KDSL: a Knowledge-Driven Supervised Learning Framework for Word Sense Disambiguation

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Abstract

We propose KDSL, a new word sense disambiguation (WSD) framework that utilizes knowledge to automatically generate sense-labeled data for supervised learning. First, from WordNet, we automatically construct a semantic knowledge base called DisDict, which provides refined feature words that highlight the differences among word senses, i.e., synsets. Second, we automatically generate new sense-labeled data by DisDict from unlabeled corpora. Third, these generated data, together with manually labeled data and unlabeled data, are fed to a neural framework conducting supervised and unsupervised learning jointly to model the semantic relations among synsets, feature words and their contexts. The experimental results show that KDSL outperforms several representative state-of-the-art methods on various major benchmarks. Interestingly, it performs relatively well even when manually labeled data is unavailable, thus provides a potential solution for similar tasks in a lack of manual annotations.

1 Introduction

Word sense disambiguation (WSD) is the task to identify the sense of a word under certain context. It is one of the central tasks for understanding natural languages. WSD has been widely used in many basic natural language processing (NLP) tasks or downstream applications, such as sentiment analysis (Huang et al., 2012) and machine translation (Neale et al., 2016).

Approaches for WSD are divided into two groups, i.e., (semi) supervised learning (Lee and Ng, 2002; Zhi and Ng, 2010; Kagebäck and Salomonsson, 2016; Iacobacci, Pilehvar, andNavigli, 2016; Yuan et al., 2016; Melamud, Goldberger, and Dagan, 2016; Raganato, Bovi, andNavigli, 2017) and knowledge-based approaches (Lesk, 1986; Banerjee and Pedersen, 2003; Agirre and Soroa, 2009; Miller et al., 2012; Moro, Raganato, andNavigli, 2014; Basile, Caputo, andSemeraro, 2014a). In general, the former approaches perform better than the latter in most benchmarks. However, most supervised learning approaches for WSD are heavily dependent on the amount of sense-labeled data. Unfortunately, sense-labeled data is far from adequate for supervised systems to perform well due to the high cost of manual annotations. For synsets never occurred in the training corpora, these methods can not learn to make plausible predictions.

Motivated by this, we propose KDSL, a new framework to combine supervised learning and knowledge-based approaches for WSD by automatically generating sense-labeled data from explicit knowledge bases as the training dataset for supervised learning. More precisely, we first build a high quality semantic knowledge base from WordNet (Miller, 1995) that highlights the differences among word senses. Then, we utilize this knowledge base to generate sense-labeled data from raw sentences. Finally, these automatically generated data are fed to a neural network to model the semantic relationships among word senses, feature words and their contexts.

For the first step, we construct DisDict, a semantic KB customized for WSD, which is automatically extracted from WordNet by a statistic model. It selects simple feature words to highlight the differences among word senses, i.e., synsets. DisDict contains a number of triples of the form (synset, feature words, confidence score) for all synsets in WordNet 3.0, which contains a total number of 117659 synsets covering nouns, verbs, adjectives and adverbs. The feature words are selected based on two criteria. Firstly,
they should have similar semantics with the synset. Secondly, different from previous semantic KBs such as WordNet and ConceptNet, DisDict specifically aims at WSD, i.e., to highlight the differences among different synsets during knowledge extraction. For instance, depicted in Figure 1a, the word “accident” has two synsets, namely “accident.n.01” for “an unfortunate mishap; especially one causing damage or injury”, and “accident.n.02” for “anything that happens suddenly or by chance without an apparent cause”. For the synset “accident.n.01”, DisDict chooses “misadventure”, “wreck”, “mishap” as the feature words with highest confidence scores, while for “accident.n.02”, the top three feature words are “chance event”, “happenstance” and “happy chance”. Clearly, those two sets of feature words provide significant discriminative information between these two synsets.

The second step is to generate sense-labeled data automatically by DisDict from raw sentences. Since a synset is semantically similar to its feature words in DisDict, if one of these words occurs in a sentence, we label the context with the synset as a new instance. For instance, depicted in Figure 1b, since “happy chance” serves as a feature word for “accident.n.02”, the context in which “happy chance” occurs is labeled with “accident.n.02” and can be fed into supervised learning. In this way, we can generate much new labeled data for target synsets.

The final step is to design a neural framework conducting learning on these generated data, together with manually labeled data and unlabeled data. Depicted in Figure 2a given a sentence and a word in it to be disambiguated, the neural network takes the left context before the word and the right context after the word as the input, and uses a binary long short-term memory (BLSTM) encoder to encode them as a fixed-length context embedding, which is fed into a fully connected network with multi softmax outputs for predictions. As a supervised learning task, this encoder is trained jointly on data automatically generated by DisDict as well as data manually labeled to predict the proper synsets by their contexts. We set a param to control the ratio of samples from the two data sources. To improve the generalization ability, we also design an unsupervised learning task, i.e., training the encoder on unlabeled corpora to predict words by their left and right contexts, as depicted in Figure 2b.

We conduct empirical evaluations on various major WSD datasets and our method outperforms a number of representative approaches. Experiments show that incorporating supervised learning on the data generated by DisDict improves the performance for WSD. Even when there is no sense-labeled data, our work also performs well and beats MFS, which is a state-of-the-art knowledge-based WSD method. Our approach illustrates that the combination of semantic knowledge and unlabeled data is useful to generate high quality sense-labeled data and provides a potential solution for similar tasks without manually labeled data.
2 Related Work

In this section, we will briefly review previous approaches about supervised WSD, knowledge-based WSD, combined methods and data generation strategies for this task.

2.1 Supervised WSD

Supervised WSD is trained on sense-labeled corpora. The labels and features for training are extracted either manually or automatically. Zhi and Ng (2010) utilized surrounding words, POS tags of surrounding words and local collocations as features and trained a classifier for WSD. Rothe and Schütze (2015) leveraged WordNet to generate synset embeddings from word embeddings and convert them into features of a supervised learning system. Kagebäck and Salomonsson (2016) proposed an approach based on bidirectional LSTM to model sequence of words surrounding the target word without hand-crafted features. Iacobacci, Pilehvar, and Navigli (2016) published a full evaluation study on equipping supervised WSD with word embeddings. To alleviate the lack of sufficient manually labeled corpora, Yuan et al. (2016) proposed a semi-supervised framework with label propagation to expand training corpora. Melamud, Goldberger, and Dagan (2016) proposed a generic model for representation of context, i.e., context2vec, and fed it into a classifier for WSD. Uslu et al. (2018) proposes fastsense, a neural WSD model with high learning efficiency.

2.2 Knowledge-based WSD

Knowledge-based approaches rely on manually constructed human knowledge base. Lesk (1986) proposed definition (gloss) overlap measure, i.e., to calculate overlaps among the definitions of the target word and those surrounding it in the given context to determine word sense. It was enhanced by Banerjee and Pedersen (2003) to take definitions of related words into consideration. Chen and Liu (2011) combined both WordNet and ConceptNet to judge word sense. Taking advantages of distributional similarity (Miller et al., 2012; Basile, Caputo, and Semeraro, 2014b; Chen, Liu, and Sun, 2014; Camacho-Collados et al., 2016) has also been shown effective. Agirre and Soroa (2009); Guo and Diab (2010); Agirre, de Lacalle, and Soroa (2014); Moro, Raganato, and Navigli (2014); Weissborn et al. (2015); Tripodi and Pelillo (2017) modeled knowledge bases as graphs, i.e., words as nodes and relations as edges. The senses preferences of each word are updated iteratively according to certain graph-based algorithms. Pasini and Navigli (2018) proposed two knowledge-based methods for learning the distribution of senses.
2.3 Combined methods and data generation strategies

Rothe and Schütze (2015) leveraged WordNet to generate synset embeddings from word embeddings and convert them into features of a supervised learning system; Raganato, Bovi, and Navigli (2017) introduced several advanced neural sequence learning models to WSD and design a multi-task mechanism to predict synsets as well as their coarse-grained semantic labels. Taghipour and Ng (2015) proposed OMSTI, a sense-labeled corpus generated through the disambiguation of a multilingual parallel corpus; Pasini and Navigli (2017) proposed Train-O-Matic, a data generation strategy based on random walk in WordNet.

3 Models

3.1 Problem Formalization

Suppose there is a sentence \( c \) with words in order: \( w_1, w_2, ..., w_L \), each of which is tagged with its POS. For instance, in a sentence “Knowledge is power”, \( w_1=\text{"knowledge\_NOUN"} \), where the suffix “\_NOUN” means its POS is noun. For each \( w_i \) in \( c \), there is a set of candidate synsets \( CS(w_i) = \{s_1(w_i), s_2(w_i), ..., s_K(w_i)\} \). If two synsets are both candidate synsets for a certain word, it is called that they have competitive relations in this paper. The goal of word sense disambiguation (WSD) is to identify the correct synset of \( w_i \) given the context \( c \).

For a corpus \( T \) with sentences \( c_1, c_2, ..., c_N \), the collection of all target words to be disambiguated in \( T \) is denoted as \( T_W \), the collection of all candidate synsets for words in \( T_W \) is denoted as \( T_S \). And in DisDict, there are several feature words to interpret the semantics of each synset, the collection of all feature words is denoted as \( F_W = \bigcup_i F_W(s_i) \), while \( F_W(s_i) \) is the collection of feature words of synset \( s_i \).

3.2 Knowledge Base for WSD: DisDict

Motivations

For our work, we need a semantic KB to generate sense-labeled data. However, existing semantic KBs are hard to use directly. There are two main disadvantages:

a) Coarse-grained. Some semantic KBs, e.g., ConceptNet, only provide word (or phrase) level knowledge and do not distinguish different potential senses of a given word (phrase) explicitly;

b) (Partially) unstructured. WordNet and BabelNet (Navigli and Ponzetto, 2012) provide glosses of synsets by unstructured texts which are hard to encode and utilize by neural models.

Motivated by these disadvantages, we propose DisDict, a semantic KB aiming at WSD. The ideas for DisDict are also twofold:

a) Establishing synset level semantic knowledge;

b) Extracting high-quality semantic information from (partially) unstructured knowledge to highlight the distinction among candidate synsets. In DisDict, only words having high statistic correlations with the target synset are selected as its feature words. These words are tagged with confidence scores by a statistic model. Noisy words or words with little discriminative information for synsets are removed.

Construction of DisDict

To build DisDict, firstly, words from Synonymy, Hyponymy/Hypernymy and Gloss in WordNet are harvested as potential feature words. A word in a synset’s gloss is likely to be its feature word only if it has the same POS with the synset. For instance, since the gloss of synset “english.n.01” is “the people of England”, then “people” and “England” are considered as potential feature words of “english.n.01”.

Then a statistic model is implemented to select words having high statistical correlations with the target synset are selected as its feature words. These words are tagged with confidence scores by a statistic model. Noisy words or words with little discriminative information for synsets are removed.
Table 1: A glance of DisDict

| Synset 1 | Synset 2 | Confidence Score |
|----------|----------|------------------|
| player.n.01, playmaker, 0.11 | arrive.v.01, flood in, 0.21 | (brainy.s.01, brainy, 0.52) |
| player.n.01, seeded player, 0.11 | arrive.v.01, plump in, 0.21 | (brainy.s.01, smart as a whip, 0.36) |
| player.n.01, dart player, 0.11 | arrive.v.01, drive in, 0.16 | (brainy.s.01, impressive, 0.06) |
| player.n.01, most valuable player, 0.11 | arrive.v.01, move in, 0.16 | (brainy.s.01, unusual, 0.05) |
| player.n.01, volleyball player, 0.11 | arrive.v.01, get in, 0.05 |
| player.n.01, pool player, 0.09 | arrive.v.01, come in, 0.04 |
| player.n.01, lacrosse player, 0.09 | arrive.v.01, draw in, 0.04 |
| player.n.01, grandmaster, 0.09 | arrive.v.01, set down, 0.04 |
| player.n.01, scorer, 0.09 | arrive.v.01, roll up, 0.04 |
| player.n.01, billiard player, 0.09 | arrive.v.01, attain, 0.03 |

DisDict is organized as a number of triples, i.e., \((s_i, w_j, r_{ij})\). Table 1 provides a glance of DisDict, i.e., three competitive synsets pairs in DisDict \((N_f = 10)\), i.e., “player.n.01” (“a person who participates in or is skilled at some game”) and “musician.n.01” (“someone who plays a musical instrument (as a profession)”; “arrive.v.01” (“make a prediction about; tell in advance”) and “arrive.v.02” (“succeed in a big way; get to the top”); “brainy.s.01” (“having or marked by unusual and impressive intelligence”) and “brilliant.s.02” (“of surpassing excellence”). Synsets in the same column have competitive relations with each other.

**Sense-Labeled Data Generation by DisDict**

The second step is to generate sense-labeled data automatically by DisDict from raw sentences. Since in DisDict a synset is semantically similar to its feature words, if one of them occurs in a sentence, label the sentence with the synset as a new instance. Depicted in Figure 1b since “happy chance” serves as a feature word for “accident.n.02”, the context in which “happy chance” occurs is labeled with “accident.n.02” and can be fed into supervised learning. In this way, we can generate much new labeled data for target synsets.

Synsets in corpora follow a certain frequency distribution. Different synsets may have different frequencies. Since we do not know this distribution a priori, we can only design a model to simulate it, i.e.,

\[
p(s_i, w_j) \propto p(s_i, w_j) + 2. \tau \text{ is an adjustable parameter to control the effect of word frequencies. For each target synset } s_i, \text{ only a small number } (\leq N_f) \text{ of feature words with the highest } r_{ij} \text{ are preserved, others are dropped out. Confidence scores for these } N_f \text{ feature words are normalized such that their sum is } 1.0 \text{ which is:}
\]

\[
r_{ij} \leftarrow \frac{r_{ij}}{\sum_{w_j' \in FW(s_i)} r_{ij'}}, w_j \in FW(s_i)
\]

\[\text{(2)}\]

where \(w_j\) is a word of which \(s_i\) is one of the candidate synsets, i.e., \(s_i \in CS(w_j)\); \(l_{ij}\) denotes the ranking of \(s_i\) among synsets in \(CS(w_j)\), e.g., the ranking of “english.n.01” is 1 among the candidate synsets of
| Methods                      | Test Datasets | Concatenation of All Test Sets |
|------------------------------|---------------|-------------------------------|
|                              | SE2  | SE3  | SE13 | SE15 | Nouns | Verbs | Adj. | Adv. | All   |
| IMS                          | 70.9 | 69.3 | 65.3 | 69.5 | 70.5  | 55.8  | 75.6 | 82.9 | 68.9  |
| IMS-s+emb                    | 72.2 | 70.4 | 65.9 | 71.5 | 71.9  | 56.6  | 75.9 | 84.7 | 70.1  |
| Context2vec                  | 71.8 | 69.1 | 65.6 | 71.9 | 71.2  | 57.4  | 75.2 | 82.7 | 69.6  |
| Le et al. (2017)             | 70.0 | -    | 66.6 | -    | -     | -     | -    | -    | -     |
| Raganato et al. (2017)       | 72.0 | 69.4 | 66.4 | 70.8 | 71.6  | 57.1  | 75.6 | 83.2 | 69.9  |
| Ours                         |       |      |      |      |       |       |      |      |       |
| MLab                         | 69.2 | 68.3 | 66.1 | 67.4 | 69.4  | 54.6  | 75.7 | 82.4 | 68.0  |
| MLab+ULab                    | 70.2 | 69.9 | 69.3 | 72.9 | 72.3  | 56.8  | 77.4 | 81.1 | 70.4  |
| MLab+ULab+MFS                | 70.8 | 69.9 | 69.8 | 73.0 | 72.8  | 56.8  | 77.3 | 81.2 | 70.7  |
| MLab+DisDict+ULab            | 72.0 | 70.5 | 70.9 | 72.7 | 74.3  | 55.6  | 77.7 | 82.4 | 71.4  |
| MLab+DisDict+ULab+MFS        | 72.0 | 71.2 | 70.9 | 72.9 | 74.4  | 56.0  | 78.3 | 82.1 | 71.7  |

Table 2: F1-scores (%) for English all-words fine-grained WSD with the utilization of manually labeled training data

"English_Noun" in WordNet: \( f(w_j) \) is the frequency of \( w_j \) which is counted in a large corpus; \( p \) is an adjustable param to control the bias towards synsets with high rankings.

The instances for \( s_i \) are generated by its feature words, i.e., \( FW(s_i) \). The number of instances contributed by \( w_k \in FW(s_i) \) for \( s_i \), denoted as \( f(s_i, w_k) \), is set as:

\[
f(s_i, w_k) = f(s_i) \cdot r_{ik}, w_k \in FW(s_i)
\]

### 3.3 Learning Framework

The learning process has two parts:

a) Supervised Learning: training a model to predict synsets by contexts in sense-labeled corpora. As shown in Figure 2a, suppose there is a sentence “I speak English very loudly...” where the word “English” is to be disambiguated. The model is trained to make prediction of “english.n.01” over all synsets given the left (“I speak”) and right (“very loudly...”) context of “English”.

b) Unsupervised learning: training the model in a) to predict words by contexts in large unlabeled corpora. As shown in Figure 2b, suppose there is a sentence “To master a language, you have to practice listening and speaking ...” where the word “language” is one of the feature words in DisDict, the model is trained to make prediction of “language” given its left (“To master a”) and right (“you have to practice listening and speaking ...”) context. This training process promotes the ability to model context and extract semantic features, which improves the generalization performance.

During training, instances are sampled from manually labeled data and data generated by DisDict. We set a param to control the ratio of samples from the two data sources.

### 3.4 Neural Model

LSTM [Hochreiter and Schmidhuber, 1997] is a gated type of recurrent neural network (RNN), which is a powerful model for NLP. We follow to choose BLSTM [Graves and Schmidhuber, 2005] as our basic neural encoder. As shown in Figure 1, suppose in a sentence \( c \) with words \( w_1, w_2, ..., w_t, w_{t+1}, ..., w_N \), \( w_t \) is the target word to be disambiguated. We arrange words surrounding \( w_t \) in order, which are denoted as \( left_{word} = [w_{t-T}, w_{t-T+1}, ..., w_{t-1}] \) and \( right_{word} = [w_{t+1}, w_{t+2}, ..., w_{t+T}] \), where \( T \) is the maximal distance we consider. Then the two groups of word sequences are fed into a BLSTM structure with two LSTMs in different directions. The words on the left side of the target word are fed into a left-to-right LSTM while those on the right side of target are fed into right-to-left LSTM. The left-to-right LSTM generates a sequence of hidden state vectors \( [h_1, ..., h_T] \) and the right-to-left LSTM generates a sequence of hidden state vectors \( [\tilde{h}_1, ..., \tilde{h}_T] \).
Then we get two feature vectors $\overrightarrow{h_l}$ and $\overrightarrow{h_r}$ for left and right context of $w_l$:

$$\overrightarrow{h_l} = \overrightarrow{h_T}, \overrightarrow{h_r} = \overrightarrow{h_T}$$

(5)

Since the left and right contexts of $w_l$ do not contain $w_l$ itself, they are denoted as $c_l \{w_l\}$. The vector representation for context $c_l \{w_l\}$, i.e., $\overrightarrow{c_l}$, is calculated by a fully connected module which takes the concatenation of $\overrightarrow{h_l}$ and $\overrightarrow{h_r}$ as input:

$$\overrightarrow{c_l} = \text{Relu}(W_2 \cdot \text{Relu}(W_1 : \overrightarrow{h_l} : \overrightarrow{h_r}) + b_1) + b_2$$

(6)

Let $SW$ be all synsets occurred in the training corpora. Let $s_t$ be the correct synset for $w_t$, the probability distribution $p(s_t|c_l \{w_l\})$ over all the synsets $s_t \in SW$ is calculated by a softmax layer:

$$p(s_t|c_l \{w_l\}) = \frac{\exp(\overrightarrow{w_l}^T \cdot \overrightarrow{c_l})}{\sum_{s_t \in SW} \exp(\overrightarrow{w_l}^T \cdot \overrightarrow{c_l})}$$

(7)

For a word $w$ in context $c$, the probability distribution $p(w|c_l \{w_l\})$ over all words $w'$ is calculated by another softmax layer:

$$p(w|c_l \{w_l\}) = \frac{\exp(\overrightarrow{w_l}^T \cdot \overrightarrow{c_l})}{\sum_{w'} \exp(\overrightarrow{w}^T \cdot \overrightarrow{c_l})}$$

(8)

In the labeled corpus $T = \{c_1, c_2, ..., c_N\}$, for each sentence $c_j \in T$, the training objective is:

$$J_a = - \sum_{c_j \in T} \log(p(s_t|c_j \{w_l\}))$$

(9)

The training process for (9) is illustrated in Figure 2a.

As an unsupervised task, in the unlabeled corpus, the model is trained to make prediction of word $w$ from context $c_j \{w_l\}$. The objective is illustrated as Figure 2b and formulated by:

$$J_u = - \sum_{c_j \in T} \sum_{w \in c_j \cap FW} \log(p(w|c_j \{w_l\}))$$

(10)

where $\theta$ is an adjustable parameter. The final objective $J$ is the weighted aggregation of $J_a$ and $J_u$:

$$J = J_a + \alpha J_u$$

(11)

where $\alpha$ is an adjustable parameter. $J$ is trained to be minimized and equation (7) and (8) are approximated by sampled softmax [Jean et al., 2015] during training. During inferencing, for $w_l$ in $c_j$ to be disambiguated, the model chooses the candidate synset with highest probability conditioned on $c_j$ as output ($s_o$), which is formulated by:

$$s_o = \arg \max_{s_t} p(s_t|c_j \{w_l\}), s_t \in S(w_l)$$

(12)

where $S(w_l)$ is the set of candidate synsets for $w_l$, $p(s_t|c_j \{w_l\})$ is the outputs of our BLSTM encoder.

4 Experiments

4.1 Setup

**Baseline Methods:** The baselines include some state-of-the-art approaches, i.e., MFS (to directly output the Most Frequent Sense in WordNet); IMS [Zhi and Ng, 2010], a classifier working on several handcrafted features, i.e., POS, surrounding words and local collocations; Babelfy [Moro, Raganato, and Navigli, 2014], a state-of-the-art knowledge-based WSD system exploiting random walks to connect synsets and text fragments; Lesk_ext+emb [Basile, Caputo, and Semeraro, 2014a], an extension of Lesk by incorporating similarity information of definitions; UKB_gloss [A girre and Soroa, 2009] [A girre, de Lacalle, and Soroa, 2014], another graph-based method for WSD; A joint learning model for WSD and entity linking (EL) utilizing semantic resources by [Weissenborn et al., 2015]; IMS-s+emb [Iacobacci,
Table 3: F1-scores (%) for English all-words fine-grained WSD in the absence of manually labeled training data

| Methods       | Concatenation of All Test Sets |
|---------------|--------------------------------|
| MFS           | 65.8                           |
| Babelfy       | 66.4                           |
| UKB_gloss     | 61.1                           |
| Lesk_ext+emb  | 64.2                           |
| Ours          | 66.2                           |
| DisDict+MFS   | 67.2                           |

Table 4: F1-scores (%) for nouns disambiguation

| Methods                  | Test Datasets |
|--------------------------|---------------|
|                          | SE2 | SE3 | SE13 | SE15 |
| MFS                      | 72.0| 72.0| 63.0 | 66.3 |
| OMSTI                    | 73.3| 67.5| 62.5 | 63.4 |
| Train-O-Matic            | 71.1| 67.8| 65.8 | 68.1 |
| Weissenborn et al. (2015)| -   | 68.8| 72.8 | 71.5 |
| Ours                     | 73.2| 69.0| 66.2 | 70.1 |
| DisDict+MFS              | 74.6| 72.0| 65.3 | 71.0 |
| MLab+DisDict+ULab+MFS    | **78.0**| **76.0**| **70.9**| **75.1** |

Datasets: We choose Semcor 3.0 (Miller et al., 1994) (226,036 manual sense annotations), which is also used by baselines, as the manually labeled data. We also extract 27,616,880 word-context pairs from Wikipedia April 2010 dump with 1 billion tokens which was preprocessed and utilized by Sun et al. (2016). From which, we generate 11,925,166 sense labeled instances by DisDict. The trained models are evaluated on the fine-grained English all-words WSD task under the standardized evaluation framework released by Navigli, Camacho-Collados, and Raganato (2017). We tune parameters on SemEval-07 task 17 (Pradhan et al., 2007) and test models on four datasets, i.e., Senseval-2 (Edmonds and Cotton, 2001) with 2282 synset annotations, Senseval-3 task 1 (Snyder and Palmer, 2004) with 1850 annotations, Senseval-13 task 12 (Navigli, Jurgen, and Vannella, 2013) with 1644 annotations and Senseval-15 task 13 (Moro and Navigli, 2015) with 1022 annotations. The word embeddings we use are pretrained on 2 billion ukWac (Baroni et al., 2009) corpus, the same corpus as that used in baseline methods.

Settings: We design a series of experiments based on the combination of four basic settings, i.e., M Lab (conducting supervised learning on manually labeled data); U Lab (conducting unsupervised on unlabeled data); DisDict (conducting supervised learning on data generated by DisDict); MFS (adding a bias towards the output score of most frequent synset when inferencing). For M Lab, if with MFS,
we select it as the backoff strategy when the target word is unseen in the training corpora; elsewise, we randomly select a candidate synset to output under such circumstance. For the combination of MLab and DisDict, during training, we sample instances from the two datasets with a ratio to control the balance.

For data generation, \( N_f \) is set as 10, \( \tau \) in (1) is set as 0.66 and \( p \) is set as 0.3 in (3); For training, the BLSTM has 2 layers and 400 hidden units for each individual LSTM; the learning rate for \( J \) in (11) is set as 0.1 and \( \alpha \) is 5.0, we use Mini-batch Gradient Descent to optimize \( J \), and the batch size is 80; we apply Dropout (Srivastava et al., 2014) with a rate of 0.5 to prevent over-fitting; the dimension of word and synset embedding is 400; the ratio of samples from manually labeled data and that generated by DisDict is set as 1.0 : 0.3; During inferencing, for MFS, the bias added to the most frequent synset is set as 0.5.

4.2 Results and Analysis

Table 2 posts the results for English all-words fine-grained WSD with the utilization of manually labeled training data. From the comparison between MLab and MLab+ULab setting, it shows that unsupervised learning improves the generalization performance. From the comparison between MLab+ULab and MLab+DisDict+ULab setting, it illustrates the knowledge in DisDict has a good quality and the combination of knowledge and unlabeled data really generates reliable sense-labeled data, thus improves the overall performance. From the comparison between MLab+DisDict+ULab and MLab+DisDict+ULab+MFS setting, it shows that MFS has a good complementarity to supervised WSD.

Table 3 reports the results of WSD in the absence of manually labeled training data. For fairness, in Table 3, we only make comparison with methods do not need manually labeled data. As shown in Table 3, when there is no manually-labeled data, the combination of our model and MFS, i.e., DisDict+MFS, has outperformed the MFS and Babelfy baseline, thus provides a potential solution for similar tasks in a lack of manual annotations.

Table 4 reports the results of nouns disambiguation on several test sets. Among these settings, MFS, OMSTI, Train-O-Matic, DisDict and DisDict+MFS do not require manually labeled data while Weisborn et al. (2015) and MLab+DisDict+ULab+MFS require. For data generation methods which are closest to ours, i.e., OMSTI and Train-O-Matic, we train our supervised model on their generated data and post the results. Compared them with DisDict, we can concludes that our new data generation method beats these two approaches by two points. First, these methods only focus on nouns disambiguation, while our work is appropriate to any POS in English. Second, our generated data has a higher quality with a better overall performance on nouns disambiguation.

For fine-grained analysis, we divide synsets in the test sets into four groups according to their frequen-
cies $f$ in the manually labeled training corpus, i.e., $0 \leq f \leq 5$, $5 < f \leq 30$, $30 < f \leq 150$, $f > 150$, and calculate F1-scores for these groups, as shown in Figure. It shows that incorporating data generated by DisDict is beneficial consistently to synsets in each frequency interval from the comparison between $MLab+ULab$ and $MLab+DisDict+ULab$.

5 Conclusion and Future Work

In this paper, we propose a new framework to combine supervised learning and knowledge-based approaches for word sense disambiguation (WSD). Under this framework, we automatically construct a semantic KB, i.e., DisDict, to highlight the semantic differences among synsets, and utilize DisDict to generate reliable sense-labeled data from unlabeled corpora. Then we apply a neural model to conduct both supervised and unsupervised learning for WSD. Evident from the experiments, our framework outperforms a number of representative approaches on major standard evaluation datasets. Furthermore, our model also achieves better performance against other methods when there is no manually labeled data, thus provides a potential solution for such learning tasks in a lack of manually annotations.

For future work, we will focus on two research lines. First, we will study more powerful approaches to acquire knowledge from unstructured data automatically. Second, we will study a better combination of the data manually labeled and that generated by DisDict.

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