Emoji-based Co-attention Network for Microblog Sentiment Analysis

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Abstract. Emojis are widely used in online social networks to express emotions, attitudes, and opinions. As emotional-oriented characters, emojis can be modeled as important features of emotions towards the recipient or subject for sentiment analysis. However, existing methods mainly take emojis as heuristic information that fails to resolve the problem of ambiguity noise. Recent researches have utilized emojis as an independent input to classify text sentiment but they ignore the emotional impact of the interaction between text and emojis. It results that the emotional semantics of emojis cannot be fully explored. In this paper, we propose an emoji-based co-attention network that learns the mutual emotional semantics between text and emojis on microblogs. Our model adopts the co-attention mechanism based on bidirectional long short-term memory incorporating the text and emojis, and integrates a squeeze-and-excitation block in a convolutional neural network classifier to increase its sensitivity to emotional semantic features. Experimental results show that the proposed method can significantly outperform several baselines for sentiment analysis on short texts of social media.

Keywords: Sentiment analysis · Emoji · Attention mechanism.

1 Introduction

Nowadays, online social media such as Twitter, Facebook, and Weibo (the biggest Chinese microblog platform) have become the mainstream communication tools for the public, where people are inclined to express their emotions, attitudes, and opinions. Microblogs contain a vast amount of valuable emotional information and have become a hot research target for sentiment analysis [6, 10]. Sentiment analysis has been a crucial component in many commercial applications such as recommendation systems, customer feedback classification, advertising strategy, and public opinion poll due to its effectiveness in constructing user portraits and analyzing their personality characteristics [14]. Recently, emojis have emerged as a popular way in social communication, and have a high frequency of occurrence in microblogs. Emojis are used to provide additional emotional information, change the tone, engage recipients or maintain relationships, etc. [1].
They can play an emotion-oriented role to express sentiment, which is analyzed statistically to be the most popular intention for using them [5].

Therefore, it is crucial to combine emojis with text to explore the emotional semantics for sentiment analysis tasks. The most common method is to utilize emojis as an important feature [15, 20] or a natural annotation [2, 3, 12] to obtain better performance. However, existing work [2] show that using emojis directly as emotional tags will generate diverse noise because of the ambiguity of emoji labels, that is, the sentiments conveyed by the same emoji may vary according to the context. Many researchers also use emojis as an independent input to judge the emotional polarity of the entire text, without considering the impact of the interaction between emojis and plain text on sentiment analysis. Based on the above problems, we propose an Emoji-based Co-attention Network (ECN) to learn the mutual emotional semantics between text and emojis.

2 Related work

As a significant branch of natural language processing (NLP), text sentiment analysis aims to mine and analyze the emotions, opinions, and attitudes of people from texts. In recent years, the rapid development of deep learning has played an important role in boosting the development of sentiment analysis researches. Socher et al. [17] applied Recursive Neural Network to text sentiment classification with the consideration of the syntactic structure information; Santos et al. [16] proposed Character to Sentence Convolutional Neural Network (CharSCNN) to analyze sentiment on the short text.

Emojis can be regarded as important semantic features about emotions towards the recipient or subject [18] for sentiment classification. For instance, Jiang et al. [7] combined structure features, sentence structure features, and emoji features in a SVM model to classify texts. This strategy fails to reflect the emotional impact of emojis on the text. Many studies also use emojis as heuristic information in social texts [2, 3, 12], where emojis serve for unsupervised learning in a large number of unlabeled data. Among existing research, the most similar work to our motivation is that Lou et al. [13] constructed an emoji-based Bi-LSTM model, which combined the attention mechanism to weigh the contribution of each word on the emotional polarity based on emoji. But this method only analyze the microblog data that contains a single emoji and cannot be generalized to process multiple types of emojis.

3 Model

In this paper, we propose a new neural network model called the Emoji-based Co-attention Network. Its architecture is illustrated in Figure 1.

The model consists of three main components: Text Feature Extractor, Co-attention Network, and SE-based CNN Classifier. In the text feature extractor,
we build two stacked Bi-LSTM layers with skip-connection to obtain text features. Then we adopt a co-attention network to learn high-level emotional semantic features incorporating the text and emojis from their interaction. Finally, these features are fed into a CNN classifier integrated with a SE block to predict the probability distribution of sentiment labels of the microblog posts.

3.1 Text Feature Extractor

The plain text can be embedded into $X = [x_1, x_2, ..., x_L]$. Since the microblog emojis are converted into textual tags by Weibo API\[^3\] the emojis can also be encoded into vectors by word embedding layer $E = [e_1, e_2, ..., e_N]$.

LSTM can overcome the problem of gradient vanishing and explosion with the capability to learn long-range dependencies in sequences. In order to capture both past and future information, the feature extractor adopts two stacked Bi-LSTM layers to learn the text representation bidirectionally. And we concatenate the hidden vectors from both directions to represent every single word as the output $h_l$ of the layer. The second Bi-LSTM layer takes the output of the previous one as its input $H_1 = [h_{11}, h_{12}, ..., h_{1L}]$, and computes unit stats of network in the same pattern before producing the output $H_2 = [h_{12}, h_{22}, ..., h_{L2}]$.

3.2 Co-attention Network

**Intra-Text Attention Module** Through a skip-connection, the outputs of the below three layers (the embedding layer and the two Bi-LSTM layers) are concatenated as a whole vector, which will be sent into the text attention module as input. The $l$-th word in the input text can be denoted as $u_l = [x_l, h_{1l}, h_{2l}]$, where $x_l \in \mathbb{R}^d$, $h_{1l} \in \mathbb{R}^d$, and $h_{2l} \in \mathbb{R}^d$, $d$ is the dimension of word feature. For the $l$-th word, the attention score is measured by

$$
\alpha_l = \frac{\exp(W_\beta u_l)}{\sum_{i=1}^{L} \exp(W_\beta u_i)}, \quad (1)
$$

\[^3\]https://api.weibo.com/2/emotions.json
where \( W_\alpha \) is the weight matrix and \( W_\alpha \in \mathbb{R}^{1 \times 3d} \), \( \alpha_l \in \mathbb{R}^L \), which corresponds to the attention probability of each word. Using the attention scores as weights, the text can be represented as \( v_t \), that aggregates the weights of individual words and transform the dimension to \( d \) through a fully connected layer.

**Text-Guided Attention Module** In most cases, emoji occurrences in a post are related to the emotional semantics, but it depends on the contextual text that the different contribution of each emoji to predict the sentiment label. Therefore, we apply a text-guided attention module to decide crucial emoji by using the new text vector \( v_t \) to conduct the attention. We feed text feature \( v_t \) and emoji feature \( E \) through a fully connected network followed by a softmax function to obtain the attention distribution over the emojis in the post:

\[
z_n = \tanh(W_E e_n + W_{v_t} v_t + b_1),
\]

\[
\beta_n = \frac{\exp(W_\beta z_n)}{\sum_{i=1}^N \exp(W_\beta z_i)},
\]

where \( v_t \in \mathbb{R}^d, e_n \in \mathbb{R}^d, W_E, W_{v_t} \) and \( W_\beta \) are weight matrices, and \( W_E \in \mathbb{R}^{k \times d}, W_{v_t} \in \mathbb{R}^{k \times d}, W_\beta \in \mathbb{R}^{1 \times k} \), and \( b_1 \) is the bias. \( \beta_n \in \mathbb{R}^N \) is corresponding to the attention probability of each emoji given text representation \( v_t \). Based on \( \beta_n \), the new emoji representation \( v_e \) can be generated by weighted sum.

**Emoji-Guided Attention Module** The emoji-guided attention module joins text and emoji information together to measure the weight of each word that decides which words in the text should be attended to. We learn the emoji representation \( v_e \) from text-guided attention module, and higher-level text representation \( H_2 \) is obtained from the top Bi-LSTM layer. Similar to text-guided attention, we use these features to generate the attention distribution over the word embeddings and get a new text representation \( v_h \) that joins the semantics of text and emoji together.

### 3.3 SE-based CNN Classifier

After the text feature extractor and co-attention network, we obtain the text vector \( v_t \in \mathbb{R}^d \), text-based emoji vector \( v_e \in \mathbb{R}^d \) and emoji-based text vector \( v_h \in \mathbb{R}^d \). We take these vectors as three-channel input \( V \in \mathbb{R}^{d \times c} \) and transfer them into a CNN classifier to predict the probability distribution of sentiment labels of the microblog posts.

For the convolutional operation, we use \([w_1, w_2, ..., w_c]\) to represent the set of filter kernels that map the input \( V \in \mathbb{R}^{d \times c} \) to a new feature map \( U \in \mathbb{R}^{d' \times c'} \).

Since not all features contribute equally to predict the final sentiment label, we employ the SE block to measure the importance of each feature channel by modeling the correlation between channels and learning their weights \( \mathbb{A} \). Two
parts are included in a SE block: \textit{squeeze}[^4] and \textit{excitation}[^5].

\[
    z_j = F_{sq}(u_j) = \frac{1}{d'} \sum_{i=1}^{d'} u_j(i),
\]

\[
    \tilde{v}_j = F_{scale}(u_j, s_j) = s_j u_j = \sigma(W_2 \delta(W_1 z_j))u_j,
\]

where $\sigma$ and $\delta$ denote the sigmoid and ReLU function respectively, weight matrices $W_1 \in \mathbb{R}^{d \times C}$, $W_2 \in \mathbb{R}^{C \times d}$, and $F_{scale}$ represents to channel-wise multiplication.

## 4 Experiment

### 4.1 Dataset and Implementation Details

The labeled data used in our work are obtained from a public dataset[^4] with positive and negative labels. We filter images, videos, and other URL links to eliminate noisy information. For stop word, we adopt the list from Harbin Institute of Technology’s stop word database[^5]. We use Python Chinese word segmentation module Jieba[^6] to segment the sentences of the microblog posts and feed the segmentation results into the word embedding layer by pre-trained word vectors[^7]. During the process, words and emojis are trained simultaneously since each emoji is transformed into Chinese characters by Weibo API.

Using a trained word2vec model, we trained our ECN method with 10 epochs and the performance achieved the highest value when the hidden units of bi-directional LSTM layers were set as 300 and dropout was applied at the rate of 0.5. We randomly split the emoji-rich posts into the training, validation and test sets in the proportion of 7:2:1 with balanced categories. We used the Adam algorithm[^9] for optimization and initial learning rate was set to $10^{-3}$. The whole framework was implemented in PyTorch[^8].

### 4.2 Baselines and Performance Comparison

To evaluate the performance of ECN, we employ several representative classificational baseline methods (TextCNN[^8], TextRCNN[^11], Att-Bi-LSTM[^21], TextGCN[^19], EA-Bi-LSTM[^13]) for sentiment analysis. In Table[^1] ECN outperforms all four baseline methods. The results prove that our proposed method is more effective than the old methods that do not pay attention to the emojis. Looking more closely, the three shallow methods (TextCNN, TextRCNN, and Att-BLSTM) achieves an accuracy above 0.95. It is remarkable to find that ECN achieves an accuracy above 0.98 as it improves on the former methods by 1 to 2

[^4]: https://github.com/SophonPlus/ChineseNlpCorpus
[^5]: https://github.com/goto456/stopwords
[^6]: https://github.com/fxsjy/jieba
[^7]: https://github.com/Embedding/Chinese-Word-Vectors
[^8]: https://pytorch.org/docs/stable/nn.html
percent approximately. A possible explanation for this might be that the architecture of ECN combines the Bi-LSTM and CNN, which could embed words into high-dimensional vectors and learn richer semantic representation for sentiment analysis incorporating emojis and text features. ECN also outperforms the EA-Bi-LSTM, the latest work on emojis, which demonstrates the effectiveness of our model. Comparing with other baseline models, the performance of TextGCN is worse than all other methods with an accuracy below 0.94. It might be explained that in text classification, GCN ignores the word features of sequence, which is of great importance for sentiment analysis.

Table 1. The Results of ECN and baseline methods

| Models       | P(%) | R(%) | F(%) | Acc(%) |
|--------------|------|------|------|--------|
| TextCNN      | 96.66| 95.63| 96.55| 96.24  |
| TextRCNN     | 95.93| 97.72| 96.19| 96.52  |
| Att-BLSTM    | 97.19| 99.20| 97.59| 97.09  |
| TextGCN      | 94.02| 93.86| 93.94| 93.72  |
| EA-Bi-LSTM   | 96.73| 98.29| 98.04| 97.53  |
| ECN(our model)| 97.46| 99.88| 98.66| 98.59  |

1 P represents the precision, R is the recall, and F is the F1-score

4.3 Model Analysis

The Power of Emojis To further explore the influences of emojis in ECN, we conduct the subsequent experiments by removing the inputs of emojis or simplified architecture of ECN to evaluate the effectiveness of emojis. N-ECN detaches the emoji inputs. T-ECN removes the text-guided attention module of emoji representation learning. E-ECN removes the emoji-guided attention module of text representation learning.

Test accuracy of the modified model is illustrated in Table 2. We find that ECN significantly outperforms the N-ECN and T-ECN (the differences are statistically significant at the 22.02% and 11.57%), both of which only consider the text features before classification. That demonstrates the plain text does not contain rich emotional semantic information as emojis do occasionally in sentiment analysis. T-ECN outperforms the N-ECN by 10.45% in accuracy. This shows emoji-guided text representation learning can effectively improve the ability of the model to learn the emotional semantic. It also explains why our emoji-based method can achieve better accuracy compared to other baseline methods. The accuracy of E-ECN is also significantly higher than T-ECN by the 9.20% and slightly lower than the complete ECN model since E-ECN extracts sentiment information from text-guided emoji representation but fails to capture sentiment patterns of emoji-guided text representation.
Effectiveness of Co-Attention To further explore the effect of co-attention mechanism in our proposed method, we compare the ECN model architecture to several attention-modified models. In RA1-ECN, we remove the intra-text attention module and take the output of last cell of the Bi-LSTM as the plain text representation \( v_t \). In RA2-ECN, we replace the text-guided attention module with the average value of the emoji vectors \( E = [e_1, e_2, \ldots, e_N] \) as the emoji representation \( v_e \). In RA3-ECN, we replace the emoji-guided attention module with the average value of the text representation \( H_2 = [h_{12}, h_{22}, \ldots, h_{L2}] \) as the text representation \( v_h \). In RSE-ECN, we remove the SE-Net module and concatenate the output of co-attention module(\( v_t, v_e, v_h \)) to a full-connected layer with a softmax function as a classifier.

The data of last two lines of the Table 2 show the improvements of SE-Net, which illustrates that this module can improve the accuracy. On the other hand, the difference between last two lines is slighter than the improvements of the whole ECN model compared with baselines. That indicates the co-attention module play the main role in our model.

Comparing the difference between these attention-simplified models in Table 2 it can be seen that the accuracy of the RA2-ECN has dropped the most. That model directly changes the attention mechanism of the emoji vector \( v_e \) to the average value of all emoji vectors, indicating that emojis take most of the weight for the emotional semantic analysis of the model. That means when the model cannot distinguish which emoji dominates the text emotion, the accuracy rate drops significantly. The slight difference of accuracy between the RA1-ECN and RA3-ECN model reveals that when the self-attention of the text is removed, the simplified \( v_t \) vector will further affect the representation of \( v_e \) as the emoji feature, and it results in the lower accuracy. While the RA3-ECN retains the first two representation of \( v_t \) and \( v_e \) features, only the last step of the text vector representation is replaced, it has the least impact on the model performance, indicating that the model can still make correct predictions from the \( v_e \) vector with a greater probability.

Table 2. performance of ECN and its simplified versions

| Models     | P(%) | R(%) | F(%) | Acc(%) |
|-----------|------|------|------|--------|
| N-ECN     | 75.79 | 77.03 | 76.04 | 76.57 |
| T-ECN     | 95.08 | 77.65 | 85.49 | 87.02 |
| E-ECN     | 95.85 | 99.90 | 97.83 | 97.82 |
| RA1-ECN   | 95.02 | 96.18 | 95.04 | 95.57 |
| RA2-ECN   | 93.06 | 94.18 | 94.08 | 94.22 |
| RA3-ECN   | 97.32 | 98.59 | 97.92 | 97.92 |
| RSE-ECN   | 96.80 | 99.03 | 97.89 | 98.25 |
| ECN(our model) | 97.46 | 99.88 | 98.66 | 98.59 |
5 Conclusion

We leverage emojis as important features to capture emotional patterns for sentiment analysis, and evaluate ECN with several representative baselines and our method achieves better performance with good interpretability.

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