Task-Specific Dependency-based Word Embedding Methods

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Abstract

Two task-specific dependency-based word embedding methods are proposed for text classification in this work. In contrast with universal word embedding methods that work for generic tasks, we design task-specific word embedding methods to offer better performance in a specific task. Our methods follow the PPMI matrix factorization framework and derive word contexts from the dependency parse tree. The first one, called the dependency-based word embedding (DWE), chooses keywords and neighbor words of a target word in the dependency parse tree as contexts to build the word-context matrix. The second method, named class-enhanced dependency-based word embedding (CEDWE), learns from word-context as well as word-class co-occurrence statistics. DWE and CEDWE are evaluated on popular text classification datasets to demonstrate their effectiveness. It is shown by experimental results they outperform several state-of-the-art word embedding methods.

1 Introduction

A word is represented by a real-valued vector through word embedding. The technique finds applications in natural language processing (NLP) tasks such as text classification, semantic search, parsing, and machine translation [Zou et al., 2013; Chen and Manning, 2014; Liu et al., 2018; De Boom et al., 2016; Wang and Kuo, 2020]. Although contextualized word embedding methods [Devlin et al., 2018; Peters et al., 2018] offer state-of-the-art performance, static word embedding methods [Levy and Goldberg, 2014b; Mikolov et al., 2013] play a role because of their simplicity. Static word embedding methods can be categorized into count- and prediction-based two types. Positive point-wise mutual information (PPMI) matrix factorization method [Levy and Goldberg, 2014b] is a count-based model, while the word2vec method [Mikolov et al., 2013] is a prediction-based model. GloVe [Pennington et al., 2014] is a hybrid model consisting of both. Although these two models have different model structures, both learn word embedding from the co-occurrence information of words and their contexts.

Context selection is a key research topic in word representation learning. Most word embedding methods adopt linear contexts. For a target word, its surrounding words are chosen as its contexts. The importance is ordered according to the distance. The farther the distance, the less the importance. An alternative is the dependency-based context. For each sentence, a syntactic dependency parse tree can be generated by a dependency parser. The neighbors of a target word in the tree are chosen as its contexts. Dependency-based contexts have been studied in count-based methods [Pado and Lapata, 2007] and prediction-based methods [Levy and Goldberg, 2014a]. As compared to linear contexts, dependency-based contexts can find long-range contexts and exclude less informative contexts. One example is shown in Fig. 1 where the target word is ‘found’. Guided by the dependency parsing tree, its closely related words (e.g., ‘he’, ‘dog’) can be easily identified. In contrast, less related words (e.g., ‘skinny’, ‘fragile’) are gathered by linear contexts.

Text classification, which assigns a class label to a sequence of texts, is an application of the word embedding technique. One can compute the text embedding from word embeddings and feed the information to the classifier for class prediction. One issue in most existing word embedding models is that they only consider the contextual information but do not take the task-specific information into account. The task-specific information can be valuable for performance improvement. It is wor
thwhile to mention that some word embedding methods were proposed for text classification with improved performance by including the topical information \cite{Liu2015} or the syntactic information \cite{Komninos2016}.

Most recent work on dependency-based word embedding \cite{Levy2014a,Komninos2016} adopts word2vec’s skip-gram model. It uses a target word to predict its contexts constructed by dependency parsing. After parsing, we obtain triples from the tree, each of which contains a head word, a dependent word, and the dependency relationship between them. For a target word, the concatenations of its head or dependent words and their corresponding dependency relation form dependency contexts (e.g., the contexts of ‘found’ are he/nssubj, dog/obj, backyard/obl in Fig. \ref{fig:example}). Methods derived by this approach share one common shortcoming. Although they use a dependency parse tree to construct contexts, all contexts are treated equally. Since the dependency relation generated by a dependency parser captures the syntactic information of a word in the sentence, more relevant contexts can be extracted and exploited for more effective word embedding.

In this work, two task-specific dependency-based word embedding methods are proposed for text classification. Our methods follow the PPMI matrix factorization framework and derive word contexts based on the dependency parse tree. The first one, called the dependency-based word embedding (DWE), chooses keywords and neighbor words of a target word in the dependency parse tree as contexts to build the word-context matrix. The second method, named class-enhanced dependency-based word embedding (CEDWE), learns from word-context as well as word-class co-occurrence statistics. DWE and CEDWE are evaluated on popular text classification datasets to demonstrate their effectiveness. It is shown by experimental results they outperform several state-of-the-art word embedding methods.

There are three main contributions of this work as summarized below.

- We exploit the dependency relation in the dependency parse tree to construct more effective contexts consisting of both keywords and neighbor words.
- We propose a mechanism to merge word-context and word-class mutual information into a single matrix for factorization so as to enhance text classification accuracy.
- We conduct extensive experiments on large-scale text classification datasets with the logistic regression and the XGBoost classifiers to evaluate the effectiveness of the proposed DWE and CEDWE methods.

## 2 Related Work

Most word embedding methods learn the word representation with the distributional hypothesis \cite{Firth1957,Harris1954}. That is, words with similar contexts are expected to have similar meanings. It is natural to take the context information into account in word embedding learning. Several word embedding methods were developed by following this idea. Matrix factorization methods \cite{Levy2014b} represent word contexts using global corpus statistics. They construct a word-context co-occurrence matrix and reduce its dimensionality. Neural models such as word2vec’s skip-gram and CBOW \cite{Mikolov2013} learn word embeddings by predicting contexts of the target word. GloVe combines the two strategies and uses the gradient decent to reconstruct the global co-occurrence matrix to learn word embeddings \cite{Pennington2014}. Although these models appear different, they share some similarities. It was theoretically proved in \cite{Levy2014b} that the learning process of “skip-gram with negative sampling (SGNS)” actually factorizes a shifted PPMI matrix implicitly. Further study in \cite{Levy2015} offered a connection between PPMI, skip-gram, and GloVe models. Experimental results conducted on several intrinsic tasks indicate that none of these models are significantly better than others.

The syntactic information can be exploited in context construction to learn better word embeddings. For example, research in \cite{Padov1997} takes syntactic relations into account in constructing the word-context co-occurrence matrix. The syntactic information was introduced to the skip-gram model in \cite{Levy2014a}. Furthermore, word embedding can be learned by predicting the dependency-based context. The second-order dependency contexts were proposed in \cite{Komninos2016}. In \cite{Li2018}, weights were assigned to different dependencies in the stochastic gradient descent process so that selected contexts are not equally treated. More important contexts get higher weights.

In this work, we focus on word embedding learning for the text classification task. Word embedding methods have been tailored to text classification for performance improvement. For example, the input text can be classified into positive, negative, or neutral in sentiment analysis. A neural model was proposed in \cite{Tang2014} to predict sentiment polarity in the word embedding training so that the sentiment class information will have an impact on word vectors. It was shown in \cite{Komninos2016} that the dependency-based word embedding can improve the performance of the sentence classification tasks because of the use of the syntactic information. Our work shares some similarities with the task-oriented word embedding method proposed in \cite{Liu2018}. They modified skip-gram models by regularizing the word class distribution to allow a clearer classification boundary in the word embedding space. Here, we adopt the matrix factorization method to learn embeddings from the word-context as well as the word-class distribution statistics.

### 3 Proposed DWE and CEDWE Methods

We propose two new word embedding methods in this section. They are: DWE (Dependency-based Word Embedding) and CEDWE (Class-Enhanced Dependency-based Word Embedding). CEDWE is an enhanced version of DWE. Both use the PPMI matrix factorization method as the basic word embedding framework, which is briefly reviewed below.

Pointwise mutual information between a pair of word-context \((w, c)\) is defined as

\[
PMI(w, c) = \log \frac{P(w, c)}{P(w)P(c)}
\] (1)
where \( P(w) \), \( P(c) \) and \( P(w, c) \) represent the probability of word \( w \), context \( c \) and joint probability of word \( w \) and context \( c \), respectively. The PMI can be estimated by

\[
PMI(w, c) = \log \frac{N(w, c) \cdot |N|}{N(w) \cdot N(c)}
\]  

(2)

where \( N(w) \), \( N(c) \) and \( N(w, c) \) represent the number of \( w \), \( c \) and \( (w, c) \) pair occur in corpus, respectively. \(|N|\) is the total number of all possible \((w, c)\) pairs.

The PPMI matrix factorization method first counts the co-occurrence of word-context pairs in the training text and estimate the PMI matrix. Then the PPMI matrix \( X \) is built by replacing all negative elements in the PMI matrix by 0.

\[
PPMI(w, c) = \max(\text{PMI}(w, c), 0)
\]  

(3)

Matrix \( X \) is factorized with singular value decomposition (SVD) in form of

\[
X = U\Sigma V^T
\]  

(4)

and the lower dimension matrix, \( U\Sigma \), is adopted as the learned word embedding representation. By following this framework, we study the use of dependency parsing to construct the word-context matrix. Then, we show how to enhance word embedding by exploiting word distributions in different classes.

### 3.1 Contexts Selection in Dependency Parse Tree and DWE Method

Most previous work on dependency-based embeddings uses the concatenation of the dependency relation and connected words as the context [Ley and Goldberg, 2014a, Komninos and Manandhar, 2016, Li et al., 2018]. This choice increases the vocabulary size of contexts rapidly. As a result, the solution is not scalable with a large corpus size. Besides, it demands larger memory space for matrix factorization. By focusing on text classification, we can utilize dependency parsing to collect related words for a target word and use them as contexts in constructing the word-contexts co-occurrence matrix. The dependency relation can be dropped.

Our DWE method chooses two types of words in a dependency parse tree as contexts. They are:

- **Neighbor Words**
  - The dependency parse tree for each sentence can be viewed as a graph. As compared with linear contexts where contexts are surrounding words of the target word, the dependency parse tree can offer informative contexts from words at a farther distance. We collect the words in the \( n \)-hop neighborhood as contexts, where \( n \) is a hyperparameter. The co-occurrence counts of words and contexts are weighted by their distance.

- **Keywords**
  - The main meaning of one sentence can generally be expressed by several keywords in the sentence, such as subject, predicate, and object. Other words have fewer impacts, such as function words. Keywords carry important information of a sentence, although the diversity of semantic meanings and syntactic structures constructed by keywords only is less than those of the whole sentence. Generally speaking, constructing contexts using keywords and paying more attention to them can provide more informative and robust contexts.

Each word has its own dependency relation with other words in a sentence through dependency parsing. Each relation represents a syntactic relation of a dependent against its head word. It also stands for the dependent word’s syntactic function in the sentence.

Dependency relations have been classified by linguists into different categories based on their function, as shown in Table 1 [De Marneffe et al., 2014]. We first exclude all stop words and punctuations in the dependency parse tree. Then, we locate dependent words whose dependency relations are in the core arguments (or the root) and use them as keywords in the sentence. Examples are shown in Fig. 2, where keywords found by our method are marked in red. The main parts are captured by the keywords, like “semiconductor”, “starts”, “shipping”, “chips” and so forth in the first sentence, and “researchers”, “plan”, “build” and “devices” in the second sentence. Other words provide supplementary information to make the sentence complete, and they can be discarded without harming the main meaning of the sentence. For examples, in the second sentence, “100 tb tape storage” give us more details about the “devices”. Nevertheless, other words still contain information toward the sentence meaning. So they are used as contexts if they are in neighboring hops. Besides the words in neighboring hops, keywords are always chosen as part of contexts. All context words are weighted by the distance (in terms of the number of hops) from the target word as defined in the dependency parse tree.

Counting co-occurrence with the keyword context provides a simple context weighting scheme. Note that some keywords may play a dual role. That is, they may be neighbor words within \( n \)-hops as well. If this occurs, we double the count of the word-keywords context so as to increase its importance.

### 3.2 Class-Enhanced Word-Context Matrix Construction and CEDWE Method

The word distribution in each class can vary in the text classification task. That is, some words may have unique distributions in some classes. By class-specific words, we mean those words that have special distributions in specific classes. Class-specific
words are one of the prominent features in text classification. To exploit class-specific words, our idea is to build a word-class co-occurrence matrix and use its row vectors as word features for classification.

It is worthwhile to point out that, when we learn word embedding with the word-contexts co-occurrence statistics, the class information is incorporated in learned word embedding implicitly. This is because contexts, which are essentially words, are distributed differently in each class. However, it is still possible to improve the classification accuracy furthermore to use the word class distribution explicitly to enhance the word embedding quality. This leads to the proposed class-enhanced dependency-based word embedding (CEDWE) method. It is detailed below.

To inject the class information into the word-context matrix, we modify the raw word-context PPMI matrix, which is constructed by the whole dataset, using the word distribution in each class. Generally speaking, we compute the probabilities of words in each class and use them to extend the row vectors of the PPMI matrix. Mathematically, $X$ denotes the raw word-context co-occurrence matrix. There are $n$ classes. The probability of word $i$ in each class is $p_i = [p_{i1}, p_{i2}, \cdots, p_{in}]$. For word $i$, we multiply its row vector, $X_{i,:}$, in the PPMI matrix with its class probabilities and get an extended row vector in form of

$$X'_{i,:} = [p_{i1}X_{i,:}, p_{i2}X_{i,:}, \cdots, p_{in}X_{i,:}],$$

which is the row vector of the extended PPMI matrix $X'$. Then, we apply SVD to the new matrix $X'$ for dimensionality reduction and get the learned word embeddings.

After modifying the raw word-context PPMI matrix by the class information, the new PPMI matrix contains both the word-context information and the word-class information. The embedding of words that appear frequently in the same classes are closer in the embedding space. On the other hand, the embeddings for words that do not appear frequently in the same classes are pulled away even they have similar contexts. Then, the learned word embeddings are more suitable for classification tasks.

4 Experiments

In this section, we conduct experiments to show the effectiveness of the proposed DWE and CEDWE word embedding methods and benchmark them with several other popular word embedding methods. For DWE and CEDWE, texts are parsed using the Stanza package [Qi et al., 2020]. Generally, the classification performance of DWE and CEDWE increases as the hop number becomes larger at the cost of higher complexity. Since the performance improvement is limited after 3 hops, we search contexts inside the 3-hop neighborhood to balance the performance/complexity trade-off.

4.1 Datasets, Experiment Setup, and Benchmarks

We adopt several large-scale text classification datasets from [Zhang et al., 2015] to train our word embedding methods and conduct performance evaluation. If a random initialization is needed, all results are obtained by averaging the results of 10 trials.

- **AG_NEWS.** AG_NEWS is a 4-topic dataset extracted from AG’s corpus. Each topic has 30K training samples and 1.9K test samples.
- **DBpedia.** DBpedia is a project aiming to extract structured content from the information in Wikipedia. The DBpedia text classification dataset is constructed using 14 topics from DBpedia. Each topic has 40K training samples and 5K test samples, where each sample contains the title and abstract of an article.
- **YahooAnswers.** YahooAnswers is a 10-topic classification dataset extracted from the Yahoo! Webscope program. Each topic has 140K training samples and 5K test samples. Each sample has a question and an answer.
- **YelpReviewPolarity & YelpReviewFull.** Yelp review is a sentiment classification dataset extracted from the 2015 Yelp Dataset Challenge. It has full and polarity two versions. YelpReviewFull has 5 classes ranging from one to five, where each class has 130K training samples and 10K test samples. In YelpReviewPolarity, stars 1 and 2 are treated as negative while stars 4 and 5 are viewed as positive. Each class has 280K training samples and 19K test samples.
- **AmazonReviewPolarity & AmazonReviewFull.** Amazon review is also a sentiment classification dataset built upon Amazon customer reviews and star rating. It has full and polarity two versions as well. In AmazonReviewPolarity, each class has 600K training samples and 13K test samples.
Table 2: Test accuracy comparison of several word embedding methods with the Logistic Regression classifier, where the best and the second best results are displayed in boldface and with underbar, respectively.

| Word Embedding | AG_NEWS | DBpedia | YahooAnswers | Yelp.P | Yelp.F | Amazon.P | Amazon.F |
|----------------|---------|---------|---------------|--------|--------|----------|----------|
| Word2vec       | 89.08   | 96.63   | 68.21         | 88.77  | 52.95  | 84.30    | 46.87    |
| GloVe          | 89.64   | 96.85   | 67.78         | 86.79  | 51.10  | 82.38    | 44.76    |
| EXT            | 89.49   | 97.30   | 68.16         | 87.29  | 51.64  | 82.94    | 45.57    |
| PPMI/LC        | 89.87   | 97.33   | 69.22         | 91.19  | 55.12  | 87.13    | 48.55    |
| DWE (Ours)     | 90.10   | 97.40   | 69.34         | 91.30  | 55.23  | 87.47    | 48.58    |
| CEDWE (Ours)   | 90.86   | 97.80   | 70.95         | 92.94  | 57.63  | 89.68    | 52.48    |

Table 3: Test accuracy comparison of several word embedding methods with the XGBoost classifier, where the best and the second best results are displayed in boldface and with underbar, respectively.

| Word Embedding | AG_NEWS | DBpedia | YahooAnswers | Yelp.P | Yelp.F | Amazon.P | Amazon.F |
|----------------|---------|---------|---------------|--------|--------|----------|----------|
| Word2vec       | 89.71   | 96.60   | 68.37         | 88.23  | 51.77  | 84.46    | 46.25    |
| GloVe          | 90.63   | 96.87   | 68.57         | 86.67  | 49.89  | 82.77    | 44.54    |
| EXT            | 89.89   | 97.12   | 68.31         | 86.66  | 50.31  | 82.82    | 44.74    |
| PPMI/LC        | 90.65   | 97.36   | 69.86         | 89.87  | 53.77  | 86.55    | 47.99    |
| DWE (Ours)     | 90.87   | 97.45   | 69.95         | 90.11  | 54.22  | 86.78    | 48.06    |
| CEDWE (Ours)   | 91.75   | 97.88   | 71.80         | 92.19  | 57.03  | 89.28    | 51.85    |

4.2 Results and Analysis

Experimental results with the logistic regression classifier and the XGBoost classifier are shown in Tables 2 and 3, respectively. Word2vec, GloVe, and EXT are trained on general large-scale corpora which have more than billions of tokens. In contrast, PPMI/LC, DWE and CEDWE are directly trained on the text classification dataset. We see some performance gain of word embeddings trained on the text classification dataset (i.e., the last three rows) over pre-trained word embedding methods (i.e., the first three rows). Such gains are especially obvious with the two proposed methods. DWE outperforms PPMI/LC consistently. After incorporating the class information in the word embedding mechanism, CEDWE achieves the best performance. The performance improvement of DWE and CEDWE is primarily due to the design of a word embedding method to match its target task. We see the benefit of re-training or fine-tuning of a word embedding scheme in specific tasks.

Effect of Embedding Dimension. Generally, word embeddings of a larger dimension have better classification performance. We show the classification accuracy curves as a function of word embedding dimensions with the XGBoost classifier in Fig. 3. Furthermore, we see a significant performance gap between CEDWE and other word embeddings when the dimension is lower. We can see our proposed method also performs well when the dimension is low. It indicates that the proposed CEDWE is a good choice when a lightweight model is essential in an application scenario.

Linear vs. Dependency-based Contexts. We see from Tables 2 and 3 that there is a clear performance gap between the PPMI/LC and DWE. As compared with general word embeddings trained on large-scale corpora, word embedding methods trained for specific tasks usually have much less training texts. For such an environment, dependency-based contexts are more informative than linear contexts. The use of a syntactic dependency parser can make obtained contexts more robust and stable.
Table 4: Classification accuracy results and the number of word-context sample pairs (in the unit of million) for the dependency-based contexts, where “DWE w/o K” means the proposed DWE method without the use of the keyword context.

|                  | AG     | DBpedia | Y.A. | Yelp.P  | Yelp.F  | A.P   | A.F   |
|------------------|--------|---------|------|---------|---------|-------|-------|
| 3-hop DWE        |        |         |      |         |         |       |       |
| w/o K            | 90.62  | 97.38   | 69.79| 90.01   | 54.00   | 86.76 | 48.08 |
| (sample pairs)   | (25.9M)| (130M)  | (427M)| (254M)  | (302M)  | (872M)|       |
| 3-hop DWE        | 90.87  | 97.45   | 69.95| 90.11   | 54.22   | 86.78 | 48.06 |
| (sample pairs)   | (33.9M)| (141M)  | (516M)| (293M)  | (348M)  | (1077M)|       |
| 5-hop DWE        | 90.80  | 97.47   | 70.03| 90.21   | 54.23   | 86.80 | 48.11 |
| w/o K            | (47.4M)| (200M)  | (660M)| (372M)  | (442M)  | (1348M)|       |
| (sample pairs)   |        |         |      |         |         |       |       |

Figure 3: The classification accuracy curves as a function of embedding dimensions for three datasets: (a) AG_NEWS, (b) DBpedia and (c) YelpReviewPolarity, where the tested dimensions are set to 50, 100, 200 and 300.

Figure 4: The classification accuracy as a function of hop sizes for the AG_NEWS dataset, where the results are obtained by using only \(n\)-hop neighbor words in the dependency parse tree as contexts (namely, the keyword contexts are ignored), where \(n = 1, \cdots, 6\).

Effect of Keyword Contexts. It is observed in our experiments that the classification performance increases as the neighbor-hop size in dependency-based contexts (or the window size in linear contexts) increases. This is because more word-context pairs are collected with a larger hop number (or window size). Nevertheless, the improvement is diminishing when the hop size (or the window size) reaches a certain level as illustrated in Fig. 4, where the classification accuracy is plotted as a function of the hop size for the AG_NEWS dataset.

Interestingly, we can leverage keywords and use them as extra contexts to allow a smaller hop size to reduce the computational complexity as shown in Table 4. We compare three ways to choose word contexts based on the dependency parse tree:

1. DWE with 3-hop neighbor contexts only;
2. DWE with 5-hop neighbor contexts only;
3. DWE with 3-hop neighbor contexts and keyword contexts;

Since the default DWE has both neighbor and keyword contexts, we use the notation “DWE w/o K” (DWE without keyword contexts) to denote the first two cases. The classification accuracy results reported in the table are obtained using the XGBoost classifier. For AmazonReview dataset, the number of sample word-context pairs is already enough for hop size 3 and using more word-context pairs won’t increase the performance. For AG_NEWS, DBpedia, YahooAnswers, and YelpReviewFull datasets, we can see the effectiveness of using keywords as additional contexts. The performance of the second and third cases is close to each other while the number of sample pairs in the third case is significantly smaller than that in the second case.

Effect of Explicit Class Information. Some words have similar contexts but appear in different classes in text classification. For example, adjectives in different classes can modify the same object in movie review datasets (e.g., “a nice movie”, “a funny movie”, “a disappointed movie”, “a terrible movie”). General word embedding methods may have these adjectives closer since they have some similar contexts. This is, however, undesirable for classification tasks. The proposed CEDWE method takes the word class information into account in forming the word-context PPMI matrix to address this shortcoming. In the embedding space, the boundaries of class-specific words of different classes becomes clearer and words that frequently appear in the same class are pulled together.

Task-specific words frequently appear in some specific classes so that they have higher occurrence probabilities in the corresponding classes. We use the chi-square test to select class-specific words and denote them with the class that has the highest occurrence probability. Then, t-SNE dimensionality reduc-
tion is used to visualize these task-specific words in the embedding space. The t-SNE plots of the embedding spaces of DWE and CEDWE for AG NEWS and YelpReviewPolarity are shown in Figs. 5 and 6, respectively. As compared with DWE, class-specific words in different classes are better separated in CEDWE. This explains why CEDWE has better classification performance than DWE.

5 Conclusion and Future Work

Two dependency-based word embedding methods, DWE and CEDWE, were proposed in this work. DWE uses keywords in sentences as extra contexts to build the word-context matrix. It provides informative contexts in a larger scope. As a result, as compared with the scheme that only uses neighbor words as contexts, it achieves comparable text classification performance with less word-context sample pairs. To improve the text classification performance furthermore, CEDWE incorporates the word class distribution. The t-SNE plot visualization tool was introduced to explain the superior performance of CEDWE.

As future extensions, it would be interesting to exploit more well-defined weighting function on contexts based on the dependency relation. It is also worthwhile to learn effective word embedding methods for intrinsic and extrinsic tasks that go beyond text classification.

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