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Group Emotion Recognition for Weibo Topics Based on BERT with TextCNN

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Abstract: Social media platforms, including Weibo, have become an integral part of people's daily lives, where users engage in discussions, share opinions, and express their emotions regarding trending topics. However, as the volume of information and content continues to increase, individuals face challenges in accessing relevant information. To address this issue, sentiment analysis has been employed in this study to focus on group sentiment identification for Weibo topics. Due to the potential involvement of multiple sentiment categories in Weibo topics, the main algorithm used in this research combines BERT and TextCNN for text multi-label classification. This approach aims to predict the possible collective emotional reactions of the public. Macro-F1 has been chosen as the evaluation criterion, with the baseline algorithm achieving a score of 0.3339, while our model achieved a slightly improved score of 0.3514. This improvement demonstrates the efficacy of the proposed algorithm. This paper makes full use of the self-attentive mechanism of BERT combined with the convolutional layer and pooling operation of TextCNN to extract local features. The generalization ability and sentiment classification accuracy of the model are improved. The results of text multi-label classification for group sentiment recognition of microblog topics demonstrate the superiority of the model algorithm in this paper. This study carries significant implications for understanding the public's emotional responses to popular topics on social media. It provides valuable insights for further exploration and advancement in the field of sentiment analysis within the realm of social media.

Keywords: BERT, TextCNN, Text Classification, NLP

1. Introduction

Social media platforms, like Weibo, have seamlessly integrated into people's daily lives, allowing users to engage in discussions, express their opinions, and share their emotions [1]. However, the sheer volume of user comments has made it challenging to effectively capture and analyze sentiment from the overwhelming amount of available information.

To address this problem, our study focuses on using a combination of two algorithms, BERT [2] and TextCNN [3], to identify the group sentiment of Weibo topics and predict the potential collective sentiment of the public. In order to capture real-time sentiment, we selected the top five comment texts based on their time of posting as input data. These comments serve as immediate responses from users and accurately reflect the public's feelings and emotional orientation towards the trending topics. The dataset used in our study consists of two parts: the hashtag and the top five user comments. Our objective is to analyze these comment texts and map them to sentiment tags using three emoji tags, representing different sentiment categories. The dataset contains a total of 24 expression tags, each indicating a specific emotional expression such as '[微笑]' (Smile), '[憧憬]' (Longings), '[怒]' (Anger), '[笑 cry]' (Smile cry), and so on. Previous research has mainly focused on sentiment analysis of individual authors, while relatively less attention has been given to analyzing public and group sentiment responses to Weibo topics. However, understanding public sentiment reactions to trending topics holds great significance in areas such as government decision-making, public opinion analysis, and market research. To achieve our goal, we propose a textual multi-label classification method based on the BERT and TextCNN algorithms to identify the group sentiment of Weibo topics. BERT, as a powerful pre-trained language model, can extract rich semantic features from Weibo texts. On the other hand, TextCNN, a convolutional neural network model, captures local and global information in texts, making it suitable for emotion detection tasks. By combining these two algorithms, we can more accurately predict the group sentiment evoked by Weibo topics. To evaluate the performance of our model, we use Macro-F1 as the evaluation criterion for multiple classifications. The Macro-F1 value considers the prediction results for each sentiment category and provides an objective assessment of the overall performance of the emotion detection model. The baseline algorithm, based on existing studies, achieved a Macro-F1 score of 0.3339. In comparison, our model achieved a slightly improved result of 0.3514 with the same evaluation criterion, indicating a slight enhancement in the classification effectiveness. In our experiments, we utilized an annotated training dataset containing Weibo topic descriptions and corresponding sentiment tags. The evaluation metric used was Macro-F1, which integrates the prediction results for each sentiment category, providing an overall assessment of the model's performance. Our experimental results demonstrate that the proposed algorithm achieved a Macro-F1 score of 0.3514, indicating a slight improvement compared to the baseline algorithm's score of 0.3339.

The contribution of this study is a textual multi-label classification for the group sentiment recognition task of Weibo topics by combining BERT and TextCNN algorithms. By predicting the possible group reaction sentiment of the public, we can better understand the public's attitude and sentiment tendency towards hot topics. This has important implications for the fields of public opinion analysis, social survey and public decision making, and provides insights for further exploration of social media sentiment analysis.

2. Related Work

Text multi-classification is a significant task in the field of NLP (natural language processing) [4-6], and numerous studies have been conducted in this area. Previous works primarily focused on text classification algorithms and sentiment analysis techniques to identify sentiments, topics, or categories within texts. These approaches often relied on handcrafted features like bag-of-words models [7] and TF-IDF [8-10] weights, combined with classifiers such as naive Bayes and support vector machines. Although these methods performed well on certain tasks, they heavily relied on manual feature engineering and had limitations in capturing the full expressive power of text.

In recent years, deep learning methods have shown remarkable progress in text classification tasks. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are widely used models in this domain. CNNs extract and integrate local text features through convolutional and pooling layers, effectively capturing local dependencies between words. On the other hand, RNNs process text sequences through recurrent structures, allowing them to capture contextual information. Kim introduced the use of CNNs in text classification tasks, simplifying text extraction and improving classification accuracy. Zaremba et al. proposed the recurrent neural network (RNN) [11], which has demonstrated excellent classification performance by effectively learning contextual information from text. However, as the input length increases, RNNs suffer from issues such as gradient vanishing and exploding. To overcome these shortcomings, Hochreiter et al. [12] introduced the gate mechanism and developed the long short-term memory (LSTM) model. LSTM has been successfully applied to text classification by Liu et al. [13], yielding noteworthy results.

Despite the advancements, traditional models still struggle to effectively learn and process important internal location semantics in text. The introduction of BERT, capable of generating contextual word embeddings, marked a significant turning point in the development of text classification and other NLP techniques. BERT has demonstrated superior performance in various NLP tasks, including text classification. In this paper, we leverage the combination of BERT and TextCNN algorithms for the group sentiment recognition task in Weibo topics, specifically focusing on text multi-label classification. By extracting semantic representations and key features, our approach predicts the potential collective sentiment of the public.

3. Methods

In this paper, we propose a model composed of two modules: a feature extraction module and a emotion detection module. The feature extraction module is built upon the BERT pre-trained language model, which enables us to extract semantic representations and contextual information from the text. This module effectively captures the semantic relationships between words, providing rich feature representations for subsequent classification tasks. On the other hand, the emotion detection module employs a convolutional neural network (CNN) to extract local features from the text. Once it receives the text feature representation from the feature extraction module, it applies convolutional and pooling layers to extract and integrate local dependencies between words, which are then used for the emotion detection task. Figure 1 illustrates the structure of our proposed model.

3.1. Feature Extraction Modules

The primary purpose of the feature extraction module is to leverage the pre-training capability of the BERT model to enhance the generalization ability of our model. This helps prevent the model from becoming overly dependent and overfitting to the specific text data. Additionally, the feature extraction module is designed to capture local semantics and focused information within the text more effectively. This provides richer information for the subsequent emotion detection module, ultimately improving the accuracy of the emotion detection task. The BERT model takes the original word vectors of each word/token in the text as its main input. These word vectors can be randomly initialized or pre-trained using algorithms like Word2Vec [14-16] to obtain initial values. The output of the BERT model is a vector representation of each word/token in the text, which incorporates the complete semantic information of the entire text. As text data is unstructured, it cannot be directly used as the input format for our model. The feature extraction module with the BERT model preprocesses the text data, transforming it into meaningful and informative representations that can be further utilized by the emotion detection module.

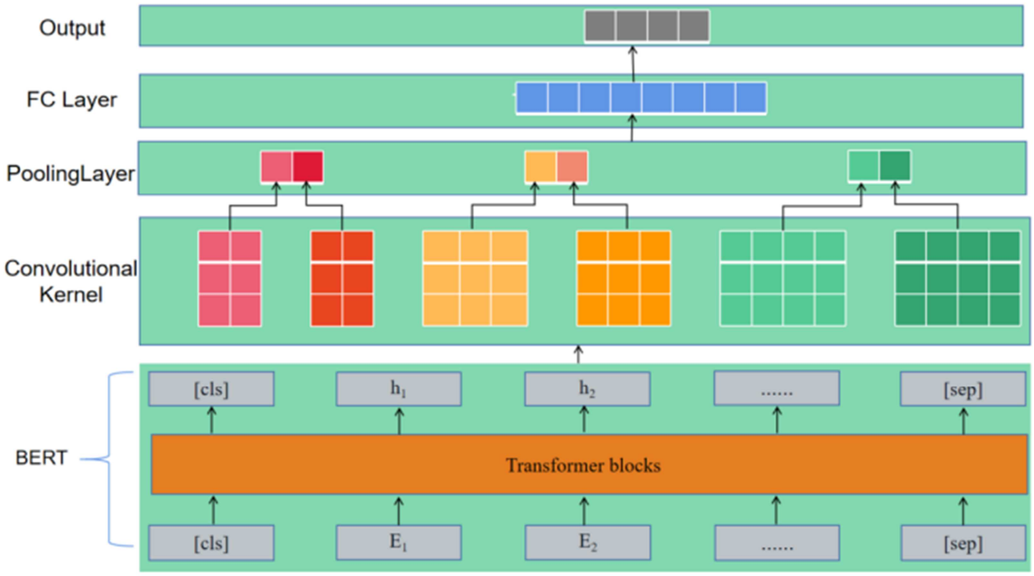

Figure 1. *The structure of BERT-TextCNN.*

Before inputting text data into the classification model, these unstructured text sequences must be converted into structured feature vectors. The initial input to the BERT model is a set of sentences, and the BERT model converts each word in the text into a one-dimensional vector by querying the word vector table as the model input, and the model output The model output is the vector representation of the input words corresponding to the fused full-text semantic information. As shown in equations (1) through (2).

$$E = \sum_{i=1}^{n} E_i \tag{1}$$

$$h_1 = BERT(E_1) \tag{2}$$

Where h_1 represents the vector representation after fusing the full text semantic information. In our task, x is the text part of the 1st news item. the BERT input vector consists of a word embedding vector, a segment embedding vector, and a location encoding vector. The word embedding vector is derived from the BERT embedding matrix to find the vector representation corresponding to each word. BERT can be trained in the form of sentence pairs and segment embedding vectors are used to identify sentences. In the positional encoding vector, BERT uses the learned positional encoding to identify the positional information of each word.

3.2. Emotional Classification Module

The emotion detection module is mainly used to receive the text features extracted by the feature extraction module to perform convolution and pooling operations on the text, combine them through the fully connected layer, and finally output them through the output layer. In the TextCNN model, the convolution and pooling operations are used to extract local features from the text data. The convolution layer performs convolution operations on the text data by means of sliding windows to capture the local features. Multiple convolution kernels (filters) of different sizes are usually used to extract features of different lengths. Each convolution kernel performs a convolution operation on the text data to generate a feature map. As shown in equation (3).

$$C = CK(\mathrm{E}) \tag{3}$$

After applying convolutional operations in the feature extraction module, each feature map is reduced in dimensionality by a pooling layer, usually using a maximum pooling operation that selects the maximum value in each feature map as a representative of that feature. This allows the features of the text data to be extracted and compressed. After convolution and pooling, the resulting features are spread into a one-dimensional vector. As shown in equation (4).

$$\mathrm{P} = \mathrm{PoolingLayer(C)} \tag{4}$$

Then, further nonlinear transformations and combinations of these features are performed by one or more fully connected layers. Neurons in the fully connected layers can learn specific combinatorial patterns and abstract representations. As shown in equation (5).

$$F = \text{FC Layer}(P) \tag{5}$$

Finally, the output of the fully connected layer is connected to the output layer and the output of the model is transformed into a probability distribution using an appropriate activation function for the prediction of multi-category text classification tasks. As shown in equation (6).

$$\text{Output} = \text{softmax}(F) \tag{6}$$

4. Experiment

4.1. Data Preparation

Our experimental data comes from CCAC 2022 Task 2. The input data of this task contains two parts: the hashtag and the top five user comments, and the output is the emotions of users under that topic, represented by three emoji tags. The data set contains a total of 24 emoji tags which is shown in Table 1.

Table 1. *Table of 24 emoji tags.*

Column1	Column2	Column3	Column4
微笑 (Smile)	嘻嘻 (Xixi)	笑 cry (Smile cry)	怒 (Anger)
泪 (Tears)	允悲 (Allow sadness)	憧憬 (Longings)	doge (Doge)
并不简单 (Not so simple)	思考 (Reflections)	费解 (Incomprehensible)	吃惊 (Surprised)
拜拜 (Byebye)	吃瓜 (Eat melons)	赞 (Praise)	心 (Heart)
伤心 (Sadness)	蜡烛 (Candles)	给力 (Awesome)	威武 (Formidable)
跪了 (Kneeling)	中国赞 (China Praise)	给你小心心 (Heart for you)	酸 (Acid)

4.2. Evaluation Metrics

In this paper, the dataset used for our use belongs to textual multi-label data, and we use the Macro-F1 score as a measure of model performance. For multi-label text classification, we first load the text data, then preprocess the data, convert the data into id form. And then we feed it into dataloader for the training process to provide batch data to the model. Then, processing by BERT and TextCNN, we get the category of each label, where each label is indicated by a binary variable. One text may correspond to more than one label. For each label, Precision denotes the proportion of samples correctly predicted as positive cases to all samples predicted as positive cases, and Recall denotes the proportion of samples correctly predicted as positive cases to all samples with true positive cases. As shown in equations (7) to (10).

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \tag{7}$$

$$\text{Pr}ecision = \frac{TP}{(TP + FP)} \tag{8}$$

$$\text{Re}call = \frac{TP}{(TP + FN)} \tag{9}$$

$$F1 = \frac{2 \times \text{Pr}ecision \times \text{Recall}}{(\text{Pr}ecision + \text{Recall})} \tag{10}$$

Where TP represents the number of positive classes predicted as positive, FN represents the number of positive classes predicted as negative, FP represents the number of negative classes predicted as positive, and TN represents the number of negative classes predicted as negative. The sum of these four values provides a total number of samples tested.

Finally, we use Macro-F1 to evaluate the performance of the entire multi-label classification task. It is the mean value of the F1-score for all labels. As shown in equation (11).

$$Macro\ \text{F1} = \frac{1}{n}\sum_{i=1}^{n} F1_i \tag{11}$$

By calculating Precision, Recall and F1-score for each label and taking their mean values as Macro-F1, we can comprehensively evaluate the performance of the model in the text multi-label classification task.

4.3. Baselines

For evaluating the performance of our proposed model, the officially given BERT model is taken as baselines. We evaluate the performance by comparing the Macro-F1 of different models on the test set by comparing with baselines, we can verify whether our proposed model has better performance and stronger robustness.

4.4. Experimental Results

To validate the effectiveness of our proposed model, we conducted a comparison with baseline, utilizing Macro-F1 as the evaluation metric. On the test dataset, our model achieved a Macro-F1 score of 0.3514, indicating a slight improvement over the baseline. This improvement can be attributed to the combination of two algorithms, TextCNN and BERT, which leverage their respective strengths. TextCNN effectively captures local features through convolution and pooling operations, while BERT captures global semantic information using a self-attentive mechanism. By combining these approaches, our model comprehensively extracts features from textual data, resulting in a better representation of semantic and sentiment information. Furthermore, our model is specifically designed for text multi-label classification tasks. We employ loss functions and evaluation metrics tailored for multi-label classification, ensuring a better alignment with the task's characteristics. As shown in Table 2.

Table 2. *Results of 24 emoji tags (English translation in brackets).*

	Precision	Recall	F1
Doge (Doge)	0.5889	0.8189	0.6851
中国赞(China Praise)	0.2526	0.1714	0.2043
伤心(Sadness)	0.5147	0.3889	0.4430
允悲(Allow sadness)	0.6905	0.6732	0.6818
吃惊(Surprised)	0.4375	0.3271	0.3743
吃瓜(Eat melons)	0.4604	0.3924	0.4237
嘻嘻(Xixi)	0.1667	0.0110	0.0206
威武(Formidable)	0.0000	0.0000	0.0000
并不简单(Not so simple)	0.0000	0.0000	0.0000
微笑(Smile)	0.4531	0.1559	0.2320
心(Heart)	0.6081	0.7937	0.6886
怒(Anger)	0.6206	0.5764	0.5977
思考(Reflections)	0.0000	0.0000	0.0000
憧憬(Longings)	0.5287	0.7026	0.6034
拜拜(Byebye)	0.4000	0.0351	0.0645
泪(Tears)	0.6289	0.6676	0.6477
笑 cry (Smile cry)	0.5896	0.4540	0.5130
给你小心心(Heart for you)	0.3333	0.0341	0.0619
给力(Awesome)	0.4030	0.1875	0.2559
蜡烛(Candles)	0.6276	0.5942	0.6104
费解(Incomprehensible)	0.5059	0.4993	0.4961
赞(Praise)	0.5469	0.7071	0.6167
跪了(Kneeling)	0.4167	0.0549	0.0971
酸(Acid)	1.0000	0.0469	0.0896
Macro Avg	0.4489	0.3473	0.3514

5. Discussion

After conducting research and experiments, we have obtained some results using the BERT-TextCNN model in the task of group emotion recognition focused on Weibo topics. In comparison to the baseline algorithm, our BERT-TextCNN model achieves slightly better results in group sentiment recognition for Weibo topics. The Macro-F1 evaluation metric for the baseline algorithm is 0.3339, while our model achieves a Macro-F1 of 0.3514. Although the improvement is not significant, it does demonstrate the advantages of the BERT-TextCNN model in this task. Given that the group sentiment recognition task for Weibo topics involves multiple sentiment labels, our model performs well in conducting multi-label classification. By leveraging BERT's semantic understanding and TextCNN's ability to capture local features. Our model accurately identifies the group sentiment of different users within Weibo topics. While our BERT-TextCNN model shows promising results in group sentiment recognition tasks for Weibo topics, there is still room for improvement. With additional training data and more complex model structures, we believe that the adaptability and generalization ability of the model can be further enhanced to achieve superior results. However, we are also aware of numerous challenges and issues that need to be addressed, such as effectively handling text noise and accommodating the diverse range of sentiment expressions found in social media. Therefore, future research can focus on further exploration and refinement of the model to enhance its performance and effectiveness in this domain.

6. Conclusion

In this paper, we use a combination of BERT and TextCNN algorithms to explore group sentiment recognition for Weibo topics. Through the use of the technique of text multi-labeling classification, we are able to predict the possible group reaction sentiment of the public to microblog topics. The combination of BERT and TextCNN algorithms has multiple advantages. Firstly, BERT can effectively capture the contextual information and semantic associations of text, providing a rich representation of text. Secondly, TextCNN is able to extract local features and semantic information of the text, enabling the model to better understand the sentiment expressions in the text. The combination of these two algorithms takes full advantage of their strengths in text processing and feature extraction to improve the accuracy of sentiment classification. In Summary, the algorithm combination based on BERT and TextCNN in this study achieves some improvements in the group sentiment recognition task of Weibo topics. This study has important implications for understanding public sentiment reactions to hot topics and provides useful insights for future research on social media sentiment analysis. A further study can explore more algorithm combinations and techniques to improve the performance and application of sentiment classification.

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References

[1] Harwit E. The rise and influence of Weibo (microblogs) in China [J]. Asian Survey, 2014, 54 (6): 1059-1087.

[2] Devlin, J., Chang, M. W., Lee, K., Toutanova, K., 2018. BERT: Pretraining of deep bidirectional transformers for language understanding. arXiv preprint arXiv: 1810.04805.

[3] Kim, Y., 2014. Convolutional neural networks for sentence classification. Eprint Arxiv.

[4] Cambria E, White B. Jumping NLP curves: A review of natural language processing research [J]. IEEE Computational intelligence magazine, 2014, 9 (2): 48-57.

[5] Strubell E, Ganesh A, McCallum A. Energy and policy considerations for deep learning in NLP [J]. arXiv preprint arXiv: 1906.02243, 2019.

[6] Kang Y, Cai Z, Tan C W, et al. Natural language processing (NLP) in management research: A literature review [J]. Journal of Management Analytics, 2020, 7 (2): 139-172.

[7] Sadeghian A, Sharafat A R. Bag of words meets bags of popcorn [J]. CS224N Proj, 2015: 4-9.9.

[8] Xiao, K., Wang, C., Zhang, Q., Qian, Z., 2019. Food safety event detection based on multi-feature fusion. Symmetry 11, 1222.

[9] Qaiser S, Ali R. Text mining: use of TF-IDF to examine the relevance of words to documents [J]. International Journal of Computer Applications, 2018, 181 (1): 25-29.

[10] Yun-tao Z, Ling G, Yong-cheng W. An improved TF-IDF approach for text classification [J]. Journal of Zhejiang University-Science A, 2005, 6: 49-55.

[11] Zaremba, W., Sutskever, I., Vinyals, O., 2014. Recurrent neural network regularization. Eprint Arxiv.

[12] Hochreiter, S., Schmidhuber, J., 1997. Long short-term memory. Neural computation 9, 1735–1780.

[13] Liu, P., Qiu, X., Huang, X., 2016. Recurrent neural network for text classification with multi-task learning. arXiv preprint arXiv: 1605.05101.

[14] Mikolov T, Sutskever I, Chen K, et al. Distributed representations of words and phrases and their compositionality [J]. Advances in neural information processing systems, 2013, 26.

[15] Goldberg Y, Levy O. word2vec Explained: deriving Mikolov et al.'s negative-sampling word-embedding method [J]. arXiv preprint arXiv: 1402.3722, 2014.

[16] Ling W, Dyer C, Black A W, et al. Two/too simple adaptations of word2vec for syntax problems [C]//Proceedings of the 2015 conference of the North American chapter of the association for computational linguistics: human language technologies. 2015: 1299-1304.