Abstract

In previous similarity-based WSD systems, studies have allocated much effort on learning comprehensive sense embeddings using contextual representations and knowledge sources. However, the context embedding of an ambiguous word is learned using only the sentence where the word appears, neglecting its global context. In this paper, we investigate the contribution of both word-level and sense-level global context of an ambiguous word for disambiguation. Experiments have shown that the Context-Oriented Embedding (COE) can enhance a similarity-based system’s performance on WSD by relatively large margins, achieving state-of-the-art on all-words WSD benchmarks in knowledge-based category.

1 Introduction

Word sense disambiguation (WSD) is aimed at selecting the correct sense for a word given its context. Potential senses of a word are from a sense inventory such as WordNet (Miller, 1995). WSD can be classified into lexical sample WSD and all-words WSD. The former focuses on disambiguating some particular words in many sentences, while the latter conducts WSD on every ambiguous word in the provided text.

The nature of all-words WSD allows the task to be more compatible to downstream applications. Nevertheless, the task becomes more difficult (Pradhan et al., 2007) while it also provides more context information (rather than a single sentence). Utilizing such global context can assist the systems to tackle WSD from an overall perspective.

Recent development of contextual representation models, has accelerated the progress of WSD. Many systems are proposed to tackle WSD by employing BERT either by extracting features (Vial et al., 2019; Loureiro and Jorge, 2019) or fine-tuning (Peters et al., 2019; Levine et al., 2020). However, these systems are mostly implemented with a single sentence context, especially for the systems (Huang et al., 2019; Blevins and Zettlemoyer, 2020) that fine-tune BERT (Devlin et al., 2019). As for the others (Scarlini et al., 2020a; Wang and Wang, 2020, Scarlini et al., 2020b), efforts are allocated to construct sense embeddings using WordNet or SemCor (Miller et al., 1994), while context embeddings for ambiguous words are learned merely from a single sentence. This has led to an issue that the information volume of context embeddings and sense embeddings is not balanced.

In this paper, we introduce COE, a context-oriented embedding technique to learn comprehensive context representations for ambiguous words. This is aimed at enhancing the context embeddings by considering both the global and local sentences in the provided document. In summary, our approach has the following contributions:

• We propose a novel technique to capture both local and global context information for context representation learning. The obtained...
context embeddings are further enhanced with the embeddings of senses appeared in the context.

- We show that the proposed technique can elevate previous systems' performance on all-words WSD to new state-of-the-art in the knowledge-based category.

2 Method

2.1 Similarity-based WSD

Given a document \( d \) that contains several sentences, a system is required to determine the correct sense \( s_{k,w_{i,j}} \) of each word \( w_{i,j} \in \{w_{l,1}, w_{l,2}, \ldots, w_{l,m}\} \) in sentence \( S_l \in \{S_1, S_2, \ldots, S_n\} \). \( s_{k,w_{i,j}} \) is one of the potential senses in \( S_{w_{i,j}} \) retrieved from WordNet by the lemma and part-of-speech (POS) of word \( w_{i,j} \). In previous similarity-based WSD models (Loureno and Jorge, 2019; Scarlini et al., 2020a; Wang and Wang, 2020; Scarlini et al., 2020b), sense embeddings of all WordNet senses are first learned using their definitions and other available resources. Then, in order to disambiguate \( w_{i,j} \), the sense embedding \( V_{k,w_{i,j}} \) of its potential sense \( s_{k,w_{i,j}} \) is retrieved from the learned sense embedding pool. Then, the dot product of each potential sense embedding \( V_{k,w_{i,j}} \) and the context embedding \( P_{w_{i,j}} \) is used to select the optimal sense \( \hat{s}_{w_{i,j}} \) shown in formula (1). \( P_{w_{i,j}} \) is learned using only the sentence where \( w_{i,j} \) appears.

\[
\hat{s}_{w_{i,j}} = \arg\max_{s_{k,w_{i,j}} \in S_{w_{i,j}}} V_{k,w_{i,j}} \cdot P_{w_{i,j}} \tag{1}
\]

Typically, \( P_{w_{i,j}} \) is the sum of BERT’s last four layers at the position of \( w_{i,j} \), taking \( s_{i} \) as its input. When \( w_{i,j} \) is tokenized into several pieces, the sum of all its pieces’ embeddings is taken as \( P_{w_{i,j}} \).

However, this naïve context representation learning process has limited the system’s ability to capture global context information. In order to relieve this issue, we devise several methods to learn more comprehensive context embeddings by combining \( S_l \) and the other sentences in the same document. Note that, this work does not involve any attempt on sense embedding learning.

2.2 Context Embedding Learning

Local Context Embedding Following the approaches in prior works (Agirre et al., 2018, Wang et al., 2020), we utilize the directly surrounding sentences \( \{S_1, \ldots, S_{i-1}, S_{i+1}, \ldots, S_n\} \) of the ambiguous sentence \( S_i \) for a more effective local context embedding. Here, we use a development set to select the optimal number of surrounding sentences on both sides of \( S_i \) and use the expanded sentence set as BERT’s input to get the local context embedding \( p_{i,w_{i,j}}^l \).

Global Context Embedding Except for the sentences that are in the same small window as the ambiguous sentence \( S_i \), distant sentences are also beneficial for understanding the words in \( S_i \) in many cases. Here, we transform the problem into a sentence selection problem, i.e., to determine which sentences can better incorporate global context information for the disambiguation of the words in \( S_i \).

We hence formally define the problem as follows: for each sentence \( S_l \in \{S_1, S_2, \ldots, S_n\} \) under disambiguation, we aim at ranking the other sentences in the same document according to their contributions from different perspectives. Then, we use \( S_i \) and its top ranked sentences to learn the global context embedding \( p_{i,w_{i,j}}^g \). We design three methods to rank the sentences: word overlap (WO), TF-IDF score (TF-IDF WO), gloss-expanded word overlap (GeWO).

- Word overlap: the overlap count between \( S_i \) and \( S_j \), i.e., the sum of the number of times that \( S_i \)’s words appear in \( S_j \).
- TF-IDF weighted word overlap: we regard each sentence \( S_l \in \{S_1, S_2, \ldots, S_n\} \) as a document and calculate the TF-IDF score of each word in the sentences; the TF-IDF score is then used to weight the overlap count between \( S_i \) and \( S_j \) for each word. The score of \( S_j \) with respect to \( S_i \) is calculated as follows:

\[
\text{score}_{S_i,S_j}^g = \sum_{w \in S_i} \text{tfidf}_w \ast \text{count}(w,S_j) \tag{2}
\]

- Gloss-expanded word overlap: we first expand each sentence \( S_l \in \{S_1, S_2, \ldots, S_n\} \) with all the synsets’ definition words of each monosemous word \( w_{i,j} \) and then calculate the overlap between expended \( S_i \) and \( S_j \).

After we obtain the score of sentence \( S_j \in \{S_1, \ldots, S_{i-1}, S_{i+1}, \ldots, S_n\} \) with respect to \( S_i \), we rank them based on the scores and combine \( S_i \) and its top related sentences to learn a global context embedding. We note that, the sentence order is maintained when using them to learn the context.
embedding. For instance, if $S_{i-4}$ and $S_{i+9}$ are the top 2 related sentences of $S_i$, we take $\{S_{i-4}, S_i, S_{i+9}\}$ as BERT’s input for learning the global context embedding of each word in $S_i$. We also employ a development set to acquire the optimal number of related sentences for the global context embedding learning.

Sense-aware Context Embedding In most cases, the words in a given document are not always polysemous. This is verified by the statistics that 16.4% of words are monosemous in SemCor. These monosemous words can provide some general background information about the whole document. Here, we utilize the sense embeddings of the monosemous words to compose a sense-aware context embedding $P_{w_{i,j}}$.

In detail, all the sense embeddings of the monosemous words in the same document as $w_{i,j}$ are added together to obtain $P_{w_{i,j}}^s$ only when $w_{i,j}$ is a noun or verb. This is because the disambiguation of adjectives and adverbs tend to rely more on the local context information, indicating that it is a modifier (adjective or adverb) of which word (noun or verb) in the same sentence. We note that, for the knowledge-based approach, we also use the sense embedding of WordNet 1st sense for polysemous words in the document.

We combine the above local and global context embeddings after normalization to get the final enhanced context embedding $\hat{P}_{w_{i,j}}$, detailed in formula (3).

$$\hat{P}_{w_{i,j}} = P_{w_{i,j}}^l + P_{w_{i,j}}^g + P_{w_{i,j}}^s$$  (3)

2.3 Try-again Mechanism (TaM)

Wang and Wang (2020) proposed a try-again mechanism that exploits WordNet synset relations and super-sense connections to conduct a second WSD. Precisely, when disambiguating $w_{i,j}$, the method takes into account two similarity scores. One is from Formula (1). The other is calculated from a broader perspective, e.g., the maximal similarity between $p_{w_{i,j}}$ and one potential sense’ ($s_{k,w_{i,j}}$) related synsets ($R_{skw_{i,j}}$). These related synsets are connected to $s_{k,w_{i,j}}$ by WordNet synset relations and the super-sense connection. Here, synsets that are in the same super-sense category are regarded as connected by the super-sense connection. For example, toy.n.03 (toy) {a device regarded as providing amusement} and bell.n.01 (bell) {a hollow device made of metal that makes a ringing sound when struck} are both in the super-sense category of noun.artifact.

Formula (4) illustrates the final WSD calculation. The method manages to boost the knowledge-based system’s performance by a relatively large margin, while slightly damages the performance of the supervised system.

$$\hat{s}_{w_{i,j}} = \arg\max_{s_{k,w_{i,j}} \in S_{w_{i,j}}} \left( V_{skw_{i,j}} \cdot P_{w_{i,j}} + \max_{s_t \in R_{skw_{i,j}}} V_{s_t} \cdot P_{w_{i,j}} \right)$$  (4)

We improve the original mechanism by utilizing a higher quality of synset category named coarse sense inventory (CSI, Lacerra et al., 2020). CSI defines 45 labels in its inventory and covers 83,000 WordNet synsets. We replace the super-sense connection with CSI in the modified try-again mechanism. The revised mechanism leads our model to a better performance.

3 Experiment

3.1 Datasets and Systems

We use the evaluation framework in (Raganato et al., 2017b) to evaluate our method’s effectiveness.

In the following section, we report the performance of systems in the knowledge-based category for all-words WSD task, in comparison with ours. They consist of UKB (Agirre et al.,...
Throughout the whole paper, we utilize the knowledge-based version of SREF (Wang and Wang, 2020) sense embeddings to validate the effectiveness of our method. Except for the knowledge-based version, we also implement the proposed method in some supervised similarity-based systems, achieving better performance than their original versions. However, the margin is not significant. Details are shown in Appendix.

4 Evaluation

4.1 Ablation Analysis

Table 1 demonstrates the ablation study on the combined dataset (ALL). An overall conclusion can be drawn that each of the proposed factors manages to raise the system’s performance. F1 measure is reported in percentage in all the tables. As one can see, although the sense-aware context embedding is simple and easy to implement, the strategy alone enhances the system’s performance by 2 F1. This astonishing contribution owes to a fine quality sense embedding and the employment of WordNet 1st senses, an essential prior knowledge in WordNet. As for the other two factors regarding context sentence usage, the contribution of each factor is not as significant.

Viewing from another perspective, when both the local and global context embeddings are removed, the performance drop exceeds that of the system that ignores the sense-aware embeddings. This has illustrated a fact that both word-level and sense-level context embeddings are crucial for WSD. It is interesting to note that merely adding the sense-aware context embedding can ruin the contribution of TaM, which makes the last two systems (use only $P_{wi,j}$ as the context embedding) perform identically on ALL.

In Table 2, the performance of COE$_{kb}$ on ALL has shown that the simplest strategy (WO) has led to the best performance, although the margin is not significant.

4.2 Overall Results

Table 3 shows how different systems perform on several partitions of ALL. Our system in both categories produces a new state-of-the-art. The knowledge-based version of our system, COE$_{kb}$, outperforms the previous state-of-the-art system (SREF) on ALL by a relatively large margin, 2.8 F1. From the perspective of POS performance, COE$_{kb}$ is the first system that reaches 80 F1 on noun disambiguation, surpassing the previous SOTA by 3.1 F1.

In fact, the performance of COE$_{kb}$ has exceeded that of many supervised systems including GLU. GLU utilizes BERT as a feature extraction tool in a supervised manner. The fact that it merely relies on SemCor hampers the system’s generalization ability since SemCor only covers a small proportion of WordNet senses. It is shown that those systems (EWISE and GLU) that fail to

| Pretrained Model | Systems | Test Datasets | Concatenation of all Test Datasets |
|-----------------|---------|---------------|-----------------------------------|
|                 | SE2 | SE3 | SE07 | SE13 | SE15 | ALL | N | V | A | R |
| / UKB (2018)     | 68.8 | 66.1 | 53.0 | 68.8 | 70.3 | 67.3 | 71.2 | 50.7 | 75.0 | 77.7 |
| WSD-TM (2018)   | 69.0 | 66.9 | 55.6 | 65.3 | 69.6 | 66.9 | 69.7 | 51.2 | 76.0 | 80.9 |
| KEF (2020)      | 69.6 | 66.1 | 56.9 | 68.4 | 72.3 | 68.0 | 71.9 | 51.6 | 74.0 | 80.6 |
| SyntagNet (2019)| 71.2 | 71.6 | 59.6 | 72.4 | 75.6 | 71.5 | -   | -   | -   | -   |
| BERT             | 70.8 | 65.4 | 58.0 | 74.8 | 75.0 | 70.1 | 75.9 | 50.3 | 74.3 | 80.9 |
|                 | 72.7 | 71.5 | 61.8 | 76.4 | 79.5 | 73.5 | 78.5 | 56.6 | 79.0 | 76.9 |
|                 | 76.0 | 74.2 | 69.2* | 78.2 | 80.9 | 76.3* | 80.6 | 61.4 | 80.5 | 81.8 |

Table 3: All-words WSD performance on different partitions of ALL, including dataset and POS (noun-N, verb-V, adjective-A and adverb-R) partitions. * indicates the performance that are obtained (partially) as a development set. Bold and underlined figures represent the current and previous state-of-the-art performance.

| overlap | SREF$_{kb}$ | COE$_{kb}$ |
|---------|-------------|------------|
| non-overlap | 310     | 482     |
| ambiguity | 7.17 | 8.27   |
| noun     | 54%      | 55%      |
| verb     | 33%      | 31%      |
| adjective | 10%    | 10%      |
| adverb   | 3%       | 5%       |

Table 4: Correctly predicted instances by two models in ALL.

2018), Babelfy (Moro et al., 2014), WSD-TM (Chaplot and Salakhutdinov, 2018), KEF (Wang et al., 2020), SyntagNet (Maru et al., 2019) and SREF (Wang and Wang, 2020).
incorporate WordNet knowledge (especially definitions) perform poorly on SE13 and cannot outperform many lately proposed knowledge-based systems such as SyntagNet, SREF and COE. The performance of the systems in supervised category is shown in Appendix.

4.3 Case Study

In this subsection, we compare the experimental result of SREF\(_{kb}\) and COE\(_{kb}\) in a detailed manner so as to find out on what aspects COE\(_{kb}\) performs well and poorly respectively. Table 4 shows the number of instances in ALL that are correctly disambiguated by SREF\(_{kb}\) or COE\(_{kb}\) only (non-overlap). It also details the ambiguity (average number of potential senses per instance) and POS proportions of the above instances.

A key factor is revealed that COE\(_{kb}\) does not outperform SREF\(_{kb}\) incrementally, which means COE\(_{kb}\) has falsely predicted many, 310, instances that are correctly predicted by SREF\(_{kb}\). In this case, although COE\(_{kb}\) can disambiguate more ambiguous instances, it has somehow compromised the ability of disambiguating easier instances. This has triggered a question regarding how to customize the context exploitation for different instances. Nevertheless, the POS proportions of the instances that are only correctly predicted by each model is almost identical.

4.4 Error analysis

In Table 5, a falsely predicted example, among others, from SE15 is given to demonstrate what kind of instance COE\(_{kb}\) are typically weak at disambiguating. It is shown that the similarity of the top ranked senses to the context of *contact* is very close to each other. This is logical since the definition of these senses are semantically similar, which are hard to distinguish even for human beings.

The above dilemma has raised concerns about whether the systems have reached the upper bound of their capability, 80%. This is an estimated inter-annotator agreement in Navigli (2009), which means the percentage of words tagged with the same sense by two or more human annotators. Further, if a system’s performance outperforms this upper bound, is it because of overfitting? To tackle the above issue, a plausible choice might be to construct a coarse-grained sense inventory, similar to Navigli et al. (2007). This might also lead to an easier application of WSD to downstream tasks.

5 Conclusion

In this paper, we have presented COE, a context-oriented embedding technique for similarity-based WSD systems. It takes better advantage of both word-level and sense-level information from the document where an ambiguous word appears. Experiments have shown that the proposed method can enhance a system’s performance on all-words WSD by relatively large margins. The ablation study has shown the contribution of each proposed factor. The source code will be made available at GitHub for further development.

6 Ethics Impact Statement

This paper does not involve the presentation of a new dataset, an NLP application and the utilization of demographic or identity characteristics in formation.

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Appendix

1 COE<sub>sup</sub>

To implement the supervised version of our system, we utilize the supervised sense embedding from SREF<sub>sup</sub>. For COE<sub>sup</sub>, the context embedding is a concatenation of two embeddings, with one from COE<sub>kb</sub> (\(\hat{P}_{w_{ij}}\)) and the other (\(P_{w_{ij}}\)) from the output of BERT using only the original sentence \(S_i\) as input. This is to guarantee an information symmetry of the embeddings since LMMS supervised sense embeddings in SREF<sub>sup</sub> are learned from SemCor with one sentence as input at each time. The calculation before TaM is shown in formula (5). To be consistent with the sense embeddings, we use BERT<sub>LARGE_CASED</sub> to learn the context embeddings.
\[ \hat{s}_{w_{i,j}} = \argmax_{s_{k,w_{i,j}} \in S_{w_{i,j}}} \left[ V_{s_{k,w_{i,j}}}^{kb} \cdot \lambda_{\text{class}} S_{\text{w_{i,j}}} \cdot \hat{P}_{w_{i,j}} \cdot P_{w_{i,j}} \right] \]

(5)

2 Systems

Supervised systems include EWISE (Kumar et al., 2019), LMMS (Loureiro and Jorge, 2019), GlossBERT (Huang et al., 2019), GLU (Hadiwinoto et al., 2019), Sense Vocabulary Compression (SVC, Vial et al., 2019), SENSEMBERT (Scarlini et al., 2020a), SREF (Wang and Wang, 2020), ARES (Scarlini et al., 2020b), BEM (Blevins and Zettlemoyer, 2020) and EWISER (Bevilacqua and Navigli, 2020). In this category, we only report the performance obtained by using SemCor as the training set for a fair comparison.

3 Results

3.1 Overall Performance

In Table 6, COE\textsubscript{sup} outperforms its direct competitor, SREF, by 1.8 F1, although the margin between the newly proposed systems that fine-tunes BERT (BEM) is smaller. BEM is a system that fine-tunes two separate BERT for encoding context and gloss respectively. The whole training process takes 2 to 3 days with 2 GPUs, which is comparatively expensive in terms of time and device. In comparison, COE\textsubscript{kb} and COE\textsubscript{sup} take less than half an hour to learn all the necessary sense embeddings.

3.2 Rare Lemma or Sense disambiguation

In this subsection, we implement two experiments on rare sense or lemma disambiguation. Following Scarlini et al. (2020b), we also conduct an experiment on those lemmas or senses that are in ALL but not in the training data, SemCor. For zero-shot lemmas/words, 1139 instances are extracted from ALL (ALL\textsubscript{LFW}). In terms of senses that do not appear in SemCor, we extract 222 polysemous instances from ALL (ALL\textsubscript{LFS}).

Table 8 shows that COE\textsubscript{kb} has attained the best performance on both subsets, outperforming SREF\textsubscript{kb} 1.6 and 4.9 F1 on ALL\textsubscript{LFS} and ALL\textsubscript{LFW}, respectively. The margin between COE\textsubscript{kb} and other newly proposed systems is even larger, revealing the tremendous potential of our system regarding zero-shot learning in WSD. It is also worth mentioning that COE\textsubscript{sup} performs 8.4 F1 lower than the knowledge-based version on ALL\textsubscript{LFS}. This has raised a question regarding how to balance the exploitation of the sense embeddings learned from SemCor and WordNet knowledge. In addition, an essential conclusion can be drawn that knowledge-based systems (SREF\textsubscript{kb} and COE\textsubscript{kb}) have an overwhelming advantage on zero-shot sense disambiguation.

3.3 Sense Embeddings

Table 9 shows the performance of our systems using different sense embeddings, compared with the original system. Precisely, the proposed method is proven valid and robust when utilizing three different sense embedding sets. The largest margin is obtained in the knowledge-based

| Models             | \text{ALL\textsubscript{WN,1st}} (n=4728) | \text{ALL\textsubscript{WN,other}} (n=2525) |
|--------------------|-----------------------------------------|-------------------------------------------|
| WordNet S1         | 100                                     | 0                                         |
| Lesk\textsubscript{enhanced} | 92.7                                    | 9.4                                       |
| Babelfy            | 93.9                                    | 12.2                                      |
| BiLSTM             | 93.4                                    | 22.9                                      |
| EWISE              | 93.5                                    | 31.2                                      |
| LMMS               | 87.6                                    | 52.6                                      |
| BEM                | \textbf{94.1}                            | 52.6                                      |
| SREF\textsubscript{kb} | 83.2                                    | 55.2                                      |
| SREF\textsubscript{sup} | 91.0                                    | 53.2                                      |
| COE\textsubscript{kb} | 86.3                                    | \textbf{57.7}                             |
| COE\textsubscript{sup} | 92.0                                    | 56.2                                      |

Table 7: Performance on Lemmas Whose Sense Label is Ranked 1\textsuperscript{st} in Wordnet and the Others
category, 2.4 F1. On the contrary, the proposed approach has only elevated ARES’s performance by 0.5 F1.

| Models   | ALL_{LET} (n=1139) | ALL_{LET} (n=222) |
|----------|---------------------|-------------------|
| LMMS     | 61.6                | 74.8              |
| GlossBERT| 62.0                | 75.6              |
| ARES     | 65.2                | 81.1              |
| SREF_{kb} | 75.9                | 82.9              |
| SREF_{sup}| 67.3                | 82.4              |
| COE_{kb}  | 77.5                | 87.8              |
| COE_{sup} | 69.1                | 87.8              |

Table 9: Systems’ Performance on ALL with different sense embedding set. † indicates our

| Sense Embedding | Model | F1  | Δ   |
|-----------------|-------|-----|-----|
| LMMS            | † LMMS| 75.4| -   |
|                 | COE_{sup}| 76.5| 1.1 |
| SREF            | † SREF_{kb} | 73.9| -   |
|                 | COE_{kb}   | 76.3| 2.4 |
|                 | † SREF_{sup}| 77.8| -   |
|                 | COE_{sup}  | 79.6| 1.8 |
| ARES            | † ARES    | 77.7| -   |
|                 | COE_{sup}  | 78.2| 0.5 |

Table 6: All-words WSD performance for both supervised (Sup.) and knowledge-based (Know.) categories on different partitions of ALL, including dataset and POS (noun-N, verb-V, adjective-A and adverb-R) partitions. * indicates the performance that are obtained (partially) as a development set. Bold and underlined figures represent the current and previous state-of-the-art performance, respectively.

Table 8: Performance on Lemmas or Senses in ALL with no annotation in SemCor

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