Text Emotion Analysis of BGRU Model Based on the Fusion of Emoticons

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June 29, 2020

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ABSTRACT

Micro-blog is a platform for users to get information and convey their own ideas. In recent years, the emotional analysis of micro-blog has gradually become a hot topic. The publication of micro blog not only includes text, but also emoticons are a part that cannot be ignored. Traditional research methods ignore the importance of emoticons to the emotional polarity of text when preprocessing the micro blog. This paper proposes a research method of text emotion analysis based on the fusion of emoticons. By micro-blog to crawl the data preprocessing, selected text in the emoticons, using emotional dictionary gives corresponding weights and calculate the score, then transform text into the corresponding word vector sequence, using Bidirectional Gated Recurrent Unit network context information text emotion tendency, finally selects the Conditional Random Field polarity judgment of text. The experimental results show that the accuracy of the proposed method is up to 89%.
Keywords: GRU,sentiment analysis,BLSTM,machine learning,CRF,CNN, BGRU, emoticons

1. INTRODUCTION

With the progress of science and technology, the Internet has gradually changed and occupied people's lives. With the increasing number of Internet users, online social platforms have gradually emerged and become an indispensable part of social life. Since sina launched "sina micro-blog " in August 2009, micro-blog has gradually become an information platform for users to express their feelings. According to statistics, the monthly active users of micro-blog reached 465 million in 2019, and the daily active users reached 203 million. For hot events, whether it is entertainment, gossip or people's news, every qualified user has the right to freedom of speech, and users gradually occupy the dominant position. Due to the large number of micro-blog users, the complex and diverse information content and the huge amount of information data, the emotional analysis of micro-blog has gradually become a hot spot, attracting the research interest of many scholars.

In recent years, emotion analysis has become a hot topic in the field of natural language processing [1]. Emotion analysis is to analyze and process this content of micro-blog with emotional color, and finally get the polarity of text emotion. Its purpose [2] is to understand users' emotional tendency by judging the polarity of the text, so as to understand users' life rules, and to help government departments to monitor public opinions and control inappropriate comments in a timely manner. With the progress of society, machine learning and deep learning are constantly changing our lives, and the era of artificial intelligence [3] has arrived. Deep learning is used to detect the abnormal movement of unmanned aerial vehicles [4]. Prediction of unknown semantic characteristics through self-supervised learning [5]; The image is analyzed through MADNet network [6]; The underwater image was observed by the fast joint trigonometric filtering dehazing algorithm. [7]. Technology is gradually changing our lives.

The experimental data selected in this paper are 100000 micro-blog texts crawled on micro-blog, among which 78932 micro-blog texts contain emoticons. Therefore, the study of emoticons in micro-blog can more accurately grasp users' emotional tendencies.

2. RELATED WORK

Natural language processing [8] refers to the emotional analysis of texts, also known as opinion mining. The natural language division's early natural language processing was machine translation, when people underestimated the complexity and cost of natural language. Modern natural language processing is based on machine learning and deep learning, and emotional analysis of natural language is conducted through supervised learning [9], semi-supervised learning and unsupervised learning. Liang jun et al. [10] analyzed weibo emotions through a recursive neural network, saving the traditional workload of manual annotation analysis. Wu wei [11] et al. combined dictionary method with machine learning algorithm to analyze the emotion of micro-blog text. Yang yong et al. [12] established an emotion lexicon and classification model based on SVM to classify the text based on emotion polarity, but the accuracy of the experimental results was not high. Compared with traditional emotion analysis, although it has made some progress, it still faces such problems as complex text, long training time and inaccurate training results. With the progress of the Internet era, the content published on weibo is no longer limited to words. By adding emoticons and pictures to express, the emotions expressed by users on the platform become more vivid and vivid, adding color to the expression of the whole text, which is more appropriate to the users' inner feelings. Research has shown that users are keen to use emojis, which are crucial in determining the emotional orientation of a text. Semi-supervised learning [13] is a learning method combining supervised learning with unsupervised learning. At present, supervised learning is the most commonly used method in natural language processing.

By analyzing the content of previous micro-blog posts and improving the traditional text research methods, this paper proposes a text emotion analysis method by integrating emoticons. Through the annotation and classification of micro blog emoticons to express emotions, the emoticons were divided into different levels. After the bidirectional GRU was used to classify the emotional polarity of the text, the emoticons' emotional tendency was integrated, and the result of emotional polarity was finally obtained. Compared with the traditional emotion analysis model, this method can improve the accuracy of training results.

3. FUSION MODEL ANALYSIS

3.1 The word vector

There are many ways to convert experimental data into word vectors. In this paper, the method of Continuous Bag-Of-Words [14] (CBOW) is used to vectorize the text. The CBOW includes the input layer, the projection layer, and the output layer, as shown in figure 1.

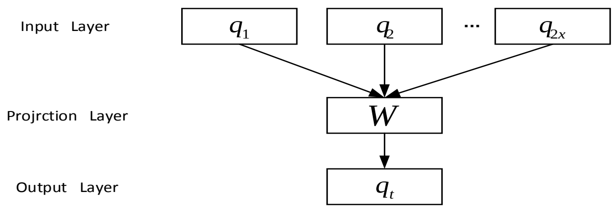

Fig. 1 CBOW

In contrast to skip-gram[15], CBOW predicts q_t by knowing the context-related words of $2x$ in the feature word q_t, in which the input layer includes the word vector $l(Context(q_1))$、$l(Context(q_2)) \ldots l(Context(q_{2x})) \in R^v$, of the $2x$ words in $Context(q)$, and v represents the length of the word vector. x means x words before and after the word q. Then sum and add up $2x$ vectors in the projection layer, as shown in formula (1) :

$$W = \sum_{i=1}^{2x} l(Context(q_i)) \in R^v \tag{1}$$

The objective function in the output layer is as follows:

$$f = \sum_{q \in x} \log p(q \mid Context(q)) \tag{2}$$

3.2 Polarity labeling of emoticons

Through the study of users' frequency of using emoticons [16] and the development needs of the society, micro-blog APP also slightly increases and decreases its emoticons.

In micro-blog, emoticons can appear at the beginning of a text, at the end of a text, or even in the middle of a text. For example, "the meal at work today is really ". In this sentence, through the analysis of the text, we cannot find the key words to express the user's emotion, so we cannot understand the user's emotional tendency, but we can understand the user's extremely negative state of mind through the expression of anger; "I'm so happy to hear that my bestie has been admitted to graduate school  ".In this micro-blog, the word "happy" appears. It can be analyzed that the emotions expressed by the users are positive, and at the same time, there are laughing emoticons. We can further confirm that this is a micro-blog with positive emotions. At the same time, for the sake of simplicity and convenience, many users only express their inner feelings through a single emoji. Some micro-blogs contain multiple emoticons. Therefore, we classified the 84 commonly used micro-blog emoticons and marked their corresponding emotional tendencies. As shown in table 1:

Tab.1 Commonly used micro blog emoticons emotional polarity

Emotional polarity	Emoticons	Emotional score
Positive		2
Neutral		1
Negative		−2

As the input process in the micro-blog does not limit the number of emoticons used, negative, neutral and positive emoticons may appear in the same paragraph of text at the same time, which has a certain impact on the emotional analysis of the text. We calculate the number of emojis with different polarity and compare them to get the final emojis polarity, as shown in formula (3) :

$$\text{Emotional polarity}=\begin{Bmatrix} N & n>s \\ M & n=s \\ S & n<s \end{Bmatrix} \tag{3}$$

Where N represents positive polarity of emotion, M represents neutral polarity of emotion, and S represents negative polarity of emotion. According to the comparison table 1, the number of polar positive emoticons selected from the micro-blog is represented by n, the number of polar negative emoticons is represented by s, and the number of neutral emoticons is represented by m. The resulting emoticon emotional score is expressed as o. When the extracted emoticons do not contain neutral polar emoticons, as shown in formula (4) :

$$score(o)=\begin{Bmatrix} \log 2^{n-s} & n>s \\ -\log 2^{s-n} & n<s \end{Bmatrix} \tag{4}$$

When the extracted emojis contain emojis with neutral polarity, as shown in formula (5) :

$$score(o)=\begin{Bmatrix} m^0 \log 2^{n-s} & n>s \\ m^0 \log 2^{s-n} & n<s \end{Bmatrix} \tag{5}$$

3.3 Gated Recurrent Unit

Recurrent Neural Networks [17] (RNN) appeared in the 1980s and 1990s, and has made remarkable achievements in the field of natural language processing. However, there is a gradient problem in the processing of complex text of RNN, which leads to the network instability in the operation process. The emergence of long and short term memory network[18] (LSTM) solves the gradient problem of RNN by adding gating mechanism, selectively discarding old values and adding new values. Gated Recurrent Unit [19] (GRU)is a variant of LSTM. GRU maintains the effect of LSTM while making the structure simpler and computing performance faster.

LSTM consists of three gated structures: a forgetting gate, an input gate, and an output gate, as well as a memory unit. GRU combines the forgotten gate and output gate in LSTM into one gate, the update gate. There are only two gates in the GRU, namely the update gate Z_t and reset gate r_t . The update gate is used to correlate the information of the previous period with the information of that period, while the reset gate is used to determine the degree of irrelevant information of the previous period is discarded. At the same time, memory units in LSTM are removed from GRU to convey information by hiding the state. Since the input text sequence is positive, it is shown in figure 2.

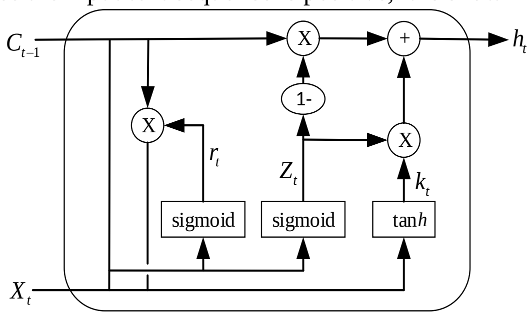

Fig. 2 GRU

The forward calculation formula of GRU at t moment is as follows:

$$Z_t = sigmiod(Q_z x_t + b_{iz} + Q_{hz} h_{t-1} + b_{hz}) \tag{6}$$

$$r_t = sigmiod(Q_r x_t + b_{ir} + Q_{hr} h_{t-1} + b_{hr}) \tag{7}$$

$$k_t = \tan h(Q_k x_t + b_k + r_t \times (Q_{hk} h_{t-1} + b_{hk})) \tag{8}$$

$$h_t = (1 - Z_t) \times k_t + Z_t \times h_{t-1} \tag{9}$$

Where Q is the gate weight vector, b is the bias value, h is the hidden state, k is the candidate hidden state, and x is the input word vector.

3.4 BGRU-CRF

GRU performed well in the experiment of contacting the above information. However, when conducting emotion analysis on micro-blog, it is not possible to accurately judge the emotional polarity of words just by connecting the above information, so it needs to be analyzed in context. Therefore, in this paper, the forward and reverse GRU will be used simultaneously, that is Bidirectional Gated Recurrent Unit [20] (BGRU). In the hidden layer, BGRU can process the forward sequence and reverse sequence of text respectively, and closely relate the captured context feature information, so that the final output result is more accurate. The update gate in the GRU contains the output gate, but the output result is only output with the maximum probability value selected at each step. There is no correlation between the output results. Therefore, a conditional random field [21] (CRF) is added to the output layer of BGRU, which not only adjusts the order of the output results of BGRU, but also integrates the emotional score of emoticons into it. The calculation formula is as follows:

$$\overrightarrow{h_t} = sigmoid(Q_{x\vec{h}} x_t + Q_{\vec{h}\vec{h}} \overrightarrow{h_{t-1}} + b_{\vec{h}}) \tag{10}$$

$$\overleftarrow{h_t} = sigmoid(Q_{x\overleftarrow{h}} x_t + Q_{\overleftarrow{h}\overleftarrow{h}} \overleftarrow{h_{t-1}} + b_{\overleftarrow{h}}) \tag{11}$$

$$y = \left\{ Q_{hy} \left[\overrightarrow{h_t} ; \overleftarrow{h_t} \right] + b_y \right\} \cdot score(o) \tag{12}$$

Where $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ are the forward and reverse GRU output respectively,and y is the final CRF output.

3.5 Model Analysis

The micro-blog emotion analysis model proposed in this paper is composed of the following parts:
In this paper, the micro-blog text sentiment analysis model based on the bidirectional gated recurrent unit of fusion emoticons is composed of the following parts. First, preprocess the captured micro-blog text, select the emoticons, and calculate the emotional score by comparing the emoticons dictionary. Then, through the continuous bag-of-words model, the preprocessed micro-blog words are transformed into corresponding word vectors and combined into word vector set. The word vector is contextualized by the update gate and reset gate of the bidirectional gated recurrent unit, and the obtained maximum probability value is input into the conditional random field. The maximum probability value and emoticons' emotion score were sorted and sorted in the conditional random field, and the maximum probability value was finally output. The model flow is shown in figure 3 below:

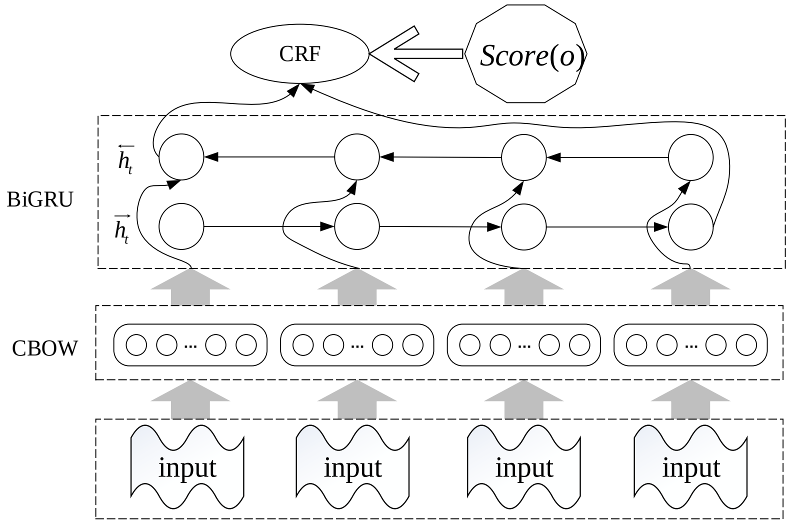

Fig. 3 Model Flow Diagram

4 THE EXPERIMENT

Experiments were conducted on the traditional methods of emotion analysis (CNN, BLSTM, BGRU) and the BGRU - CRF method of emotion analysis that integrates emoticons, and the experimental results were compared.

4.1 The data set

In order to ensure the reliability of experimental training results, the fusion model proposed in this paper USES a large amount of data for training. By crawling more than 100,000 micro-blog posts in the official micro-blog account, the model can be used as a training set and a test set. Among them, 73,036 micro-blog texts were randomly selected as the training set, and the remaining 26,944 micro-blog texts were selected as the test set. In the process of training and testing, these data were randomly scrambled for several times for experiments to ensure the authenticity of experimental results, and the average value of multiple experiments was finally selected as the final experimental results.

4.2 Data Preprocessing

The micro-blog data obtained in this paper are complex and varied. In order to ensure the accuracy of the experimental results, the text should be preprocessed before training. First, the crawling text will be cleaned, which has nothing to do with the analysis of the emotional polarity of the text of the number, stop words, links, blank symbols, punctuation marks and so on. If irrelevant information is not removed, the training process will not only take too long, but also affect the accuracy of the training results. In this paper, the text is processed through the word table of hit university of science and technology, and then the sentences in the short text are segmented through the word segmentation system of Chinese academy of sciences [22] (NLPIR), and the obtained words are marked with polarity.
The number of published content of a micro-blog shall not exceed 140 characters, so the micro-blog text is also known as the short version. Before the training, the micro-blog text should be sorted out, and the text that is too long or too short

should be deleted or supplemented. The character of the micro-blog text should be set to 60 to ensure the consistency of the text characters.

4.3 Evaluation Standard

The evaluation indexes of emotion analysis are generally divided into three categories: Accuracy(P), Recall rate(R), and weighted harmonic mean value based on accuracy and recall rate(F_1).Three evaluation criteria are adopted in this paper, and the specific formulas are as follows:

$$P=\frac{TP}{TP+FP} \tag{13}$$

$$\mathrm{R}=\frac{TP}{TP+FN} \tag{14}$$

$$\mathrm{F}_1=\frac{2PR}{P+R}=\frac{2TP}{2TP+FP+FN} \tag{15}$$

Where TP represents the number of texts retrieved and classified correctly, FP represents the number of texts retrieved but misclassified, and FN represents the number of texts not retrieved but belonging to this polarity.

4.4 Experimental Results And Analysis

In order to verify the accuracy of the model proposed in this paper, a comparison experiment was conducted with other models based on the same experimental data. The experimental results are shown in table 2.

(1) CNN: The traditional Convolutional Neural Network model [23] conducts emotional analysis on the text.

(2) BLSTM:Long and short term neural network is a kind of time circulatory neural network. The comparison experiment in this paper selects a bidirectional long and short term memory network model [24] for emotion analysis.

(3) BGRU:The emergence of BGRU can better capture the dependence between words that are far away from the text. A Bidirectional Gated Recurrent Unit model [25] was selected as a control experiment to analyze the emotional polarity of the text.

(4) BGRU-CRF model of emoticons score fusion: this paper conducts a dual analysis and research on the text part and emoticons in micro-blog. This paper proposes a new fusion model for text sentiment analysis.

Tab. 2. Comparison table of experimental results

Model	Emotional polarity	R	P	F_1
CNN	Positive	0.7032	0.7109	0.7134
	Negative	0.7045	0.7098	0.7102
BLSTM	Positive	0.7823	0.7789	0.7717
	Negative	0.7816	0.7696	0.7825
BiGRU	Positive	0.8302	0.8195	0.8471
	Negative	0.8299	0.8250	0.8411
BiGRU-CRF	Positive	0.8717	0.8691	0.8823
	Negative	0.8801	0.8512	0.8931

Through the analysis of the experimental results of each model in the table, it can be seen that the results of the model proposed in this paper are higher than those of the previous models in terms of accuracy, recall rate and F_1 value. In other words, the model in this paper has the most obvious effect on the polarity of text emotion analysis.

5 CONCLUSION

This paper improves the research method of determining the emotional polarity of texts by studying the integration of emoticons and text contents in micro-blog. Based on the comprehensive calculation of the number of emoticons in the micro-blog, the emotional polarity is finally obtained. To some extent, the emotional polarity analysis errors caused by the incorrect typing of emoticons are avoided, which greatly improves the accuracy of the training results and shortens the training time. However, the method in this paper still has some shortcomings. Since the number and types of emoticons in micro-blog are also constantly changing, and it is difficult to determine the emotional polarity of many emoticons in different contexts, the weight ratio of emoticons needs to be further studied. Due to the extensive and profound Chinese culture, the accuracy of this method is not high when it comes to the ironic texts appearing in the micro-blog text. Therefore, it is necessary to conduct further emotional analysis and research on the micro-blog text in the future.

6 ACKNOWLEDGMENTS

This work is supported by the Key R & D Plan of National Science and Technology Program Application Center(Grant:2019YFC1605306);National Key Research and Development Plan (Grant:2016YFD0401205); National Natural Science Foundation of China (Grant:61877002); Key projects of social science planning in Beijing” Research on the development of life-long education theory and policy in China——From the perspective of educational policy reference theory” project No:18JDJYA001; Construction of teaching staff-Innovation team (Scroll item) project No: IDHT20180507; Higher education in Beijing in 2019“Undergraduate teaching reform and innovation project”: Research and Reform on the management mechanism of innovative talents training in Beijing Municipal Colleges and Universities project No:201910011002; Beijing Municipal Natural Science Foundation: Mining, analysis and decision-making of learning behavior in open education based on multi-source and heterogeneous big data, project No:9192008; Project supported by the Natural Science Foundation of Beijing, China(Grant No. 4202016).

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