoder and a gloss encoder but optimizes on each word individually. Yap et al. (2020) formulated WSD as a relevance ranking task and fine-tuned BERT to select the most probable sense definition from candidate senses. The neural architecture of our semantic equivalence recognizer realizes the benefits of GlossBERT and BEM.

Knowledge-Based WSD Approaches. Closely related to our work, many knowledge-based approaches rely on Lexical Knowledge Bases (LKB), such as Wikipedia and WordNet, to enhance representations of word senses. BabelNet (Navigli and Ponzetto, 2010) creates a resource by automatically mapping encyclopedic knowledge (Wikipedia) to lexicographic knowledge (WordNet) with the aid...
of Machine Translation. Lesk (Basile et al., 2014) relies on a word-level similarity function to measure the semantic overlap between the context of a word and each sense definition. SENSEMBERT (Scarlini et al., 2020a) produces high-quality latent semantic representations of word meanings by incorporating knowledge contained in BabelNet into language models. Other approaches try to learn better gloss embeddings by considering the WordNet graph structure (e.g., hypernyms, hyponyms, synonyms, etc.) (Luo et al., 2018b; Loureiro and Jorge, 2019; Kumar et al., 2019; Bevilacqua andNavigli, 2020). For example, Kumar et al. (2019) proposed EWISE to improve model’s performance on rare or unseen senses by learning knowledge graph embeddings from WordNet. Building upon EWISE, Bevilacqua andNavigli (2020) developed a hybrid approach that incorporates more lexical knowledge (e.g., hypernymy, meronymy, similarity in WordNet) into the model through synset graph embeddings.

### 3 Overview of Our Approach

Figure 2 shows the overview of our approach. We first collect all word glosses and corresponding example sentences from six word sense inventories. We next apply the gloss alignment algorithm to find the best matching between two groups of glosses retrieved from two different inventories for every common keyword. By contrasting example sentences with the correct glosses and incorrect glosses within each inventory or across different inventories, we automatically gather rich supervision for pretraining a universal binary classifier that can determine whether the keyword in the context sentence (example sentence) and a gloss are semantically equivalent or not. The pretrained general model can be directly used in downstream WSD tasks or further fine-tuned to get an expert model.

### 4 Aligning Glosses across Word Sense Inventories

#### 4.1 Data Collection

We collected word sense inventory data by querying WordNet 3.0 (Miller, 1995) and the electronic edition of five professional dictionaries for advanced English learners: Oxford Advanced Learner’s Dictionary (Turnbull, 2010), Merriam-Webster’s Advanced Learner’s Dictionary (Perrault, 2008), Collins COBUILD Advanced Dictionary (Sinclair, 2008), Cambridge Advanced Learner’s Dictionary (Walter, 2008), and Longman Dictionary of Contemporary English (Summers, 2003). Advanced learners’ dictionaries have a good characteristic that they usually provide abundant example sentences to illustrate the usage of different word senses in context, making it possible to generate strong supervision for training a classifier. Table 1 shows statistics of six word sense inventories used. In total, we collected 557.8K glosses and 469.4K example sentences.

| Inventory | Words  | Glosses  | ES    | Gls/W | ES/W |
|-----------|--------|----------|-------|-------|------|
| Oxford    | 52.5K  | 86.2K    | 96.8K | 1.6   | 1.8  |
| Webster   | 39.8K  | 72.5K    | 100.6K| 1.8   | 2.5  |
| Collins   | 34.4K  | 61.4K    | 89.5K | 1.8   | 2.6  |
| Cambridge | 36.6K  | 67.0K    | 64.9K | 1.8   | 1.8  |
| Longman   | 36.9K  | 63.8K    | 70.2K | 1.7   | 1.9  |
| WordNet   | 147.5K | 206.9K   | 47.4K | 1.4   | 0.3  |

Table 1: Statistics of six word sense inventories used (phrases are included in word counting). ES: Example Sentences; Gls/W: average glosses per word; ES/W: average example sentences per word.

#### 4.2 Gloss Alignment as a Maximum-weight Matching Problem

Each word sense inventory is a lexical knowledge bank that provides example sentences for illustrating word senses, including senses less frequently
seen in the real world. Moreover, we observe that different inventories usually provide parallel explanations of meanings for a given word (Figure 1). Thus, if we can align explanations (glosses) from different inventories according to meanings, we can significantly expand lexical knowledge acquired, especially for rare word senses. Essentially, finding the best alignment between two groups of glosses can be converted to Maximum-weight Bipartite Matching Problem (Cormen et al., 2009; Duan and Pettie, 2014) that aims to find a matching in a weighted bipartite graph that maximizes the sum of weights of the edges.

4.3 Problem Formulation

Given a keyword, suppose we retrieved two word sense sets $S_1$ and $S_2$ from two inventories, where each set consists of a list of definition sentences (glosses). Given a reward function $r: S_1 \times S_2 \rightarrow \mathbb{R}$, we want to find a matching $2f: S_1 \rightarrow S_2$ such that the total rewards $\sum_{a \in S_1, f(a) \in S_2} r(a, f(a))$ is maximized. By finding the matching $f$, we will know the best alignment between two word sense sets $S_1$ and $S_2$. In this paper, we use the sentence-level textual similarity as the reward function to find the best word sense alignment. To measure the textual similarity between two definition sentences, we apply a pretrained model SBERT (Reimers and Gurevych, 2019) that has achieved state-of-the-art performance on many Semantic Textual Similarity (STS) tasks and Paraphrase Detection tasks. Specifically, we apply SBERT to $S_1$ and $S_2$ to get sentence embeddings and then calculate cosine similarity as the reward function.

4.4 Solving Bipartite Graph Matching by Linear Programming

The Maximum-weight Graph Matching problem can be solved by Linear Programming (Matousek and Gärtner, 2007; Cormen et al., 2009). For simplicity, let weight $w_{ij}$ denotes the textual similarity score between the $i$th definition sentence in $S_1$ and the $j$th definition sentence in $S_2$. We next introduce another variable $x_{ij}$ for each edge $(i, j)$. $x_{ij} = 1$ if the edge between $i$ and $j$ is contained in the matching and $x_{ij} = 0$ otherwise. The total weight of the matching is $\sum_{(i, j) \in S_1 \times S_2} w_{ij}x_{ij}$. To reflect every vertex is in exactly one edge in the matching, we add constraints $\sum_{j \in S_2} x_{ij} = 1$ for $i \in S_1$, and $\sum_{i \in S_1} x_{ij} = 1$ for $j \in S_2$, to guarantee that the variable $x$ represents a perfect matching. Our goal is to find a maximum-weight perfect matching such that above constraints are satisfied. To sum up, aligning glosses between two word sense inventories is equivalent to solving the following linear integer programming problem:

$$\max_{\{x_{ij}\}} \sum_{(i, j) \in S_1 \times S_2} w_{ij}x_{ij}$$

s.t. $\sum_{j \in S_2} x_{ij} = 1$, $i \in S_1$

$\sum_{i \in S_1} x_{ij} = 1$, $j \in S_2$

$x_{ij} \in \{0, 1\}$, $i \in S_1, j \in S_2$

In our implementation, we consider all possible inventory combinations (select two from six) and apply the gloss alignment solver\(^3\) to all common words shared by two inventories. For each word, the gloss alignment solver is only applied to glosses under the same POS category. Overall, we obtain 704K gloss alignment links.

4.5 Positive and Negative Training Instances

For a given word, the gloss alignment algorithm provides us the linking from word sense set $S_1$ in one inventory to $S_2$ in another inventory. Two glosses (e.g., $g \in S_1$ and $g' \in S_2$) have the same meaning if they are aligned by the algorithm or have a different meaning if they are not aligned. So we can pair the definition sentence of $g$ ($g'$) to each example sentence in $g'$ ($g$) to generate gloss-context pairs for training the semantic equivalence recognizer. Pairs are labeled as positive if $g$ and $g'$ are aligned or negative otherwise\(^4\). In experiments, we only consider aligned gloss pairs with textual similarities above a threshold (see Section 6.1) to further improve the quality of supervision. In total, we generate 421K positive and 538K negative gloss-context pairs across different inventories.

Pairs are also generated by contrasting glosses within each inventory individually. In detail, for every word in an inventory, we pair the gloss sentence with its example sentences to get positive gloss-context pairs or pair the gloss sentence with example sentences from another gloss within the

\(^2\)Note that unbalanced matching (i.e., $S_1$ and $S_2$ are different in size) can be reduced to balanced matching by adding new vertices to the smaller part and assigning weight 0 to edges pointing to them.

\(^3\)Our implementation is based on Scipy library (https://www.scipy.org/).

\(^4\)If $S_1$ and $S_2$ have a different number of glosses for a given word, we ignore the extra glosses that are not aligned.
inventory to get negative gloss-context pairs. We generate 1.3M positive and 418K negative gloss-context pairs in this way. Similarly, we also generate context-context pairs by contrasting example sentences in two glosses to reflect the task setting of WiC (Section 6.3).

5 A Unified Neural Model for Recognizing Semantic Equivalence

5.1 Model Architecture

This section introduces our model architecture (the right part of Figure 2) for recognizing semantic equivalence. Inspired by Blevins and Zettlemoyer (2020), our model first uses an encoder to get the semantic representation of the target word (within its context sentence) or the gloss sentence. Next, by comparing two representations, our model predicts whether they are semantically equivalent or not.

Semantic Encoder. We apply a pretrained BERT model to get the contextual word representation of the target word (with its context) or the sentence representation of the gloss sentence. Specifically, given an input sentence \( S \) padded by the start symbol \([CLS]\) and the end symbol \([SEP]\), we first obtain \( N \) contextualized embeddings \( \{o_i\}_{i=1}^N \) for all tokens \( \{t_i\}_{i=1}^N \) using BERT. We next select the contextualized embedding at the target word position when \( S \) is a context sentence, or select the first output embedding \( o_0 \) (corresponding to the special token \([CLS]\)) as the sentence representation when \( S \) is a gloss sentence.

Learning Objective. After deriving embeddings using BERT, both representations \( u \) and \( v \), together with element-wise difference \(|u - v|\) and element-wise multiplication \( u \cdot v \) are concatenated and multiplied with the trained weight \( W_t \in \mathbb{R}^{2n \times 2} \) with a softmax prediction layer for binary classification (semantically equivalent or not):

\[
p = \text{softmax}(W_t[u, v, |u - v|, u \cdot v])
\]

where \( n \) is the dimension of the embeddings. Our experiments consider two model sizes: SemEq-Base that is initialized with the pretrained BERT\(_{\text{Base}}\) (Devlin et al., 2019) model with 12 transformer block layers, 768 hidden size, 12 self-attention heads and SemEq-Large that is initialized with the pretrained RoBERTa\(_{\text{LARGE}}\) (Liu et al., 2019) model with 24 transformer block layers, 1024 hidden size, 16 self-attention heads. We train our model using binary cross-entropy loss and AdamW (Loshchilov and Hutter, 2018) optimizer with initial learning rate \{1e-5, 5e-6, 2e-6\}, 0.2 dropout, batch size 64 and 10 training epochs.

6 Evaluation

6.1 Accuracy of the Gloss Alignment Algorithm

To evaluate the accuracy of the gloss alignment algorithm, we randomly sample 1,000 gloss pairs from 704K alignments and ask two human annotators to judge whether two gloss sentences refer to the same meaning or not. Two annotators labeled 200 gloss pairs in common and agreed on 94% (188) of them, achieving the kappa inter-agreement score of 0.74. One gloss pair is regarded as correct when both annotators label it as correct, and the remaining 800 gloss pairs were evenly allocated to two annotators to label. Table 2 shows the accuracy of the gloss alignment algorithm on each POS type based on human annotations. The accuracy on Noun, Verb, Adjective and Adverb words is 0.90, 0.81, 0.88 and 0.85, respectively, with an overall accuracy of 0.87. In experiments, we apply a threshold of 0.6 to alignment results and only consider aligned gloss pairs with textual similarities above it, which can further improve gloss alignment accuracy to 0.98 based on human annotations. In this way, we can significantly improve the quality of training data that are generated from the automatically aligned dictionaries.

6.2 Experiments on WSD

We evaluate our model on two WSD datasets, i.e., WSD tasks standardized by Raganato et al. (2017b) that focuses on all-words WSD evaluation and FEWS dataset proposed by Blevins et al. (2021) that emphasizes low-shot WSD evaluation. Since both datasets are annotated using word senses in WordNet 3.0 (Miller, 1995), we pair the context sentence with the annotated gloss in WordNet 3.0.

| Percentage | Accuracy | Noun | Verb | Adj | Adv | ALL |
|------------|----------|------|------|-----|-----|-----|
|            |          | 55.6% | 20.6% | 20.2% | 2.5% | 100% |

Table 2: Accuracy of the Gloss Alignment Algorithm.

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5 We only contrast to glosses having the same POS tag to get negative instances.

6 If the target word is a phrase or the target word is tokenized into multiple subword pieces by the tokenizer, we average all subword embeddings to get its representation.

7 Our implementation was based on https://github.com/huggingface/transformers.
to generate positive gloss-context instances or other
glosses of the word to get negative gloss-context
instances for training. In validation or test, we ap-
ply the trained classifier to examine all possible
glosses of the target word in WordNet 3.0 and se-
llect the gloss with the highest probability score as
the prediction. To incorporate rich lexical knowl-
edge harvested from word sense inventories into
model training, we consider two strategies:

Data Augmentation. We directly augment the
build-in training set from each WSD dataset with
gloss-context pairs generated from our aligned
word sense inventories and then train the semantic
equivalence recognizer (SemEq) to do WSD.

Transfer Learning. We first train our semantic
equivalence recognizer ONLY using gloss-context
pairs generated from our aligned word sense in-
ventories. The trained classifier is a general model
(SemEq-General) capable of deciding whether a
gloss sentence and the target word in a context
sentence are semantically equivalent independent
from any specific word sense inventories. Next,
to evaluate on a specific WSD dataset, we further
fine-tune the general model on the build-in train-
ing set to get an expert model (SemEq-Expert).
The expert model can adapt to the new domain to
achieve better performance.

6.2.1 All-Words WSD Tasks

We evaluate our model on the all-words WSD
framework established by Raganato et al. (2017b).
The testing dataset contains 5 benchmark datasets
from previous Senseval and SemEval competi-
tions, including Senseval-2 (SE2) (Edmonds and
Cotton, 2001), Senseval-3 (SE3) (Mihalcea et al.,
2004), SemEval-07 (SE07) (Pradhan et al., 2007),
SemEval-13 (SE13) (Navigli et al., 2013), and
SemEval-15 (SE15) (Moro andNavigli, 2015). Fol-
lowing Raganato et al. (2017b) and other previous
work, we use SemCor (Miller et al., 1993) that con-
tains 226,036 annotated instances as the build-in
training set and choose SemEval-07 as the develop-
ment set for hyper-parameter tuning. Since all
datasets are mapped to word senses in WordNet 3.0
to form gloss-context pairs for both training and
testing.

Table 3 shows experimental results on all-words
WSD datasets (Raganato et al., 2017b). We also
report models’ performance on each POS category.
The first section includes results of the most fre-
test sense baseline and previous WSD models.

The second section presents results of our model
that adopt data augmentation strategy to incorpo-
rate multi-source inventory knowledge. SemEq-

Table 3: F1-score (%) on All-Words WSD benchmark datasets. We distinguish models based on 1) using the
Training Set (TS) SemCor or not, 2) using single (S) Inventory Knowledge (IK) (i.e., WordNet) or our multi-
source (M) inventory knowledge, 3) using WordNet synset Graph Structures (GS) or not, and 4) transformer
Model Size (MS) of Base (B) or Large (L). Baseline systems are: Lesk (Basile et al., 2014), Babelfy (Moro
andNavigli, 2015), BiLSTM (Raganato et al., 2017a), HCAN (Luo et al., 2018a), EWISE (Kumar et al., 2019),
LMMS (Loureiro and Jorge, 2019), GlossBERT (Huang et al., 2019), BEM (Blevins and Zettlemoyer, 2020),
AdaptBERTLarge (Yap et al., 2020), and EWISER (Bevilacqua and Navigli, 2020).

| Models                  | Model difference | Dev | Test | Concatenation of all Datasets |
|-------------------------|------------------|-----|------|------------------------------|
|                         | TS   IK GS MS    | SE07| SE12 | ALL                          |
| Most Frequent Sense     | ✓    -  -  -     | 54.5| 65.6 | 60.0                         |
| Leskocab (2014)         | ✓    -  -  ✓     | 56.7| 63.0 | 67.3                         |
| BiLSTM (2017a)          | ✓    -  -  -     | 71.1| 68.4 | 69.5                         |
| HCAN (2018a)            | ✓    -  -  -     | 72.8| 70.3 | 72.7                         |
| EWISE (2019)            | ✓    -  ✓  -     | 67.3| 73.8 | 74.0                         |
| LMMS (2019)             | ✓    -  ✓  L     | 68.1| 76.3 | 73.8                         |
| GlossBERT (2019)        | ✓    -  -  ✓     | 72.5| 77.7 | 79.3                         |
| BEM (2020)              | ✓    -  -  B     | 74.5| 79.4 | 81.4                         |
| AdaptBERTLarge (2020)   | ✓    S  -  L     | 72.7| 79.8 | 82.6                         |
| EwisEr (2020)           | ✓    S  ✓  L     | 75.2| 80.8 | 82.9                         |
| SemEq-Base              | ✓    -  -  B     | 72.7| 79.0 | 81.0                         |

Ours: Data Augmentation

| T2: SemEq-Base          | ✓    M  -  B     | 73.2| 81.2 | 81.9                         |

Ours: Transfer Learning

| T3: SemEq-Base-General  | -    M  -  B     | 65.7| 75.3 | 78.2                         |
| SemEq-Base-Expert       | ✓    M  -  B     | 74.1| 81.0 | 82.5                         |
| SemEq-Large-General     | -    M  -  L     | 65.1| 76.1 | 79.1                         |
| SemEq-Large-Expert      | ✓    M  -  L     | 74.9| 81.8 | 83.2                         |

| Noun Verb Adj Adv       | SEM 07 | SEM 12 | SEM 13 | SEM 15 | ALL |
|-------------------------|--------|--------|--------|--------|-----|
| 81.8 79.6 81.2 81.8     | 83.2   | 71.1   | 83.2   | 87.9  | 80.7|
Base (line 11) is our model’s performance when fine-tuning \( BERT_{\text{Base}} \) sentence encoder only on the build-in SemCor training set. Compared to line 11, when augmenting SemCor with our multi-source inventory knowledge, the same model (line 12) improves the F1 on the aggregated ALL set by 1.2%.

The third section of Table 3 reports the results of applying transfer learning strategy to exploiting our multi-source inventory knowledge. By only training on our multi-source inventory knowledge (without using SemCor), our model SemEq-Base-General (line 13) already achieves comparable performance with LMMS\(_{\text{BERT}}\) (line 6, which is based on \( BERT_{\text{Large}} \)). After further fine-tuning on the training set - Semcor, SemEq-Base-Expert (line 14) improves the performance on ALL to 79.9%, which is slightly better than using the data augmentation strategy. Moreover, increasing BERT model parameters (line 16) further boosts the WSD performance on ALL to 80.7\%.\(^8\)

Overall, our SemEq-Large-Expert model (line 16) consistently outperforms AdaptBERT (Yap et al., 2020) (line 9), the previous best model without using WordNet synset graph information, on SE07, SE2, SE3 and SE13, attaining 1.2% higher F1 on ALL. The SemEq-Large-Expert model also better disambiguates all types of words including nouns, verbs, adjectives, and adverbs than AdaptBERT. It clearly demonstrates the benefits of leveraging multiple word sense inventories via automatic alignment and transfer learning. Our final model is 0.6% higher even compared with EWISER (Bevilacqua and Navigli, 2020) that uses the extra WordNet graph knowledge. We can see that by pretraining on lexical knowledge derived from aligned inventories, our model generalizes more easily and better captures semantic equivalence between the target word and a gloss sentence for identifying the correct word meaning.

In order to understand our model’s behavior of transferring semantic equivalence knowledge from our word sense inventories to a specific WSD task, we partition word senses in the test set into groups according to their numbers of training instances found in the training set SemCor. As shown in Figure 3, by pretraining on our semantic equivalence knowledge and then fine-tuning on SemCor, SemEq-Base-Expert beats SemEq-Base (SemCor) that is only trained on SemCor across all annotation-rich and annotation-lacking word senses. Interestingly, without fine-tuning on SemCor, the general model (SemEq-Base-General) works surprisingly well on low-shot senses, which is 13.1%, 8.1% and 5.6% higher than SemEq-Base (SemCor) on 0 shot, 1-2 shot, 3-5 shot senses, respectively. After fine-tuning on SemCor, the expert models fit to the distribution of senses in the real world and achieve better overall performance.

### 6.2.2 Few-Shot and Zero-Shot WSD Tasks

By pretraining on massive semantic equivalence knowledge generated from aligned word sense inventories, we expect our model performs better on annotation-lacking senses. We next evaluate our model on the FEWS dataset (Blevins et al., 2021), a new WSD dataset that focuses on low-shot WSD evaluation. FEWS is a comprehensive evaluation dataset constructed from Wiktionary and covers 35K polysemous words and 71K senses. Overall, the build-in training set of FEWS consists 87K sentence instances. The test (development) set consists of two evaluation subsets, i.e., a few-shot evalua-

\(^8\)We also tried \( BERT_{\text{Large}} \) which is slightly worse than \( \text{RoBERTa}_{\text{Large}} \).
Table 4: F1-score (%) on the FEWS Low-Shot WSD benchmark dataset. WSI refers to knowledge extracted from aligned Word Sense Inventories. TS stands for the Training Set of FEWS.

| Models                          | TS   | Dev         | Test         |
|--------------------------------|------|-------------|--------------|
|                                | Full Set | Few-shot | Zero-shot    | Full Set | Few-shot | Zero-shot |
| Most Frequent Sense            | ✔️ 26.4 | 52.8 | 0.0          | ✔️ 25.7 | 51.5 | 0.0 |
| Lesk (Basile et al., 2014)     | ✔️ 42.5 | 44.9 | 40.1         | ✔️ 41.5 | 44.1 | 39.0 |
| BEM (Blevins and Zettlemoyer, 2020) | ✔️ 73.8 | 79.3 | 68.3         | ✔️ 72.8 | 79.1 | 66.5 |
| BEMSemCor (Blevins et al., 2021) | ✔️ 74.4 | 79.7 | 69.0         | ✔️ 73.0 | 78.9 | 67.1 |
| SemEq-Base                     | ✔️ 73.5 | 78.7 | 68.3         | ✔️ 72.4 | 78.5 | 66.3 |
| Ours: Data Augmentation        | ✔️ 26.8 | 52.8 | 0.0          | ✔️ 25.7 | 51.5 | 0.0 |
| SemEq-Base (+WSI)              | ✔️ 74.2 | 78.4 | 69.9         | ✔️ 73.7 | 78.6 | 68.7 |

Table 5: Accuracy (%) on the WiC benchmark dataset.

| Model                          | Acc.  | Parameters |
|--------------------------------|-------|------------|
| BERT_{large} (Devlin et al., 2019) | 69.6  | 340M       |
| RoBERTa_{large} (Liu et al., 2019) | 69.9  | 355M       |
| KnowBERT_{x,W} (Peters et al., 2019) | 70.9  | 523M       |
| SenseBERT_{x,W} (Levine et al., 2020) | 72.1  | 380M       |
| T5-Large (Raffel et al., 2020) | 69.3  | 770M       |
| T5-3B (Raffel et al., 2020) | 72.1  | 3000M      |
| BERTARES (Scarlini et al., 2020b) | 72.7  | 342M       |
| SemEq-Large (+WSI)              | 75.9  | 355M       |

6.3 Experiments on Context-Sensitive Word Meanings

Word-in-Context (WiC) Task (Pilehvar and Camacho-Collados, 2019) from SuperGLUE benchmark (Wang et al., 2019) provides a high-quality dataset for the evaluation of context-sensitive word meanings. WiC removes predefined word senses and reduces meaning identification to a binary classification problem in which, given two sentences containing the same lemma word, a model is asked to predict whether the two target words have the same meaning. Considering WiC uses WordNet as one lexical resource in its data construction, we completely remove WordNet from our inventory knowledge to avoid data leaking. Specifically, we simply add context-context pairs generated from the other five inventories to the training set of WiC to train a semantic equivalence recognizer. Table 5 shows results on the WiC task comparing to other models.10 The results indicate that incorporating semantic equivalence knowledge from aligned inventories improves RoBERTa_{large}’s performance by 6%, which also surpasses a large language model T5-3B (9X parameters) by 3.8%. It demonstrates the superiority of incorporating our high-quality multi-source lexical knowledge than blindly increasing the size of plain pretraining texts in language models.

7 Conclusion

Based on the observation that glosses of a word from different inventories usually are different expressions of a few meanings, we have proposed a gloss alignment algorithm that can unify different lexical resources as a whole to generate abundant semantic equivalence knowledge. The general model pretrained on derived equivalence knowledge can serve as a universal recognizer for word meanings.

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9We generate 3.3M positive pairs and 1.7M negative pairs.
10We submit our model predictions to the competition page of WiC (https://competitions.codalab.org/competitions) to get the test results.
meanings in context or adapt to a specific WSD task by fine-tuning to achieve new state-of-the-art performance. Our results also point to an interesting future research direction: how to develop a robust fine-tuning approach that is able to retain the excellent performance of the general model on low-resource senses while still improving performance on high-resource senses.

**Ethical Considerations**

Copyrights of data used in this paper belong to their respective owners. The authors are permitted to use data under the permission of the non-commercial research purpose and following the principle of fair use. The authors will not reproduce, republish, distribute, transmit, or link data used on any other website without the express permission of respective owners. The authors bear the responsibility to comply with the rules of copyright holders.

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