Structure Regularized Neural Network for Entity Relation Classification for Chinese Literature Text

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Abstract

Relation classification is an important semantic processing task in the field of natural language processing. In this paper, we propose the task of relation classification for Chinese literature text. A new dataset of Chinese literature text is constructed to facilitate the study in this task. We present a novel model, named Structure Regularized Bidirectional Recurrent Convolutional Neural Network (SR-BRCNN), to identify the relation between entities. The proposed model learns relation representations along the shortest dependency path (SDP) extracted from the structure regularized dependency tree, which has the benefits of reducing the complexity of the whole model. Experimental results show that the proposed method significantly improves the $F_1$ score by 10.3, and outperforms the state-of-the-art approaches on Chinese literature text\textsuperscript{1}.

1 Introduction

Relation classification is the task of identifying the semantic relation holding between two nominal entities in text. Recently, neural networks are widely used in relation classification. \textit{Wang} et al. (2016) proposes a convolutional neural network with two levels of attention. \textit{Zhang} et al. (2015) uses bidirectional long short-term memory networks to model the sentence with sequential information. \textit{Bunescu} and \textit{Mooney} (2005) first uses SDP between two entities to capture the predicate-argument sequences. \textit{Wang} et al. (2017) explores the idea of incorporating syntactic parse tree into neural networks. \textit{Liu} et al. (2017) proposes a noise-tolerant method to deal with wrong labels in distant-supervised relation extraction with soft labels. In recent years, we have seen a move towards deep learning architectures. \textit{Liu} et al. (2015) develops dependency-based neural networks. \textit{Xu} et al. (2015) applies long short term memory (LSTM) \textit{(Hochreiter and Schmidhuber, 1997)} based recurrent neural networks (RNNs) along with the SDP.

In this paper, we focus on relation classification of Chinese literature texts, which to our knowledge has not been studied before, due to the challenge that it brings. Chinese literature text tends to express intuitions and feelings rather than presenting scientific analysis. It has a wide range of topics. Many literature articles express feelings in a subtle and special way, making it more difficult to recognize entities. Chinese literature text is not organized very logically, whether among paragraphs or sentences. They tend to use various forms of sentences to create free feelings. Sentence structure of them is very flexible. The sentences are not associated with each other by evident conjunctions. Besides, Chinese is a topic-prominent language, the subject is usually covert and the usage of words is relatively flexible.

In short, sentences of Chinese literature text contain many non-essential words, and embody very complex and flexible structures. Existing methods make intensive use of the syntactical information, such as part-of-speech tags, and dependency relations. However, the automatically generated information is not reliable and of poor quality for Chinese literature text. It is of great challenge for the existing methods to achieve satisfying performance.

To mitigate the noisy syntactical information, we propose to apply structure regularization to the structures used in relation classification. Structured prediction models are commonly used to solve structure dependent problems in a wide variety of application domains. Recently, many existing systems on structured prediction focus

\textsuperscript{1}The Chinese literature text corpus, which this paper developed and used, is available at https://github.com/lancopku/Chinese-Literature-NER-RE-Dataset
on increasing the level of structural dependencies within the model. However, the theoretical and experimental study of Sun (2014a) suggests that complex structures are tending to increase the overfitting risk, and can potentially be harmful to the model accuracy. As pointed out by Sun (2014a), complex structural dependencies have a drawback of increasing the generalization risk, because more complex structures are easier to suffer from overfitting.

In this paper, we focus on the study of applying structure regularization to the relation classification task of Chinese literature text. To summarize, the contributions of this paper are as follows:

- To our knowledge, we are the first to develop a corpus of Chinese literature text for relation classification. The corpus contains 837 articles. It helps alleviate the dilemma of the lack of corpus in Chinese Relation Classification.
- We develop the tree-based structure regularization methods and make progress on the task of relation classification. The method of structure regularization is normally used on the structure of sequences, while we find a way to realize it on the structure of trees. Comparing to the origin model, applying structure regularization substantially improves the $F_1$ score by 10.3.

2 Chinese Literature Text Corpus

In Figure 1, we show two examples from the annotated corpus. We label the entities and relations of the text on a sentence level. There are 6 kinds of entities and 9 kinds of relations. The task aims at predicting the labels of these relations, given the sentences as well as the entities and their types. The corpus is part of the work of Xu et al. (2017).

We obtain over 1,000 Chinese prose articles from the website and then filter and extract 837 articles. Too short or too noise articles are not included. Due to the difficulty of tagging Chinese prose texts, we divide the annotation process into three steps.

First, we attempt to annotate the raw articles based on defined entity and relation tags. In the tagging process, we find a problem of data inconsistency. To solve this problem, we design the next two steps. Second, we design several generic disambiguation rules to ensure the consistency of annotation guidelines. For example, remove all adjective words and only tag “entity header” when tagging entities (e.g., change “a girl in red cloth” to “girl”). In this stage, we re-annotate all articles and correct all inconsistency entities based on the heuristic rules. Even though the heuristic tagging process significantly improves dataset quality, it is too hard to handle all inconsistency cases based on limited heuristic rules. Finally, we introduce a machine auxiliary tagging method. The core idea is to train a model to learn annotation guidelines on the subset of the corpus and produce predicted tags on the rest data. The predicted tags are used to be compared with the gold tags to discovery inconsistent entities, which largely reduce annotators’ efforts. After all annotation steps, we also manu-
Table 1: The set of relation tags. The last column indicates each tag’s relative frequency in the full annotated data.

| Tag                | Description                  | Example                               | %  |
|--------------------|------------------------------|---------------------------------------|----|
| Located            | locate in                    | 蘭兰(or orchid)-山谷(valley)           | 37.43 |
| Part-Whole         | be a part of                 | 花(flower)-仙人掌(cactus)               | 23.76 |
| Family             | be family members            | 母亲(mother)-奶奶(grandmother)        | 10.25 |
| General-Special    | be a general range and a special kind of it | 魚(fish)-鲫鱼(carp)                   | 6.99  |
| Social             | be socially related          | 母亲(mother)-邻里(neighbour)          | 6.02 |
| Ownership          | be in possession of          | 費村(villager)-旧屋(house)             | 5.10 |
| Use                | do something with            | 爷爷(grandfather)-毛筆(brush)         | 4.76 |
| Create             | make happen or exist         | 男人(man)-陶器(pottery)               | 2.93 |
| Near               | a short distance away        | 山(hill)-县城(town)                   | 2.76 |

ally check all entities and relations to ensure the correctness of corpus.

We set 9 different classes for better understanding the connection between pairs of entities of proses, including “Located”, “Near”, “Part-Whole”, “Family”, “Social”, “Create”, “Use”, “Ownership”, and “General-Special”. Details of the tags are shown in 1. For building the relations between people in proses, we use the “Social” tag, which is not quite common in other corpora. At the same time, the “Family” tag represents the relation between family members, which is a special kind of relation of the “Social” tag. It is because the “Family” relation is a much stronger bond than the “Social” relation and the number of the entity pairs tagged as “Family” is almost two times of that tagged as “Social”.

In prior work, Chinese literature text corpus is very rare. Many tasks cannot achieve a satisfying result on Chinese literature text compared to other corpus. However, understanding Chinese literature text is of great importance to Chinese literature research.

3 Structure Regularized BRCNN

3.1 Basic BRCNN

The Bidirectional Recurrent Convolutional Neural Network (BRCNN) model is used to learn representations with bidirectional information along the shortest dependency path (SDP).

Given a sentence and its dependency tree, we build our neural network on its SDP extracted from tree. Along the SDP, recurrent neural networks with long short term memory units are applied to learn hidden representations of words and dependency relations, respectively. A convolution layer is applied to capture local features from hidden representations of every two neighbor words and the dependency relations between them. A max pooling layer thereafter gathers information from local features of the SDP and the inverse SDP. We have a softmax output layer after pooling layer for classification in the unidirectional model RCNN.

On the basis of RCNN model, we build a bidirectional architecture BRCNN taking the SDP and the inverse SDP of a sentence as input. During the training stage of a (K+1)-relation task, two fine-grained softmax classifiers of RCNNs do a (2K + 1)-class classification respectively. The pooling layers of two RCNNs are concatenated and a coarse-grained softmax output layer is followed to do a (K + 1)-class classification. The final (2K+1)-class distribution is the combination of two (2K+1)-class distributions provided by fine grained classifiers during the testing stage.

Bunescu and Mooney (2005) first uses shortest dependency paths between two entities to capture the predicate-argument sequences, which provided strong evidence for relation classification. Each two neighbor words are linked by a dependency relation in shortest dependency path. The order of the words will affect the meaning of relations. Single direction of relation may not reflect all information in context. Thus, we employ a bidirectional recurrent convolutional neural network to capture more information from the sentence. The corresponding relation keeps the same when we inverse the shortest dependency path.

Due to the limitations of recurrent neural networks to capture longterm dependencies, we employ LSTM in our work. LSTM performs better in tasks where long dependencies are needed.
| Models          | Information                                                                 | $F_1$ |
|----------------|------------------------------------------------------------------------------|------|
| SVM (Hendrickx et al., 2010) | Word embeddings, NER, WordNet, HowNet, POS, dependency parse, Google n-gram | 48.9 |
| RNN (Socher et al., 2011)     | Word embeddings + POS, NER, WordNet                                          | 48.3 |
| CNN (Zeng et al., 2014)        | Word embeddings + word position embeddings, NER, WordNet                     | 47.6 |
| CR-CNN (Santos et al.)         | Word embeddings + word position embeddings                                    | 52.4 |
| SDP-LSTM (Xu et al., 2015)     | Word embeddings + POS + NER + WordNet                                        | 54.9 |
| DepNN (Liu et al., 2015)       | Word embeddings, WordNet                                                     | 55.2 |
| BRCNN (Cai et al., 2016)       | Word embeddings + POS, NER, WordNet                                          | 55.0 |
| **Our Model**                 | **SR-BRCNN**                                                                 | **65.2 (+9.6)** |
|                             | **Word embeddings + POS, NER, WordNet**                                      | **65.9 (+10.3)** |

Table 2: Comparison of relation classification systems on Chinese literature text.

Some gating units are designed in a LSTM cell. Each of them are in charge of specific functions. We use two bidirectional LSTMs to capture the features of words and relations separately. Word embedding and relation embedding are initialized with two look up tables. Then we can get a real-valued vector of every word and relation according to their index. In recurrent neural networks, the input is the current embedding $x_t$ and it previous state $h_{t-1}$. For the LSTM that captures word information, $x_t$ is the word embedding and for the LSTM that captures relation information, $x_t$ is the relation embedding. The current step output is denoted as $h_t$. We consider it a representation of all information until this time step. Moreover, a bidirectional LSTM is used to capture the previous and later information, as we did in this work.

Convolutional neural network performs well in capturing local features. After we obtain representations of words and relations, we concatenate them to get a representation of a complete dependency unit. The hidden state of a relation is denoted as $h_{ab}$. Words on its sides have the hidden states denoted as $h_a$ and $h_b$. $[h_a \ h_{ab} \ h_b]$ denotes the representation of a dependency unit $L_{ab}$. Then we utilize a convolution layer upon the concatenation. We have

$$L_{ab} = f(W_{con} \cdot [h_a \oplus h_{ab} \oplus h_b] + b_{con})$$  (1)

where $W_{con}$ is the weight matrix and $b_{con}$ is a bias term. We choose $tanh$ as our activation function and a max pooling followed.

Recurrent neural networks have a long memory, while it causes a distance bias problem. Where inputs are exactly the same may have different representations due to the position in a sentence. However, entities and key components could appear anywhere in a SDP. Thus, two RCNNs pick up information along the SDP and it reverse. A coarse-grained softmax classifier is applied on the global representations $\overrightarrow{G}$ and $\overleftarrow{G}$. Two fine-grained softmax classifier are applied to give a more detailed prediction of $(2K+1)$ class.

$$\overrightarrow{y} = softmax(W_f \cdot \overrightarrow{G} + b_f)$$  (2)

$$\overleftarrow{y} = softmax(W_f \cdot \overleftarrow{G} + b_f)$$  (3)

During training, our objective is the penalized cross-entropy of three classifiers. Formally,

$$J = \sum_{i=1}^{2K+1} \tilde{t}_i \log \hat{y}_i + \sum_{i=1}^{2K+1} \tilde{t}_i \log \widehat{\hat{y}}_i$$

$$+ \sum_{i=1}^{K} t_i \log \hat{y}_i + \lambda \cdot \|\theta\|^2$$  (4)

When decoding, the final prediction is a combination of $\overrightarrow{y}$ and $\overleftarrow{y}$

$$y_{test} = \alpha \cdot \overrightarrow{y} + (1 - \alpha) \cdot z(\overleftarrow{y})$$  (5)
3.2 Structure Regularized BRCNN

The basic BRCNN model can handle the task well, but there still remains some weakness, especially dealing with long sentences with complicated structures. The SDP generated from a more complicated dependency tree consists more irrelevant words. Sun (2014b) shows both theoretically and empirically that structure regularization can effectively control overfitting risk and lead to better performance. Sun et al. (2017a) and Sun et al. (2017b) also show that complex structure models are prone to the structure-based overfitting. Therefore, we propose the structure regularized BRCNN.

We conduct structure regularization on the dependency tree of the sentences. Based on the heuristic rules, several nodes in the dependency tree are selected. The subtrees of these selected nodes are cut from the whole dependency tree. With these selected nodes as the roots, these subtrees form a forest. The forest will be connected by lining the roots of the trees of the forest. Traditional SDP is extracted directly from the dependency tree, while in our model, the SDP is extracted from the final forest. We call these kinds of SDPs as SR-SDPs. We build our BRCNN model on the SR-SDP.

3.3 Various Structure Regularization Methods

We experiment with three kinds of regularization rules. First, The punctuation is a natural break point of the sentence. The resulting subtrees usually keep similar syntax to traditional dependency trees. Another popular method to regularize the structure is to decompose the structure randomly. In our model, we randomly select several nodes in the dependency tree and then cut the subtrees under these nodes. Finally we decide to cut the dependency tree by prepositions, especially in Chinese literature text. There usually are many decorations to describe the entities, and the using of prepositional phrases is very common for that purpose. So we also try to decompose the dependency trees using prepositions.

4 Experiments

We evaluated our model on the Chinese literature text corpus. It contains 9 distinguished types of relations among 837 articles. The dataset contains 695 articles for training, 58 for validation, and 84 for testing.

4.1 Experiment settings

We use pre-trained word embeddings, which are trained on Gigaword with word2vec (Mikolov et al., 2013). Word embeddings are 200-dimensional. The embeddings of relation are initialized randomly and are 50-dimensional. The hidden layers of LSTMs to extract information from entities and relations are the same as the embedding dimension of entities and relations. We applied L2 regularization to weights in neural networks and dropout to embeddings with a keep probability 0.5. AdaDelta (Zeiler) is used for optimization.

4.2 Experimental Results

Table 2 compares our SR-BRCNN model with other state-of-the-art methods on the corpus of Chinese literature text, including the basic BRCNN, Cai et al. (2016) method. Structure regularization helps improve the result a lot. The method of structure regularization could prevent the overfitting of poor quality SDPs.

4.3 Analysis: Effect of SR

Figure 2a and Figure 2b show an example of structure regularized SDP. The relation is between the two circled elements. The main idea of the method is to avoid the incorrect structure from the dependency trees generated by the parser. The SDP in Figure 2a is longer than the SR-SDP in Figure 2b. However, the dependency tree of the example is not completely correct. The longer the SDP is, the more incorrect information the model learns.
The structure regularized BRCNN has shown obvious improvements on both English and Chinese datasets. We attribute the improvements to the simplified structures that generated by structure regularization. The internal relations of components of a sentence are more obscure due to the feature of Chinese literature text. By conducting structure regularization on the dependency tree, we get several subtrees with simpler structure, and then we extract SDP from the lined forests. In most cases, the distance between two entities will be shortened along the new SR-SDP. Without the redundant information along the original SDP. The model that benefits from the intensive dependencies will capture more effective information for classification.

4.4 Analysis: Effect of Different Regularization Methods

| Classifier     | $F_1$ score |
|----------------|-------------|
| BRCNN          | 55.6        |
| SR by punctuation | 59.7      |
| SR by random   | 62.4        |
| SR by preposition | 65.9      |

Table 3: Different structure regularization results on Chinese literature texts.

The punctuation is a natural break point of the sentence, which makes subtrees more like the traditional dependency trees in the aspect of integrity. However, the original dependency trees cannot be sufficiently regularized. Despite its drawbacks, this method still shows obvious improvements on the model and leads to further experiments.

Regularizing the structure by decomposing the structure randomly will solve the insufficient decomposition problems. The method of structure regularization has shown that the degree of loss of information is not a serious problem. It gives a slightly better result compared to cutting dependency trees by punctuation.

A more elaborate method is to cut the dependency tree by prepositions. In Chinese literature text, prepositional phrases are used frequently. Cutting by prepositions will regularize the tree more sufficiently. Meanwhile, the subtrees under the prepositional nodes are usually internally linked.

5 Conclusions

In this paper, we present a novel model, Structure Regularized BRCNN, to classify the relation of two entities in a sentence. We demonstrate that tree-based structure regularization can help improve the results, while the method is normally used in sequence-based models before. The proposed structure regularization method makes the SDP shorter and contains less noise from the unreliable parse trees. This leads to substantial improvement on the relation classification results. The results also show how different ways of regularization act in the model of BRCNN. The best way of them helps improve the $F_1$ score by 10.3.

We also develop a corpus on Chinese literature text focusing on the task of Relation Classification. The new corpus is large enough for us to train models and verify the models.

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