Decomposing Word Embedding with the Capsule Network

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Abstract
Multi-sense word embeddings have been promising solutions for word sense learning. Nevertheless, building large-scale training corpus and learning appropriate word sense are still open issues. In this paper, we propose a method for Decomposing the word Embedding into context-specific Sense representation, called DecE2S. First, the unsupervised polysemy embedding is fed into capsule network to produce its multiple sememe-like vectors. Second, with attention operations, DecE2S integrates the word context to represent the context-specific sense vector. To train DecE2S, we design a word matching training method for learning the context-specific sense representation. DecE2S was experimentally evaluated on two sense learning tasks, i.e., word in context and word sense disambiguation. Results on two public corpora Word-in-Context and English all-words Word Sense Disambiguation show that, the DesE2S model achieves the new state-of-the-art for the word in context and word sense disambiguation tasks.

1 Introduction
Word meanings are determined by their contexts (Feng and Zheng, 2018), which is generally followed by word embedding approaches (Collobert and Weston, 2008), e.g., Word2vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014). In these approaches, the words with similar semantic roles are mapped into nearby points in the embedding space. They successfully capture the word semantic properties. However, there is still an important issue left, i.e., distinguishing polysemy.

Dynamic learning-based researches are popular methods for polysemy, e.g., ELMo (Peters et al., 2018), OPENAI GPT (Radford et al., 2018), and BERT (Devlin et al., 2019). The word embeddings in ELMo are learned functions of the internal states of a deep bidirectional language model (Peters et al., 2018). The OPENAI GPT uses a left-to-right Transformer and is trained on the BooksCorpus (800M words) (Radford et al., 2018) while BERT uses the pre-trained language tasks to learn word representations with the transformer language model (Devlin et al., 2019). These methods output contextual embeddings that infer different representations induced by arbitrarily long contexts. They have had a major impact on driving progress on downstream tasks (Loureiro and Jorge, 2019).

Multi-prototype embeddings are another methods for polysemy. The polysemy is usually represented by multiple embeddings. Sense graphs (Jauhar et al., 2015; Pelevina et al., 2016), bilingual resources (Reisinger and Mooney, 2010; Guo et al., 2014; Neelakantan et al., 2014; Ettinger et al., 2016), and semantic network (Agirre et al., 2014; Moro and Navigli, 2015; Mancini et al., 2017; Pasini and Navigli, 2018) are widely used for learning multiple embeddings. Jauhar et al. (2015) proposed to apply graph smoothing and predictive maximum likelihood models to learn senses grounded in a specified ontology. Ettinger et al. (2016) proposed to retrofit sense-specific word vectors using parallel text. Pilehvar and Collier (2016) extracted semantically related words from WordNet and computed the sense embeddings in turn.

The multi-embedding usually requires well-organized knowledge bases, whose scale is usually smaller than that for unsupervised word embedding learning. Then, a natural question emerges: can we learn the proper word sense based on the unsupervised word embedding? For example, in “S1: Which fruit contains more vitamin C, apple or strawberry ” and “S2: Apple is about to release iPhone X”, the embedding “apple” gives higher similarities to the words (“strawberry” and
“iPhone”) related to one of its senses than others. This phenomenon indicates that we may infer some exact sense from the unsupervised word embedding (Huang et al., 2012).

This paper tries to answer the above question by a novel word embedding decomposing method based on the capsule network. In the capsule network, a capsule is a group of neurons that represent the instantiation parameters of the entity. A lower-level capsule prefers to hand out its output to higher-level capsules as the decomposing procedure (Sabour et al., 2017). Our main contributions are summarized as follows. 1) We propose a semantic decomposing method with the capsule network. The capsule network decomposes the unsupervised word embedding into multiple sememe-like vectors. 2) We propose a novel framework of merging sememe-like vectors, which enables the dynamic generating of context-specific sense representation. 3) We achieve the new state-of-the-art on word in context task and word sense disambiguation task, respectively.

2 Method

Figure 1 depicts the embedding decomposing with contexts and context learning procedure of the DecE2S model. The multiplications in the bracket mean the variable dimension.

Figure 2: The decomposing calculation between capsules in the initial two layers.

2.1 The Embedding Decomposing with the Capsule Network

Figure 2 depicts the decomposing calculation of two initial layers. $L = \{w_0, w_1, \ldots, w_h, \ldots, w_{n-1}\}$ denotes a sentence, and the word $w_p$ embedding $E_{w_p}$ is expanded by parameter $W$ as $\mathbb{S}_{E_{w_p}} = E_{w_p} \cdot W_i, i \in \{0, p\}$, where $p$ is the maximum number of the decomposed vectors. In the first layer, the input is $\mathbb{S}_{E_{w_p}}$, and each $\mathbb{S}_{E_{w_p}}$ corresponds to one capsule. For a capsule $i$ in the layer $L^{(1)}$ (abbr. $i_{L^{(1)}}$), we have $u_i = \mathbb{S}_{E_{w_p}}$. A weight matrix $W_{ij}$ is used for building connections with the capsule $j$ in the layer $L^{(2)}$ (abbr. $j_{L^{(2)}}$), and a prediction vector $\hat{u}_{j_{L^{(2)}}}$ is produced. Next, the total input $x_j$ to the capsule $j_{L^{(2)}}$ is a weighted sum over all $\hat{u}_{j_{L^{(2)}}}$ from the capsules in the layer $L^{(1)}$.

$$x_j = \sum_i c_{ij} \hat{u}_{j_{L^{(2)}}}, \quad \hat{u}_{j_{L^{(2)}}} = W_{ij} u_i, \quad (1)$$

where $c_{ij}$ is the coupling coefficient from capsule $i_{L^{(1)}}$ to $j_{L^{(2)}}$. The coupling coefficients sum to 1 between $i_{L^{(1)}}$ and all capsules in $L^{(2)}$.

$$\sum_{j=0}^p c_{ij} = 1. \quad (2)$$

In the capsule $j_{L^{(2)}}$, a non-linear “squashing” function is applied to keep the length by shrinking short vectors to almost 0 and long vectors to a length slightly below 1, is shown in Equation 3.

$$v_j = \frac{\|x_j\|^2}{1 + \|x_j\|^2} \cdot \frac{x_j}{\|x_j\|}, \quad (3)$$

where $v_j$ is the squashing output of the capsule $j_{L^{(2)}}$.

The coupling coefficient $c_{ij}$ is updated by the iterative dynamic routing, and it is a softmax result based on logic $b_{ij}$.

$$c_{ij} = \frac{exp(b_{ij})}{\sum_{k=0}^p exp(b_{ik})}, \quad (4)$$
we follow the processing by Sabour et al. (2017). Initially, $b_{ij}$ equals to 0 and is updated as

$$b_{ij} = b_{ij} + v_j \cdot \hat{u}_{ji},$$

(5)

which aims to measure the agreement between the output $v_j$ of $j_{L(2)}$ and the prediction $\hat{u}_{ji}$ of $i_{L(1)}$.

In the following layers, the network repeats the same calculation. The output $v$ is passed into the capsules in the next layer and goes through the weight matrix, the weighted sum and the non-linear squashing function. With $K$ layer iterations, we take the outputs of layer $K$ as the decomposed vectors $\{S_0, S_1, ..., S_{p-1}\}$, where $S_j = v_{j_{L(K)}}$.

### 2.2 Context Learning

We take the neural language model (NLM) as the context encoder to learn contextual information.

First, tokens in a sentence are converted into $\{E_{w_0}, ..., E_{w_{e-1}}\}$ by embedding lookup, and then passed into the NLM seriatim. Second, the hidden states of the neural units in the last layer are selected as the global context $G_c$, namely $G_c = \{R_{w_0}, ..., R_{w_{e-1}}\}$. Third, we extract the nearby hidden states of target word $w_k$ as the local context $L_c$ with a window size $\hat{w}$, namely $L_c = \{R_{w_0}, ..., R_{w_0}, ..., R_{w_2}\}$, where $e = \min(h - \hat{w}, 0)$, $z = \max(h + \hat{w}, n)$.

The attention weight $a^G$ on the decomposed vectors $\{S_0, S_1, ..., S_{p-1}\}$ is calculated based on the global context as

$$a^G_k = \frac{\exp(\hat{c}_k)}{\sum_{j=0}^{n} \exp(\hat{c}_j)}, \quad \hat{c}_{kj} = S_k \cdot G_c,$$

(6)

the local weight $a^L$ is also calculated in a similar way as

$$a^L_k = \frac{\exp(\hat{c}_k')}{\sum_{j=0}^{n} \exp(\hat{c}_j')}, \quad \hat{c}'_{kj} = S_k \cdot L_c.$$  

(7)

Next, we apply attention weights to its global and local context respectively, and get the context-specific vectors as

$$S^G_k = S_k + \sum_{i=0}^{n} a^G_i \cdot G_c_i + \sum_{i=0}^{z-e+1} a^L_i \cdot L_c_i.$$  

(8)

Finally, we use the L-2 norm of each $S^G_k$ to represent the weight $b = \{b_0, ..., b_k, ..., b_{p-1}\}$ in composing the final sense representation $Q_S$ in its context.

$$Q_S = \sum_{k=0}^{p} b_k \cdot S^G_k, \quad \hat{b}_k = \frac{\exp(b_k)}{\sum_{k=0}^{p} \exp(b_k)}.$$  

(9)

### 2.3 Word Matching Training

Figure 3 depicts the word matching training process to predict the matching state of the word senses for $w$ in $L'$ and $L''$, respectively.

### 3 Experiments and Results

#### 3.1 Datasets and Setup

We evaluated our DecE2S model on Pilehvar and Camacho-Collados (2019)’s Word-in-Context (WiC) dataset with the accuracy and Raganato et al. (2017a)’s cross-domain English all-words Word Sense Disambiguation (WSD) datasets (Senseval-2 (SE2) (Preiss and Yarowsky, 2001), Senseval-3 task1 (SE3) (Snyder and Palmer, 2004), SemEval-07 task 17 (SE07) (Pradhan et al., 2007), SemEval-13 task12 (SE13) (Navigli et al., 2013), and SemEval-15 task13 (SE15) (Moro and Navigli, 2015)) with the F1 score.

The WiC dataset (Pilehvar and Camacho-Collados, 2019) is a new benchmark for the evaluation of context-sensitive word embeddings (Train:5.4K, Dev:0.63K, Test:1.4K), the target words in the dataset are nouns and verbs. On WiC, we used the default training data and tested online.1 We compare our results to the methods cited

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1 https://competitions.codalab.org/competitions/20010
### Method Accuracy

| Method          | Accuracy |
|-----------------|----------|
| BoW†            | 58.7†    |
| Sentence LSTM†  | 54.0†    |
| DeConf† (2016)  | 58.7†    |
| SW2V† (2017)    | 58.1†    |
| JBT† (2016)     | 54.7†    |
| Context2vec† (2016) | 59.3†    |
| ELMo_{3/1} (2018) | 58.0/57.0† |
| BERT† base/large (2019) | 65.4/65.5† |
| TextCNNBERT (2019) | 68.6     |
| LMMS\textsuperscript{2348} (2019) | 69.1*    |
| DecE2S          | 70.6     |

Table 1: Comparisons of accuracy (%) on the WiC dataset. †- cited from WiC paper (2019) with the best results and others from the corresponding papers. * - the authors only reported the dev result. The methods with an underline, wavy-line, and dash-line correspond to the sentence-level baselines, multi-prototype models, and contextualized word-based models, respectively.

from the relevant papers (Pilehvar and Camacho-Collados, 2019; Chang and Chen, 2019; Loureiro and Jorge, 2019).

On WSD, we used the SemCor corpus as the training set (214.7K) and left 5% of the corpus as dev set (11.3k). The SemCor corpus is the largest manually annotated corpus with WordNet sense for WSD, widely used by Zhong and Ng (2010); Iacobacci et al. (2016); Raganato et al. (2017a,b); Luo et al. (2018a,b). Some published methods (Iacobacci et al., 2016; Raganato et al., 2017b; Luo et al., 2018a) and SOTA (Loureiro and Jorge, 2019) are used for comparison.

Hyper-parameters in the experiments are as the followings: the number $p$ of the decomposed vectors (10); The capsule network layers (3); The routing iterations in capsule network (3); Unless specified otherwise, the pre-trained uncased BERT base is used as the context encoder; Especially, in WordPiece tokenization, we use the head of the subtoken as the target word. As for the others, we follow the default settings.

#### 3.3 Results on English all-words WSD

Table 2 lists the results of the unsupervised word embedding-based methods and the pre-trained contextualized embedding-based methods on WSD test sets.

DecE2S outperforms other compared methods with 78.9% on Senseval-2, 77.4% on Senseval-3, 68.7% on SemEval2007, 75.6% on SemEval2013, 77.1% on SemEval 2015, and 76.9% on All. The unsupervised word embedding-based methods show competitive results with the BERT k-NN and BERTwordmatch. The main reason is that some unsupervised word embedding-based methods are well-designed with neural structure or knowledge, e.g., the sense gloss from WordNet in GAS (2018b) and the co-attention structure in HCAN (2018a). The BERT k-NN has better performances than BERTwordmatch. The improvements come from the synset, hyponym, lexname information in WordNet. The DecE2S model only relies on the single BERT random embedding and outperforms the SOTA model LMMS\textsuperscript{2348}(BERT large) (2019) on all datasets. Especially, compared with the BERT-based methods, the results are really encouraging.

#### 4 Discussion

In this section, we perform analyses on the SemCor dev set and schematize some examples. The analyses aim to quantitatively interpret some properties. The main reason may be that the WiC dataset is too small, and the scale limits such methods without any pre-training. The multi-prototype models make use of external lexical resources, which helps to learn more accurate sense. The contextualized word-based models benefit from the large-scale language pre-training, and thus show better performance than methods foregoing. Especially, LMMS\textsuperscript{2348} additional uses the full-coverge information in WordNet, the dictionary embedding, and the fastText embedding on the basis of BERT large. The main difference between DecE2S and BERT-based models, e.g. TextCNNBERT and LMMS\textsuperscript{2348}(BERT), is the capsule decomposing module. DecE2S contributes to the WiC dataset with more than 1.5% absolute improvement in the accuracy. The result indicates the potential of unsupervised word embedding under limited training data and the decomposing ability of the capsule network.
we randomly paired ten sentences of each sense. A sense similarity validation experiment is applied. F1-score(%) on English all-words WSD test sets. Table 2:

| Method                | Embedding          | SE2   | SE3   | SE07  | SE13  | SE15  | All  |
|-----------------------|--------------------|-------|-------|-------|-------|-------|------|
| MFS baseline          |                    | 65.6  | 66.0  | 54.5  | 63.8  | 67.1  | 64.8 |
| Context2Vec (2016)    | ContextVec         | 71.8  | 69.1  | 61.3  | 65.6  | 71.9  | 69.0 |
| LSTM + emb (2016)     | Word2Vec           | 72.2  | 70.4  | 62.6  | 65.9  | 71.5  | 69.6 |
| Seq2Seq multi-tasks (2017b) | Word2Vec     | 70.1  | 68.5  | 63.1* | 66.5  | 69.2  | 68.6* |
| Bi-LSTM multi-tasks (2017b) | Word2Vec | 72.0  | 69.1  | 64.8* | 66.9  | 71.5  | 69.9* |
| GlossAug S (GAS) (2018b) | GloVe            | 72.2  | 70.5  | *     | 67.2  | 72.6  | *    |
| HierCo-Att (HCAN) (2018a) | GloVe            | 72.8  | 70.3  | *     | 68.5  | 72.8  | *    |
| ELMo k-NN full-cover, (2019) | ELMo synset, hypernym, lexname | 71.5  | 67.5  | 57.1  | 65.3  | 69.6  | 67.9 |
| BERT wordmatch        | BERT random        | 73.3  | 72.2  | 59.2  | 65.3  | 72.6  | 69.8 |
| BERT k-NN full-cover, (2019) | BERT random, synset, hypernym, lexname | 76.3  | 73.2  | 66.2  | 71.7  | 74.1  | 73.5 |
| LMMS−2348 (BERT large) (2019) | BERT random, synset, hypernym, lexname | 76.3  | 75.6  | 68.1  | 75.1  | 77.0  | 75.4 |
| DesE2S                | BERT random        | 77.4  | 76.2  | 67.0  | 75.9  | 77.3  | 76.1 |
| *DesE2S               | BERT random        | **78.9** | **77.4** | **SE07** | **SE13** | **SE15** | **All** |

Table 2: F1-score(%) on English all-words WSD test sets. - BERT large as context encoder. - used as dev set. † - cited from Raganato et al. (2017a), and others from the corresponding papers. These methods are marked by underlines and wavy-lines based on the unsupervised word embedding or pre-trained contextualized embedding in use, respectively.

properties of the DesE2S model, including the context-specificity of the learned sense representation by DesE2S, the decomposing property of the capsules, the quality of the decomposed sememe-like vectors, and the linguistic meaning of the learned sense representation by DesE2S. In some experiments, the BERT base model is selected for comparison as a baseline.

4.1 Context-specificity in the Learned Sense Representation by DesE2S

A sense similarity validation experiment is applied for the context-specificity, in which we measure the similarities of the learned representations by DesE2S when the sense occurs in different contexts.

In the validation experiment, first, we randomly sampled thirty senses from the SemCor dev set, and each sense is allocated with ten sentences. Second, we randomly paired ten sentences of each sense for five times and calculated the cosine scores between the target word representations. Finally, we averaged the five cosine scores of each sense as its context-specificity value. In the BERT model, the target word sense representation corresponds to the hidden embedding in the last layer.

The visualized map of sense context-specificity values calculated by BERT and DesE2S is shown in Figure 4. The format in the column to express the word sense is consistent with the definition in WordNet 2, and the format explanation of each field can be found here 3. For the contexts with more similar sense representations, their context-specificity value will be larger, and the color of the block in Figure 4 will be darker. From Figure 4, it is evident that nearly all the blocks in the DesE2S row are darker than the corresponding ones in the BERT model. Besides, we could also see that the values by the DesE2S model are usually located on the upper parts in the color-bar while those by the BERT model on the lower parts. The validation experiment indicates that DesE2S is more capable of learning the context-specificity of the word sense.

4.2 The Decomposition Property of Capsules

To better understand the decomposition property of the capsule network, an analysis experiment is performed based on some typical words in the SemCor dev set. In the analysis experiment, we chart the composition of the context-specific sense representation by weight distributions in Table 3.

Figure 4: The visualized map of context-specificity values from the BERT and DesE2S models for sentences in the SemCor dev set. Column: the randomly selected senses. Color-bar: the context-specificity value scope.

2http://wordnetweb.princeton.edu/perl/webwn

3https://wordnet.princeton.edu/documentation/senseid5wn
Table 3: Detailed information on two senses of the top-1 used words "Way", "Take", "Little", "First" for NOUN, VERB, ADJ, and ADV, including the sense definition in WordNet, sense dependency on the decomposed sememe-like vectors (WdV) based on the L-2 norm weight \( \hat{b} \) in Equation 9, example sentences. The brackets in WdV mean the context-specific sense representation.

| Word | Sense Definition | WdV | Example Sentences |
|------|-----------------|-----|-------------------|
| Way  | A line leading to a place or point | A.D.E.G.H. (R.I) | \( S_1 \): Probably around midnight, give or take an hour either way \( S_2 \): Buster would solve that quarterback problem just as we lead that head |
| Take | A line leading to a beginning | A.E.F.G.(I,J) | \( S_1 \): I knew the only way i could beat you was to play possum \( S_2 \): If you control the way these fields are bunched, like this, or made to flow, you can enrich the body attitudes |
| Little | A point at which something begins | A.D.G.H.(R,I) | \( S_1 \): Late in 1913 or early in 1914 : this was the point at which he finally took the lead in cabinet innovation away from Brough \( S_2 \): He said no matter what stand he takes it would be misconstrued that he was sympathetic to one or the other of the republicans |
| First | The beginning of a unit of a series | A.D.F.G | \( S_1 \): At present all offenses must be taken to sixth district court for disposition \( S_2 \): Moll took his coffee into the nursery |
| First | Indicating the beginning of a unit in a series | A.D.F.G | \( S_1 \): The presto ma non assai of the first trio of the scherzo is taken literally and may shock you \( S_2 \): Man is first religious ; the instrumentalities follow |
| First | Before another in time, space, or importance | A.A.E.G.H | \( S_1 \): Jackson runs first and his cavalry are well drilled to follow their leader \( S_2 \): And just as "Laurie" Lawrence was first attracted to bright Jo March |

Table 4 reports the results on the dev set and the absolute/relative improvements on the baseline. The DecE2S model gives the best performance of 83.9% with 1.6% absolute and 9.0% relative improvements. The RandomE2S model only drops 0.4% behind the baseline. This may benefit from

4.3 Decomposed Sememe-like Vectors vs. Multi-prototype embeddings

The third issue is to validate the priority of the decomposed sememe-like vectors. For this purpose, we use a comparison experiment to further prove the decomposing quality.

In this experiment, we substituted the capsule decomposing procedure with other multi-prototype embeddings, including the random embeddings (denoted as "RandomE2S") and the DeConf embeddings (2016) (denoted as "DeconfE2S"), and maintained the context learning and word matching training procedure. In RandomE2S, the sense embeddings are randomly generated and updated during the training. In DeConfE2S, the word max senses are set to ten initially. If the word multiple embeddings are less than ten, then we padded the empty senses with zero embeddings. If they are over ten, then we kept the correct sense and randomly selected the rest nine senses. The experiment was trained on SemCor training set and tested on the dev set.
Table 4: The F1 scores of multiple random embeddings, multi-prototype embeddings, and capsule decomposed sememe-like vectors on SemCor dev set. The last column indicates the absolute(Abs) and the relative(Rel) improvements on the baseline(BERT base).

| Method      | Dev  | Abs/Rel(%) |
|-------------|------|------------|
| Baseline    | 82.3 | 0.0/0.0    |
| RandomE2S   | 81.9 | -0.4/-2.3  |
| DeConfE2S   | 82.8 | +0.5/+2.8  |
| DecE2S      | 83.9 | +1.6/+9.0  |

Table 5: The words that the DecE2S failed to distinguish their close senses.

| Word | Sense definition | Example Sentences |
|------|------------------|-------------------|
| Enough | Sufficient for the purpose | Enough food |
|       | As much as necessary | Have I eaten enough? |
| Shake | Move or cause to move back and forth | My hands were shaking |
|       | Move with or as if with a tremor | His hands shook |
| Plan  | Have the will and intention to carry out some action | He plans to be in graduate school next year |

Figure 5: The attentions weights on contexts given by sentences S1 and S2 for two senses of ”way”, respectively. The ellipsis ”...” indicates the remainder of the contexts (See Example Sentences of `Way` in Table 3).

The last important issue is to confirm whether the context-specific sense representation is the desired one in its context. However, it is hard to measure this issue with the published metrics. In the DecE2S model, we used an example to explain this by analyzing the relationships between the sense definition and the attentive context.

Figure 5 schematizes the example word ”way” and its two senses by analyzing the attention weights $a_{k}^{Q}$ in Equation 6 on the context. The titles of Figure 5(a) and (b) give two sense definitions from the WordNet. For either sense, we use the visualized map to present the attention weight distribution on the context when learning the context-specific sense representation. The darker block means the attention weight value on this word is larger than the lighter ones. The larger the value is, the more the context-specific sense representation relies on this word. From Figure 5(a) and (b), we can see that either sense relies on some words in the context, e.g. \{”give”, ”take”, ”an”, ”hour”\} for sense (a) and \{”i”, ”knew”, ”the”, ”only”, ”to”, ”play”, ”possum”\} for (b). These words are essential in determining the unique semantic in the context, which proves that the context-specific sense representation indeed maintains the proper sense for its context.

4.5 Cases that DecE2S Fails to Learn

Our experiments and analyses have proven the sense learning ability of the DecE2S model, but the experimental results also imply that DecE2S is not omnipotent. To explore the limitation of DecE2S, we collected and concluded the cases that DecE2S fails to learn on SemCor dev set.

First, in all the failed cases, the top-10 failed words are the linking verbs, which include ”see”, ”have”, ”make”, ”be”, ”give”, ”find”, ”get”, ”come”, ”take” and ”feel”. Usually, the linking verb connects the subject with a word that gives information about the subject, such as a condition or relationship. In most cases, the linking verbs do not describe any action, instead they link the subject with the rest of the sentence. It is hard for the DecE2S model to learn the link verb’s true sense, especially since one word may occur in similar contexts. In fact, not only the DecE2S model, most sense learn-
ing models are weak at these words. Second, by random sampling 10% of the failed cases, we find that except for the linking verbs, the majority are the words with quite close senses. Some typical examples are shown in Table 5. In Table 5, the DecE2S model mistakes one sense as the other and the weeny differences between the example sentences are hard to discover.

5 Related Works

For multiple senses representation learning task, the first type of methods automatically induced word senses from monolingual corpora or bilingual parallel data (Reisinger and Mooney, 2010; Guo et al., 2014; Neelakantan et al., 2014; Ettinger et al., 2016; Šuster et al., 2016). Reisinger and Mooney (2010) provided a context-dependent vector representation of word meaning with the Wikipedia and Gigaword corpus. Guo et al. (2014) proposed to learn sense-specific word embeddings by exploiting bilingual resources. Neelakantan et al. (2014) presented an extension to the Skip-gram model to learn multiple embeddings per word type. Ettinger et al. (2016) proposed to retrofit sense-specific word vectors using parallel text. Šuster et al. (2016) used bilingual learning of multi-sense embeddings with discrete autoencoders. These methods learn solely based on the statistics extracted from text corpora and do not exploit knowledge from semantic networks (Mancini et al., 2017). Besides, the induced senses are not readily interpretable and are not easily mappable to lexical resources either (Panchenko et al., 2017).

The second group of approaches is supervised one, which trains a machine learning classifier with large amounts of data with senses annotated (Kartsaklis et al., 2013; Yuan et al., 2016; Raganato et al., 2017b). Usually, they depend greatly on the annotated corpus. It is at the expense, however, of harder training and limited flexibility (Liu et al., 2018).

The third popular works are knowledge-based approaches exploiting knowledge resources like WordNet and BabelNet (Agirre et al., 2014; Moro andNavigli, 2015; Mancini et al., 2017; Pasini andNavigli, 2018). Agirre et al. (2014) presented a WSD algorithm based on random walks over large Lexical Knowledge Bases (LKB). Moro andNavigli (2015) analyzed how using a resource that integrates BabelNet might enable WSD to be solved. Pasini andNavigli (2018) presented two fully automatic and language-independent sense computing methods based on BabelNet and Wikipedia. Mancini et al. (2017) exploited large corpora and knowledge from the semantic networks to produce word and sense embeddings. Recently, in some pre-trained language model-based methods (Loureiro and Jorge, 2019; Huang et al., 2019), authors also integrated the pre-trained BERT model with the semantic resources in WordNet. For example, Loureiro and Jorge (2019) focused on the synset, hyponym, and lexname with full-coverage of WordNet on BERT. Huang et al. (2019) focused on better leveraging gloss knowledge into the BERT model. In some knowledge-based systems, they do not require sense-annotated data, but each disambiguation word is treated in isolation with a weak relationship (Raganato et al. 2017b). Moreover, these methods relies more on the WordNet knowledge.

6 Conclusion and Future Works

In this paper, we have proposed to decompose the unsupervised word embedding with the capsule network and use the context and word matching training to learn context-specific sense representation. The experimental results on WiC and WSD datasets prove that the proposed DecE2S method contributes to learning more accurate sense than other compared methods. These experiments indicate the potential of the unsupervised word embedding and the feasibility of applying the capsule network to decompose unsupervised word embedding into context-specific sense representation. Moreover, the analysis experiments enhance the interpretability of the capsule decomposing procedure and the context-specific sense representation.

Recent researches show that integrating multiple features is an efficient way to learn word sense. It is beneficial to the Word in Context and WSD tasks by merging the DecE2S representation and other relevant researches. Since this is beyond the purpose of this paper, we will leave it to future work. Considering the complexity of the word semantic, more works are needed. The other future works include 1) exploring the diversity of words for sense learning where the words in SemCor Corpus are greatly limited by the annotation cost; 2) applying the decomposed context-specific sense representation to downstream tasks; 3) proposing solid evaluation metrics to interpret the sememe-like vectors and context-specific sense representation.
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