Leveraging Multi-grained Sentiment Lexicon Information for Neural Sequence Models

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Abstract
Neural sequence models have achieved great success in sentence-level sentiment classification. However, some models are exceptionally complex or based on expensive features. Some other models recognize the value of existed linguistic resource but utilize it insufficiently. This paper proposes a novel and general method to incorporate lexicon information, including sentiment lexicons (+/-), negation words and intensifiers. Words are annotated in fine-grained and coarse-grained labels. The proposed method first encodes the fine-grained labels into sentiment embedding and concatenates it with word embedding. Second, the coarse-grained labels are utilized to enhance the attention mechanism to give large weight on sentiment-related words. Experimental results show that our method can increase classification accuracy for neural sequence models on both SST-5 and MR dataset. Specifically, the enhanced Bi-LSTM model can even compare with a Tree-LSTM which uses expensive phrase-level annotations. Further analysis shows that in most cases the lexicon resource can offer the right annotations. Besides, the proposed method is capable of overcoming the effect from inevitably wrong annotations.

1 Introduction
Sentiment classification as a classic task of natural language processing has received much attention in recent years. This task aims to classify text into positive or negative, or more fine-grained classes such as very negative, negative, neural, etc. In this field, a lot of work has been done, including traditional dictionary based methods (Peter D. Turney, 2002), and early machine learning based methods (Pang et al., 2002), and recently neural network based methods such as convolutional neural network (CNN) ((Yoon Kim, 2014); (Kalchbrenner et al., 2014); (Lei et al., 2015)), recurrent neural network (RNN) ((Tomas Mikolov, 2010); (Chung et al., 2014); (Tai et al., 2015)), lexicon enhanced methods ((Mikolov et al., 2016); (Qian et al., 2017)), attention based methods ((Wang et al., 2016); (Wu et at., 2018)) and some others.

However, many models are based on expensive features, which are not practical to real-world applications. Besides, some models recognize the value of existed linguistic resource but utilize it insufficiently. A common method is simply to encode sentiment label, usually positive and negative labels, into embedding and concatenate it with word embedding. However, except positive and negative words, negation words (e.g., no, not) and intensifiers (e.g., very, too, also) are also helpful for sentiment classification.

Therefore, we propose a novel and general method to incorporate lexicon information, including sentiment lexicons (+/-), negation words and intensifiers. Words are annotated in fine-grained and coarse-grained labels. The proposed method first encodes the fine-grained labels into sentiment embedding and concatenates it with word embedding. Second, the coarse-grained labels are utilized to enhance the attention mechanism to give large weight on sentiment-related words.

To summarize, the main contributions of our work are as follows:

- We collected a sentiment lexicon which contains 2759 positive words, 5111 negative words, 35 negation words and 62 intensifiers. The resource is now released at GitHub to promote further research.

1 https://github.com/zengyan-97/Sentiment-Lexicon
• We propose a novel and general method to incorporate lexicon information. Experimental results show that our method can increase classification accuracy for neural sequence models on both SST-5 and MR dataset. Specifically, the enhanced Bi-LSTM model can even compare with a Tree-LSTM which uses expensive phrase-level annotations.

2 Related Work

With the development of neural networks, many classical models based on neural networks have been applied in sentiment classification recently, which include Recursive Neural Network ((Socher et al., 2011); (Socher et al., 2013)), Convolutional Neural Network ((Yoon Kim, 2014); (Kalchbrenner et al., 2014); (Lei et al., 2015)), Recurrent Neural Network ((Yoon Kim, 2014); (Chung et al., 2014); (Tai et al., 2015); (Zhu et al., 2015)); Attention based methods ((Wang et al., 2016); (Wu et al., 2018)) and so on. (Wang et al., 2016) introduces a attention-based method to embed aspect information for aspect-level sentiment classification which enlightens us to embed linguistic resource for sentiment classification. Besides, Our model also refers to the attention mode in (Wu et al., 2018).

A lot of work that attempts to utilize linguistic knowledge for sentiment classification has been done. Relevant work can be seen in ((Taboada et al., 2011); (Mohammad et al., 2013); (Zhu et al., 2014); (Mikolov et al., 2016)). Applying sentiment lexicon, negation words and intensifiers in one model to sentiment classification can be seen in (Qian et al., 2017) that introduces three linguistic regularizers on intermediate outputs with KL divergence. Our work differs in that (Qian et al., 2017) applies linguistic regularizers, we propose two different granularity word annotation based on existing linguistic resources, and based on this, embed the prior knowledge into the model for sentiment analysis.

3 Methodology

We propose two different granularity word annotation based on existing linguistic resources. One is coarse-grained, which divides words into “in” linguistic resources and “not in” linguistic resources. The other is fine-grained, which divides words into five categories, including “not in” linguistic resources, positive, negative, negation words, intensifiers. To the best of our knowledge, this is the first time that two different granularity word annotations are introduced for sentiment classification in order to incorporate linguistic resources. Then we adopt following two methods to capture the supervised information.

3.1 Sentiment Embedding

The pre-trained word vectors, each of which is trained using its context, only contain faint sentiment information. To solve this problem, we propose to learn five kinds of hidden sentiment property embedding using the fine-grained annotations. Then we concatenate the sentiment property embedding to the pre-trained word vector to get a new word embedding for each word. The intuition of doing so is to add explicit "sentiment property" to word vectors.

3.2 Enhanced Attention Mechanism

The motivation to introduce the attention mechanism is that we hope the model can focus more on the hidden states whose input is a sentiment word. To improve its ability, we incorporate the lexicon knowledge into a standard attention mechanism. We adopt a new set of annotations here which only classifies a word to be "in" or "not in" any lexicon in this part.

Formally, the final hidden state is a weighted sum of all hidden states as:

$$ h = \sum_{t=1}^{T} a_t h_t $$

(1)

where \( h_t \) is the hidden state of the t-th word in a sentence, \( a_t \) is the attention weight of \( h_t \) and measures the importance of the t-th word for sentiment classification, \( \sum_{t=1}^{T} a_t = 1 \) and \( T \) is the length of the sentence. The attention weight \( a_t \) for each hidden state can be defined as:

$$ e_t = v^T tanh(W_1 h_t + W_2 s_t + b) $$

(2)
\[ a_t = \frac{\exp(e_t)}{\sum_{j=1}^{T} \exp(e_j)} \]  

(3)

where \( v \) is a weight vector and \( v^T \) represents its transpose, \( W_1 \) and \( W_2 \) are weight matrices, \( s_t \) is generated by the second set of annotation. Specifically, if a word is in a lexicon, its corresponding \( s \) is a certain vector which is learned by train. If a word isn’t in any lexicon, we set its corresponding \( s \) to zeros.

Figure 1 represents the architecture of a standard Bi-LSTM model using our method to encode the three kinds of lexicon information.

4 Experiment

4.1 Sentiment Lexicon

We collect negative and positive words from Subjectivity Lexicon (Wilson et al., 2005) and Opinion lexicon (Hu and Liu, 2004) which contains 5111 negative words and 2759 positive words in total. As for negation words and intensifiers, we collect them manually and we finally get 35 negation words and 62 intensifiers, some of which are shown in Table 2.

4.2 Dataset

Two datasets are used for evaluating the proposed method: Stanford Sentiment Treebank (SST) (Socher et al., 2013) where each sentence is annotated with five classes as very negative, negative, neutral, positive and very positive and Movie Review (MR) (Pang and Lee, 2005) with two classes as negative and positive. Though SST provides phrase-level annotation on all words, we don’t use that since one of our goals is to avoid expensive phrase-level annotation.

| Dataset | N   | V   | Avg  | P     |
|---------|-----|-----|------|-------|
| MR      | 10662| 10279| 3.789| 22.87%|
| SST-2   | 11286| 10695| 3.385| 23.27%|

Table 3: The basic statistics of Dataset. N: Number of samples in the dataset. V: Number of words in the dataset. AVG: Average number of sentiment words in each sample. P: Average proportion of sentiment words against sentence length

4.3 Experiment settings

In our experiments, all word vectors are initialized by GloVe (Pennington et al., 2014). The model is trained with a batch size of 25 samples and AdaGrad (Duchi et al., 2011) with a learning rate of 0.1. For regularization, we only employ dropout (Srivastava et al., 2014) on the penultimate with a probability of 0.5. Parameters are initialized by
Xavier (Glorot et al., 2012). Pretrained word Vectors are static in the train.

5 Results and Discussion

Results of our model against other methods are listed in table 4. Our model beats the state-of-art on both SST-5 and MR dataset and can even compare with Tree-LSTM which uses expensive phrase-level annotation.

| Model               | MR  | SST-5-S | SST-5-P |
|---------------------|-----|---------|---------|
| Bi-LSTM             | 79.3| 46.5    | 49.1    |
| Tree-LSTM           | 80.7| 48.1    | 51.0    |
| CNN-Static          | 81.0| 45.5    | -       |
| LR-Bi-LSTM          | 82.1| 48.6    | 50.6    |
| Bi-LSTM+ATTN        | 81.0| 48.8    | -       |
| Bi-LSTM+2           | 80.2| 47.7    | -       |
| Bi-LSTM+5           | 81.7| 48.8    | -       |
| Bi-LSTM+2+5         | 82.8| 50.4    | -       |

Table 4: Comparison with baselines. Bi-LSTM: (Cho et al., 2014), Tree-LSTM: (Tai et al., 2015), CNN-Static: (Yoon Kim, 2014), LR-Bi-LSTM: (Qian et al., 2017), Bi-LSTM+ATTN: (Zhou et al., 2016). ATTN: attention, 2: coarse-grained annotations, 5: fine-grained annotations. Best performances are in **bold**.

To further evaluate the performance of our model, we give some samples to analyze the advantages and the limits of our model in different ways.

| All Test Set | Our Model Failed | Percent |
|--------------|------------------|---------|
| 2255         | 76               | 3.58%   |

Table 5: when our model failed to capture the extra information: the lexicons gave appropriate annotations but the prediction is wrong.

Sample 1-3 shows the lexicons can provide correct annotations which can be used to guide model learning. Actually, what we have found is that most annotations are appropriate. On the other hand, we count the cases when our model failed to capture the extra information, i.e. the lexicons gave appropriate annotations but the prediction is wrong, by several rules and the result is the models fails 76 in all 2125 samples.

In the cases such as Sample 4 and 5, the lexicons don’t provide more information because of their limited size, but our model still works well. Since we incorporate the annotation constraint in a soft way and when the annotations are wrong the model can still utilize the semantic information from pre-trained word embedding.

However, in the cases like Sample 6 and 7, it can be seen that the word embedding gradually failed to work when the lexicons gave useless or even seriously wrong annotations. However, we can avoid this error simply by update lexicon resource on size and quality.

As for the attention part in our method, it didn’t work as what we expected. In most cases, the attention scores among hidden states have slight differences. Besides, common words tend to have higher scores. However, the Bi-LSTM+2+5 model did beat the Bi-LSTM+5 model in our experiments.

6 Conclusion

The analysis results show the lexicon resource provides useful extra information. Since our model can capture the additional supervised information, it beats the state-of-art models. Additionally, we think collecting a high-quality set of lexicons is necessary. If the lexicons could be larger and the quality could be better, we believe the classification accuracy will get considerable improvement and the lexicon resource can be reused.

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