A Multi-sentiment-resource Enhanced Attention Network for Sentiment Classification

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Outline

• Introduction
• The proposed method
• Experiments
• Summary and future work
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Task Description

Sentence-level Sentiment Classification

Given a sentence ➔ Sentiment Polarity

• Positive/ negative/neutral
• More fine-grained classes

Examples

- The food is very delicious. ➔ Positive
- The movie is so boring. ➔ Negative
- .......

...
■ Early Methods

• Machine learning based---SVM (Pang et al., 2002)
• Linguistic knowledge based----Sentiment lexicon [Turney, 2002; Taboada et al., 2011]

■ Neural Networks

• Recursive Neural Network [Socher et al. 2011]
• Convolutional Neural Network [Kim, 2014]
• Recurrent Neural Network/LSTM [Hochreiter and Schmidhuber, 1997]

■ Incorporating Linguistic Knowledge with Neural Networks

• Linguistically regularized LSTM [Qian et al., 2017]
• Lexicon integrated CNN models with attention [Bonggun et al., 2017]
Motivation

- Sentiment linguistic knowledge (e.g. sentiment words, intensity words, negation words) play important roles in sentiment detection.

- By attention mechanism, we can integrate various sentiment resource information into neural networks to boost the performance.
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Our Model

The overall framework of our model
Coupled word Embedding
Multi-sentiment-resource attention module
- Context-sentiment correlation modeling

- The implementation of context-intensity correlation modeling and context-negation correlation modeling are the same as the context-sentiment correlation modeling.

Note that in proceeding version, there are some typos in this part. The updated version can be obtained via arxiv.org: [https://arxiv.org/abs/1807.04990](https://arxiv.org/abs/1807.04990)
Multi-sentiment-resource attention

- Sentiment word attention

\[ H^c = GRU(X^c) \]
\[ H^s = GRU(X^s) \]

\[ o_1 = \sum_{i=1}^{t} \alpha_i h^c_i, \quad q^s = \sum_{i=1}^{m} \frac{h^s_i}{m} \]
\[ \beta([h^c_i; q_s]) = u^T_s \tanh(W_s [h^c_i; q_s]) \]
\[ \alpha_i = \frac{\exp(\beta([h^c_i; q_s]))}{\sum_{i=1}^{t} \exp(\beta([h^c_i; q_s]))} \]

- Intensity attention and Negation attention are computed via the similar methods with the sentiment word attention

- Finally, the multi-sentiment-resource enhanced sentence representation:

\[ \tilde{o} = [o_1, o_2, o_3] \]
Training

The predicted sentiment polarity distribution can be obtained via a fully connected layer with softmax.

\[
\hat{y} = \frac{\exp(\tilde{W}_o^T \tilde{o} + \tilde{b}_o)}{\sum_{i=1}^{C} \exp(\tilde{W}_o^T \tilde{o} + \tilde{b}_o)}
\]

Loss function:

\[
L(\hat{y}, y) = -\sum_{i=1}^{N} \sum_{j=1}^{C} y_{i}^{j} \log(\hat{y}_{i}^{j}) + \lambda \sum_{\theta \in \Theta} \theta^{2} + \mu \|\tilde{O}\tilde{O}^{T} - \psi I\|_{F}^{2}
\]  
(17)

\[
\tilde{O} = [o_1; o_2; o_3]
\]  
(18)
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Experiments

Datasets

- Movie Review (MR)---5331 positive/ 5331 negative, training/validation/test split is the same as (Qian et al., 2017);
- Stanford Sentiment Treebank (SST)---8545 training/1101 validation/ 2210 test

Sentiment Resources

- Sentiment words-----combined from (Hu and Liu, 2004) and (Qian et al., 2017), containing 10899 words;
- Intensity words and Negation words-- manually collected due to the limited number.
### Experiments----Results

<table>
<thead>
<tr>
<th>Methods</th>
<th>MR</th>
<th>SST</th>
</tr>
</thead>
<tbody>
<tr>
<td>RNTN</td>
<td>75.9%</td>
<td>45.7%</td>
</tr>
<tr>
<td>LSTM</td>
<td>77.4%</td>
<td>46.4%</td>
</tr>
<tr>
<td>BiLSTM</td>
<td>79.3%</td>
<td>49.1%</td>
</tr>
<tr>
<td>Tree-LSTM</td>
<td>80.7%</td>
<td>51.0%</td>
</tr>
<tr>
<td>CNN</td>
<td>81.5%</td>
<td>48.0%</td>
</tr>
<tr>
<td>NSCL</td>
<td>82.9%</td>
<td>51.1%</td>
</tr>
<tr>
<td>LR-Bi-LSTM</td>
<td>82.1%</td>
<td>50.6%</td>
</tr>
<tr>
<td>Self-attention</td>
<td>81.7%</td>
<td>48.9%</td>
</tr>
<tr>
<td>ID-LSTM</td>
<td>81.6%</td>
<td>50.0%</td>
</tr>
<tr>
<td><strong>MEAN (our model)</strong></td>
<td><strong>84.5%</strong></td>
<td><strong>51.4%</strong></td>
</tr>
<tr>
<td>MEAN w/o CharCNN</td>
<td>83.2%</td>
<td>50.0%</td>
</tr>
<tr>
<td>MEAN w/o sentiment words</td>
<td>82.1%</td>
<td>48.4%</td>
</tr>
<tr>
<td>MEAN w/o negation words</td>
<td>82.9%</td>
<td>49.5%</td>
</tr>
<tr>
<td>MEAN w/o intensity words</td>
<td>83.5%</td>
<td>49.3%</td>
</tr>
</tbody>
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Summary and Future work

- Integrating sentiment resources into neural networks is effective to improve the performance of sentence-level sentiment classification.

- How to design the more effective information-fusion methods is still challenging, such as regularization, attention, ....

- In future work, we can consider employing position embedding to automatically detecting various sentiment resource words.
Thanks for your attention!

Supplementary Materials:
https://drive.google.com/open?id=1KNBy50lBD7CMjack_9--M4N7EzeRmJDl

Q&A