Semantic Clustering and Convolutional Neural Network for Short Text Categorization

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Abstract

Short texts usually encounter data sparsity and ambiguity problems in representations for their lack of context. In this paper, we propose a novel method to model short texts based on semantic clustering and convolutional neural network. Particularly, we first discover semantic cliques in embedding spaces by a fast clustering algorithm. Then, multi-scale semantic units are detected under the supervision of semantic cliques, which introduce useful external knowledge for short texts. These meaningful semantic units are combined and fed into convolutional layer, followed by max-pooling operation. Experimental results on two open benchmarks validate the effectiveness of the proposed method.

1 Introduction

Conventional texts mining methods based on bag-of-words (BoW) easily encounter data sparsity and ambiguity problems in short text modeling (Chen et al., 2011), which ignore semantic relations between words (Sriram et al., 2010). How to acquire effective representation for short text has been an active research issue (Chen et al., 2011; Phan et al., 2008).

In order to overcome the weakness of BoW, researchers have proposed to expand the representation of short text using latent semantics, where the words are mapped to distributional representations by Latent Dirichlet Allocation (LDA) (Blei et al., 2003) and its extensions. Phan et al. (2008) presented a general framework to expand the short and sparse text by appending topic names discovered using LDA. Yan et al. (2013) presented a variant of LDA, dubbed Biterm Topic Model (BTM), especially for short text modeling to alleviate the problem of sparsity. However, the methods discussed above still view a piece of text as BoW. Therefore, they are not effective in capturing fine-grained semantic information for short texts modeling.

Recently, neural network related methods have received much attention, including learning word embeddings (Bengio et al., 2003; Mikolov et al., 2013a) and performing semantic composition to obtain phrase or sentence level representations (Collobert et al., 2011; Le and Mikolov, 2014). For learning word embedding, the training objective of continuous Skip-gram model (Mikolov et al., 2013b) is to predict its context. Thus, the co-occurrence information can be effectively used to describe a word, and each component of word embedding might have a semantic or grammatical interpretation.

In embedding spaces, semantically close words are likely to cluster together and form semantic cliques (or word embedding cliques). Moreover, the embedding spaces exhibit linear structure that the word vectors can be meaningfully combined using simple additive operation (Mikolov et al., 2013b), for example:

\[ \text{vec(Germany)} + \text{vec(Capital)} \approx \text{vec(Berlin)} \] (1)

\[ \text{vec(Athlete)} + \text{vec(Football)} \approx \text{vec(Football_Player)} \] (2)

The above examples indicate that the additive composition can often produce meaningful results. In Equation (1), the token 'Berlin' can be viewed that it has an embedding offset \text{vec(Capital)} to the token 'Germany' in embedding spaces. Furthermore, the embedding offsets represent the syntactical and semantic relations among words.

In this paper, we propose a method to model short texts using semantic clustering and convolutional neural network (CNN). Firstly, the fast clustering algorithm (Rodriguez and Laio, 2014), based on searching density peaks, is utilized to cluster word embeddings and discover semantic cliques, as shown in Figure 1. Then semantic composition is performed over n-gram embeddings to
detect candidate Semantic Units\(^1\) (abbr. to SUs) appearing in short texts. The part of candidate SUs meeting the preset threshold are chosen to constitute semantic matrices, which are used as input for the CNN, otherwise dropout. In this stage, semantic cliques are used as supervision information, which guarantee meaningful SUs can be extracted.

The motivation of our work is to introduce extra knowledge by pre-trained word embeddings and fully exploit the contextual information of short texts to improve their representations. The main contributions include: (1) semantic cliques are discovered using fast clustering method based on searching density peaks; (2) for fine-tuning multi-scale SUs, the semantic cliques are used to supervise the selection stage.

The remainder of this paper is organized as follows. The related works are briefly reviewed in Section 2. Section 3 introduces the semantic clustering based on fast searching density peaks. Section 4 describes the architecture of the proposed method. Section 5 demonstrates the effectiveness of our method with experiments. Finally, concluding remarks are offered in Section 6.

2 Related Works

Traditional statistics-based methods usually fail to achieve satisfactory performance for short texts classification due to their sparsity of representations (Sriram et al., 2010). Based on external Wikipedia corpus, Phan et al. (2008) proposed a method to discover hidden topics using LDA and expand short texts. Chen et al. (2011) proved that leveraging topics at multiple granularity can model short texts more precisely.

Neural networks have been used to model languages, and the word embeddings can be learned simultaneously (Mnih and Teh, 2012). Mikolov et al. (2013b) introduced the continuous Skip-gram model that is an efficient method for learning high quality word embeddings from large-scale unstructured text data. Recently, various pre-trained word embeddings are publicly available, and many composition-based methods are proposed to induce the semantic representation of texts. Le and Mikolov (2014) presented the Paragraph Vector algorithm to learn a fixed-size feature representation for documents.

Kalchbrenner et al. (2014) introduced the Dynamic Convolutional Neural Network (DCNN) for modeling sentences. Their work is closely related to our study in that \(k\)-max pooling is utilized to capture global feature vector and do not rely on parse tree. Kim (2014) proposed a simple improvement to the convolutional architecture that two input channels are used to allow the employment of task-specific and static word embeddings simultaneously.

Zeng et al. (2014) developed a deep convolutional neural network (DNN) to extract lexical and sentence level features, which are concatenated and fed into the softmax classifier. Socher et al. (2013) proposed the Recursive Neural Network (RNN) that has been proven to be efficient in terms of constructing sentences representations. In order to reduce the overfitting of neural network especially trained on small data set, Hinton et al. (2012) used random dropout to prevent

\(^1\)Semantic units are defined as \(n\)-grams which have dominant meaning of text. With \(n\) varying, multi-scale contextual information can be exploited.
complex co-adaptations. To exploit more structure information of text, based on CNN and directed embedding of small text regions, an alternative mechanism for effective use of word order for text categorization was proposed (Johnson and Zhang, 2014).

Although the popular methods can capture high-order information and word relations to produce complex features, they cannot guarantee the classification performance for very short texts. In this paper, we design a method to exploit more contextual information for short text classification using semantic clustering and CNN.

3 Semantic Clustering

Since the neighbors of each word are semantically related in embedding space (Mikolov et al., 2013b), clustering methods (Rodriguez and Laio, 2014) can be used to discover semantic cliques. For implementation, two quantities of data point $i$ are computed, include: local density $\rho_i$, defined as follows,

$$\rho_i = \sum_j \chi(d_{ij} - d_c)$$

where $d_{ij}$ is the distance between data points, $d_c$ is a cutoff distance. Furthermore, distance $\delta_i$ from points of higher density is measured by,

$$\delta_i = \begin{cases} \min_{j : \rho_j > \rho_i} (d_{ij}) , & \text{if } \rho_i < \rho_{\text{max}} \\ \max_j (d_{ij}) , & \text{otherwise} \end{cases}$$

An example of semantic clustering is illustrated in Figure 1. The decision graph shows the two quantities $\rho$ and $\delta$ of each word embedding. According to the definitions above, these word embeddings with large $\rho$ and $\delta$ simultaneously are chosen as cluster centers, which are labeled using the corresponding words.

4 Proposed Architecture

As shown in Figure 2, the proposed architecture use well pre-trained word embeddings to initialize the lookup table, and higher levels extract more complexity features.

For short text $S = \{w_1, w_2, \cdots, w_N\}$, its projected matrix $PM \in \mathbb{R}^{d \times N}$ is obtained by table looking up in the first layer, where $d$ is the dimension of word embedding. The second layer is used to obtain multi-scale SUs to constitute the semantic matrices, which are combined and fed into convolutional layer, followed by $k$-max pooling operation. Finally, a softmax function is employed as classifier.

4.1 Detection for Multi-scale SUs

Methods for modeling short text $S$ mainly have problem that its semantic meaning is determined by a few of key-phrases, however, these meaningful phrases may appear at any position of $S$. Thus, simply combining all words of $S$ may introduce unnecessary divergence and hurt the overall semantic representation. Therefore, the detection for SUs are useful, which capture salient local information, as shown in Figure 2.

In particular, to obtain the representations of candidate SUs, multiple windows with variable width over word embeddings are used to perform element-wise additive composition, as follows:

$$[SU_1, SU_2, \cdots, SU_{N-m+1}] = PM \otimes E_{\text{win}}$$

where, $E_{\text{win}} \in \mathbb{R}^{d \times m}$ is a window matrix with all weights equal to one, and

$$SU_i = \sum_{j=1}^{PM_{\text{win},i}} [PM_{\text{win},j}]$$

$PM_{\text{win},j}$ is the $j$th column from the sub-matrix $PM_{\text{win},i}$, which is windowed on projected matrix $PM$ by $E_{\text{win}}$ with the $i$th times sliding. $m$ is the width of the window matrix $E_{\text{win}}$. With $m$ varying, multi-scale contextual information can be exploited, which is helpful to reduce the impact of ambiguous words.
The meaningful SUs are assumed that they have one close neighbor at least in embedding space. Thus, we compute Euclidean distance between candidate SUs and semantic cliques. If the distance between candidate SUs and nearest word embeddings are smaller than the preset threshold, the candidate SUs are selected to constitute the semantic matrices, otherwise dropout.

4.2 Convolution Layer
In our network, the convolutional layer is used to extract local features. Kernel matrices \( k \) with certain width \( n \) are utilized to calculate convolution with the input matrices \( M \), as Equation (7).

\[
C = [c_1, c_2, \ldots, c_{4/2}]^T = K^T \otimes M
\]

where,

\[
K = [k_1, k_2, \ldots, k_{4/2}]
\]

\[
M = [M_1^{\min}, M_2^{\min}, \ldots, M_{4/2}^{\min}]
\]

\[
c_i^j = k_i \cdot (M_i^{\min})^T
\]

The \( c_i^j \) is generated from the \( j \)th \( n \)-gram in \( M \). Equation (7) produce the feature maps of convolutional layer.

4.3 K-Max Pooling
This operator is a non-linear sub-sampling function that returns the sub-sequence of \( K \) maximum values (LeCun et al., 1998), which is used to capture the most relevant global features with fixed-length. Then, tangent transformation over the results of \( K \)-max pooling is performed, the output of which is concatenated to used as representation for the input short texts.

4.4 Network Training
The last layer is fully connected, where a softmax classifier is applied to predict the probability distribution over categories. The network is trained with the objective that minimizes the cross-entropy of the predicted distributions and the actual distributions (Turian et al., 2010),

\[
J(\theta) = -\frac{1}{t} \sum_{i=1}^{t} \log p(c_i | x_i, \theta) + \alpha||\theta||^2
\]

where \( t \) is number of training examples \( x \), and \( \theta \) is the parameters set which comprises the kernels of weights used in convolutional layer and the connective weights from the fully connected layer.

| Embedding       | Senna | GloVe | Word2Vec |
|-----------------|-------|-------|----------|
| Corpus          | Wikipedia | Wikipedia | Google News |
| Dimension       | 50    | 50    | 300      |
| \( |Vocab.| \)    | 130,000 | 400,000 | 3,000,000 |

Table 1: Details of word embeddings

Table 2: The classification accuracy of proposed method against other models

5 Experiments
5.1 Datasets
Experiments are conducted on two benchmarks: Google Snippets (Phan et al., 2008) and TREC (Li and Roth, 2002).

**Google Snippets** This dataset consists of 10,060 training snippets and 2,280 test snippets from 8 categories. On average, each snippet has 18.07 words.

**TREC** The TREC questions dataset contains 6 different question types. The training dataset consists of 5,452 labeled questions whereas the test dataset consists of 500 questions.

5.2 Experimental Setup
Three pre-trained word embeddings for initializing the lookup table are summarized in Table 1. To discover semantic cliques, we take \( \rho_{\min} = 16 \) and \( \delta_{\min} = 1.54 \). Through our experiments, 6 kernel matrices in convolutional layer, \( K = 3 \) for max pooling, and mini-batch size of 100 are used.

5.3 Results and Discussions
5.3.1 Comparison with state-of-the-art methods
As shown in Table 2, we introduce 5 popular methods as baselines, and the details are described: DCNN Kalchbrenner et al. (2014) proposed D-CNN for sentence modeling with dynamic \( k \)-max pooling.
SVMs Parser, wh word, head word, POS, hy-
pernyms, and 60 hand-coded rules were used as
features to train SVMs (Silva et al., 2011).
CNN-TwoChannel An improved CNN that al-
lows task-specific and static word embeddings are
used simultaneously (Kim, 2014).
LDA+MaxEnt LDA was used to discover hid-
en topics for expanding short texts (Phan et al.,
2008).
Multi-topics+MaxEnt Multiple granularity
topics from LDA were utilized to model short
texts (Chen et al., 2011).

For valid comparisons, we respectively initial-
ize the lookup table with the word embeddings in
Table 1, and three experiments are conducted for
each benchmark. As a whole, our method achieves
the best performance, especially for TREC with
97.2% when the GloVe word embedding is em-
ployed. For Google snippets, our method achieves
the highest result of 85.1% corresponding to the
word embedding induced by Word2Vec.

5.3.2 Effect of Hyper-parameters
In Figure 2, for obtaining SUs with multi-scale,
multiple window matrices with increasing width
m are used. With respect to the variable m, the re-
sults are shown in Figure 3. We find small size of
window may result in loss of critical information,
however, the window with large size may intro-
duce noise.

Figure 4 demonstrate how preset threshold d
impact our method over benchmark Goggle snip-
pets. We can draw a conclusion that when d is too
small, only a few of SUs can be detected, where-
as meaningless features are enrolled. The optimal
threshold d can be chosen by cross-validation.
The impacts of other hyper-parameters like the
number and size of the feature detectors in convo-
lutional layer, and the variable k in k-max pooling
layer are beyond the scope of this paper.

6 Conclusion
This paper proposes a novel semantic hierarchical
model for short text classification. The model uses
pre-trained word embeddings to introduce extra
knowledge, and multi-scale SUs in short texts are
detected.

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