
Prediction and Guidance of Negative Public Opinion Dissemination Based on a Sentiment Classification Algorithm

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Abstract

The continuous spread of negative public opinion may have a detrimental impact on the stability of society, requiring timely guidance. This study used the spread of negative public opinion on Weibo as a case. Original Weibo posts related to the “Zhuhai Pedestrian Collision Case” published between 11 November 2024 and 31 November 2024 were crawled. A bidirectional gated recurrent unit (BiGRU) algorithm combined with an attention mechanism called the BiGRU-Att emotion classification algorithm was proposed to classify positive and negative public opinions. The negative public opinions were used to form time series data. A BiGRU-Att-Kalman filtering algorithm was designed to predict the spread of negative public opinions. It was found that the BiGRU-Att algorithm exhibited an F1 value of 0.9248 in sentiment classification, outperforming classification algorithms such as support vector machine. The root-mean-square error and mean absolute error (MAE) values of the BiGRU-Att-Kalman filtering algorithm in the prediction of negative

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public opinion dissemination were 201.25 and 115.62, respectively, with $R^2 = 0.98$, outperforming prediction algorithms such as GM (1,1). These results highlight the effectiveness of the proposed methods in sentiment classification and forecasting harmful opinion dissemination, thereby offering valuable insights for opinion management.

Keywords: Sentiment classification, negative public opinion, gated recurrent unit, dissemination prediction.

1 Introduction

Influenced by the rapid development of the Internet, social media platforms such as Douyin, Weibo, and other social media platforms have gradually become important venues for netizens to express their opinions and participate in public opinion discussions [1]. This trend has led to faster and broader dissemination of public opinion, posing challenges for relevant departments in managing public opinion. In particular, the dissemination of negative public opinion in some emergencies may cause panic and anxiety among netizens. If negative public opinions cannot be guided and dealt with in a timely manner, it is not conducive to social stability [2]. In the era of big data, the volume of public opinion data continues to grow. In order to extract valuable information from these data, more and more methods have been applied [3]. Zhao et al. [4] developed an aspect-based sentiment analysis model that extracted terms using association rules and the word2vec algorithm. They compared the classification performance of support vector machine (SVM) and other models, concluding that the convolutional neural network (CNN) model significantly enhanced fine-grained sentiment analysis of public opinion. Cui et al. [5] introduced a novel negative public opinion early warning assessment index. They conducted experiments on the COVID-19 Weibo sentiment dataset and discovered that the method was effective in early warning by analyzing negative public opinion topics. Peng et al. [6] established a system of online public opinion early warning indicators and built a model using the genetic algorithm-back propagation (GA-BPNN) algorithm. They found that the proposed algorithm exhibited higher accuracy than methods like decision trees. Karamouzas et al. [7] proposed an automated monitoring mechanism to track public opinion on Twitter and applied it to the 2016/2020 U.S. Presidential Election tweets dataset. This paper focuses on predicting and managing the spread of negative public opinion on the Weibo platform. A gated recurrent unit (GRU)-based sentiment

【#最高检对珠海驾车冲撞行人案表态#】11月11日，广东珠海发生一起驾车冲撞行人案，造成重大人员伤亡和恶劣社会影响。案件发生后，中共中央总书记、国家主席、中央军委主席习近平高度重视并作出重要指示，11月14日，最高人民检察院党组书记、检察长应勇率最高检调研组在上海调研时强调，广东珠海市香洲区体育中心发生驾车冲撞行人案件，造成重大人员伤亡，性质极其恶劣，检察机关要依法履职，全力协同相关部门做好查清事实、依法惩处、善后处置、维护稳定等工作，切实保障人民群众生命安全，维护社会大局稳定，对类似重大恶性犯罪，要认真做好审查批捕、审查起诉工作，从严从重追究刑事责任，有力震慑犯罪。

On November 11th, a driver collided with a pedestrian in Zhuhai, Guangdong Province, causing significant casualties and negative social impact. After the case occurred, Xi Jinping, General Secretary of the Communist Party of China Central Committee, President of the People's Republic of China, and Chairman of the Central Military Commission, attached great importance to it and issued important instructions. On November 14th, Ying Yong, Secretary of the Party Group and Prosecutor General of the Supreme People's Procuratorate, led the Supreme People's Procuratorate research team to conduct research in Shanghai, emphasizing that a case of driving and colliding with pedestrians occurred at the Xiangzhoushi District Sports Center in Zhuhai, Guangdong, resulting in significant casualties and extremely serious nature. The procuratorial organs shall perform their duties in accordance with the law, fully cooperate with relevant departments to investigate the facts, punish according to law, handle the aftermath, and maintain stability, effectively safeguarding the safety of the people's lives and maintaining social stability. For similar major malignant crimes, we must conscientiously carry out the review, approval, and prosecution of arrests, and strictly investigate criminal responsibility to effectively deter crime.

Figure 1 “Zhuhai Pedestrian Collision Case” (left: screenshot from Weibo; right: translation).

classification algorithm was developed to identify negative public opinion and forecast its future dissemination. This research aims to provide scientific support for relevant departments in guiding public opinion, understanding netizens' sentiment changes, preventing the proliferation of negative public opinion, and achieving stable public opinion management.

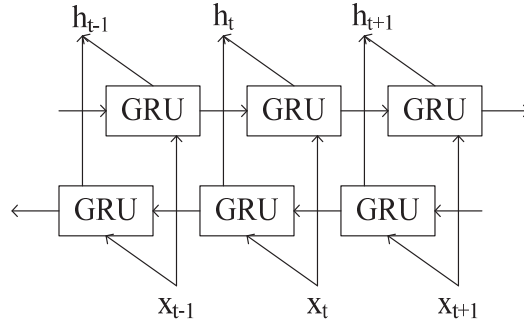
2 Sentiment Classification Algorithm

In natural language processing (NLP), sentiment classification plays a significant role [8]. Early sentiment classification algorithms identified the emotional tendencies of text based on constructed sentiment dictionaries [9]. With the advancement of machine learning and deep learning, many algorithms have been developed and applied in sentiment classification [10]. This paper took Weibo text data as examples. First, negative public opinions were classified from Weibo text data to provide support for the subsequent negative public opinion dissemination and guidance. A web crawler program collected original Weibo posts related to the “Zhuhai Pedestrian Collision Case” published between 11 November and 31 November 2024. The event description is illustrated in Figure 1. The crawling keyword was specified as “Zhuhai Pedestrian Collision.” The collected data underwent cleaning processes to eliminate symbols, emoticons, topic labels, and other irrelevant information. A total of 8408 valid text data were collected and manually labelled. 5861 positive opinions (1) and 2547 negative opinions (0) were obtained as the experimental dataset. Some examples of the texts are presented in Table 1.

The recurrent neural network (RNN) has demonstrated strong performance in processing text sequence data [11]. The GRU is an enhanced RNN structure that addresses the issues of excessive parameters and slow convergence encountered by conventional RNN models when handling long sequence data. The GRU is widely used in text processing, data prediction, and other applications [12]. In this study, the GRU is employed as a sentiment classification algorithm. Initially, the Jieba toolkit [13] was utilized for text

Table 1 Text examples

Text	Label
一定严惩凶手! 全力救治伤员! (Translation: The murderer must be severely punished! All efforts should be made to treat the injured!)	1
希望伤员都能平安无事 (Translation: Hope all the wounded can be safe and sound.)	1
太恐怖了, 明天和意外, 不知道那个先来 (Translation: It's so terrifying. Tomorrow and accidents, we don't know which one will come first.)	0
讲真, 这事儿你定性恐怖袭击都不为过, 这家伙没当场击毙真便宜丫的了! (Translation: Seriously, it wouldn't be an exaggeration to define this matter as a terrorist attack. It was too kind to him that he wasn't shot dead on the spot!)	0

**Figure 2** BiGRU structure.

segmentation. As text data cannot be directly input into the GRU, it was converted into word vectors using the word2vec model [14] before being fed into the GRU for feature extraction. To effectively capture global sequences, a bidirectional GRU (BiGRU) was adopted to integrate information from both the forward and backward sequential information. The structure is outlined in Figure 2.

As in Figure 2, the BiGRU consists of a forward GRU and a backward GRU. It is assumed that at time t , the input of the forward GRU is \vec{x}_t and the hidden layer state is \vec{h}_t . The output \vec{z}_t of the update gate is written as:

$$\vec{z}_t = \sigma(\vec{W}_t \cdot [\vec{h}_{t-1}, \vec{x}_t]), \quad (1)$$

where σ is the activation function and \vec{W}_t is the weight matrix of the update gate.

The output \vec{r}_t of the reset gate can be written as:

$$\vec{r}_t = \sigma(\vec{W}_r \cdot [\vec{h}_{t-1}, \vec{x}_t]), \quad (2)$$

where \vec{W}_r is the weight matrix of the reset gate.

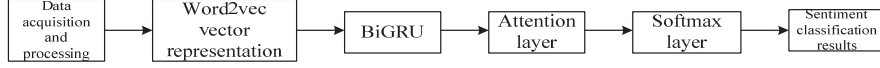


Figure 3 The BiGRU-Att sentiment classification algorithm.

The candidate state \tilde{h}_t can be written as:

$$\tilde{h}_t = \tanh(\vec{W} \cdot [\vec{r}_t \otimes \overrightarrow{h_{t-1}}, \vec{x}_t]), \quad (3)$$

where \vec{W} is the weight matrix of the candidate state.

Eventually, the hidden layer state \overrightarrow{h}_t at time t can be written as:

$$\overrightarrow{h}_t = (1 - \vec{z}_t) \otimes \overrightarrow{h_{t-1}} + \vec{z}_t \otimes \tilde{h}_t. \quad (4)$$

Similarly, the hidden layer state \overleftarrow{h}_t of the backward GRU at time t can be obtained. Finally, the hidden layer state of the BiGRU can be written as:

$$h_t = [\overrightarrow{h}_t, \overleftarrow{h}_t]. \quad (5)$$

The attention mechanism [15] can assign more weights to the areas that need attention to obtain more details related to the task. In order to improve the sentiment classification ability of the BiGRU further, this paper combined it with the attention mechanism, and firstly calculated the attention weight a :

$$M = \tanh(h_t), \quad (6)$$

$$a = \text{softmax}(\alpha^T M), \quad (7)$$

where α is the randomly initialized attention weight. The output of the attention layer is:

$$c = h_t a^T$$

Finally, the output of the attention layer was used as the input of the softmax layer, and the softmax classifier was utilized to classify the microblog text's sentiment. The flow of the designed BiGRU-Att sentiment classification algorithm is shown in Figure 3.

3 Prediction Algorithm for Negative Public Opinion Dissemination

Predicting the spread of negative public opinion involves forecasting the number of Weibo texts identified as negative public opinion during a particular event. A higher count of negative public opinions typically indicates

a broader dissemination of negative sentiment. Given that the BiGRU is suitable for predicting time-series data [16], the BiGRU-Att model developed in the preceding section was also utilized. In view of the complexity of the text sequence data, in order to further improve the prediction accuracy the BiGRU-Att model was combined with Kalman filtering (KF) [17] to dynamically adjust the results, and the BiGRU-Att-KF dissemination prediction algorithm was established. The dissemination of negative public opinions was quantified using the total number N_t of negative public opinions within unit time t . A training set $[s, y]^N$ was established. The input of the BiGRU-Att-KF model is $s = [x_1, x_2, \dots, x_j]$, and the output is $y = x_{j+1}$. For the output results of the BiGRU-Att model, the process of dynamic adjustment using KF is as follows.

(1) State variable estimation

Based on the estimated number x'_{t-1} of negative public opinions at time $t - 1$ and the control input U_{t-1} of the system, the number of negative public opinions at time t was estimated:

$$x'_t = Ax'_{t-1} + BU_{t-1}, \quad (8)$$

where A is the state transfer matrix from time $t-1$ to t and B is the conversion coefficient between the control input and state vector.

Then, mean square error matrix P_{t-1} at time $t - 1$ was used to estimate mean square error matrix P_t at time t :

$$P_t = AP_{t-1}A^T + Q, \quad (9)$$

where Q is the mean square error matrix of the process noise.

(2) State variable correction

Based on the difference between the true value at time t and the estimated value, the estimated value at time t was corrected to get the final prediction result x'_t for the number of negative public opinions:

$$K_t = P_t H^T (H P_t H^T + R)^{-1}, \quad (10)$$

$$x'_t = x'_t + K_t(x_t - Hx'_t), \quad (11)$$

where K_t is the Kalman gain matrix, x_t is the true value of the number of negative public opinions at time t , and Hx'_t is the product of the estimated state vector and measurement system parameters.

4 Results and Analysis

4.1 Experimental Setup

The experiment was carried out on a system running Windows 10, with an Intel Core i7-12600kf processor and 32 GB memory. It used Python 3.8 as the development language, the PyTorch framework as the platform, and PyCharm as the tool.

The labelled 8408 Weibo text dataset was divided into a training set and a test set according to 8:2, which was used to test the performance of the sentiment classification algorithm BiGRU-Att. The evaluation indicators are as follows.

(1) Accuracy (A)

$$A = \frac{TP + TN}{TP + TN + FP + FN} \quad (12)$$

(2) Precision (P)

$$P = \frac{TP}{TP + FP} \quad (13)$$

(3) Recall rate (R)

$$R = \frac{TP}{TP + FN} \quad (14)$$

(4) F1

$$F_1 = \frac{2 \times P \times R}{P + R}. \quad (15)$$

In the above equations, TP is the number of positive public opinions correctly categorized as positive, TN is the number of negative public opinions correctly categorized as negative, FP is the number of negative public opinions misclassified as positive, and FN is the number of positive public opinions misclassified as negative.

The labelled 2547 negative public opinions were sorted according to the times series. The dataset was split into a training set and a test set in an 8:2 ratio. The data was sorted in a rolling order by hour. The number of negative public opinions in four consecutive periods was used as input to predict the number in the fifth period. The evaluation indicators are as follows.

(1) Root mean square error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y'_i - y_i)^2} \quad (16)$$

(2) Mean absolute error (MAE)

$$MAE = \frac{1}{n} \sum_{i=1}^n |y'_i - y_i| \quad (17)$$

(3) Coefficient of determination R^2

$$R^2 = 1 - \frac{\sum_{i=1}^n (y'_i - y_i)^2}{\sum_{i=1}^n (y'_i - \bar{y})^2}. \quad (18)$$

In the above equations, y_i refers to the true value and y'_i is the predicted value of the BiGRU-Att-KF model.

4.2 Results Analysis

In sentiment classification algorithms, the dimensions of word vectors impact the classification results. The classification accuracy of the BiGRU-Att model under different word vector dimensions is presented in Figure 4.

According to Figure 4, the BiGRU-Att model achieved the highest classification accuracy of 0.9216 when the word vector dimension was set to 25. As the word vector dimension increased, the classification accuracy of the BiGRU-Att model decreased. This result suggested that the algorithm performed optimally when the word vector dimension was set to 25. Therefore, a word vector dimension of 25 was used for all subsequent experiments.

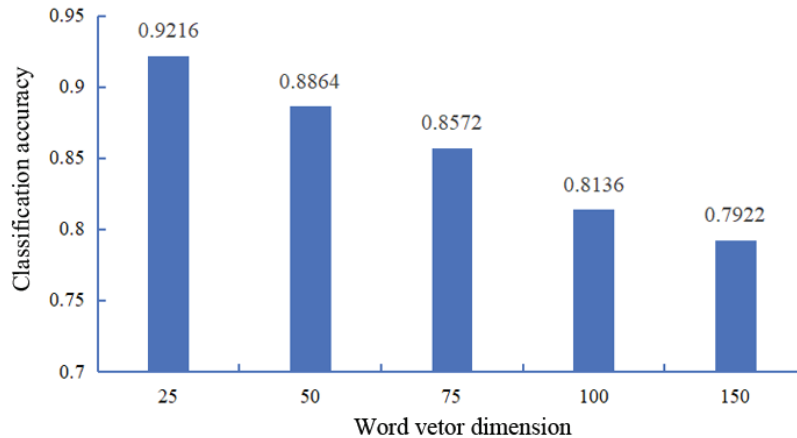


Figure 4 Classification accuracy under different numbers of word vector dimensions.

Table 2 Comparison of sentiment classification performance

	A	P	R	F1
SVM [18]	0.7352	0.7334	0.7216	0.7275
BPNN [19]	0.7764	0.7852	0.7977	0.7914
CNN [20]	0.8446	0.8321	0.8233	0.8277
BiLSTM [21]	0.8934	0.9012	0.8897	0.8954
BiGRU	0.9136	0.9177	0.9184	0.9180
BiGRU-Att	0.9216	0.9252	0.9244	0.9248

Table 3 Comparison of dissemination prediction performance

	<i>RMSE</i>	<i>MAE</i>	R^2
GM (1,1) [22]	386.45	197.51	0.84
RNN	369.84	171.22	0.89
BiLSTM	354.58	161.25	0.93
BiGRU	336.58	142.77	0.94
BiGRU-Att	248.85	131.25	0.96
BiGRU-Att-KF	201.25	115.62	0.98

Moreover, the BiGRU-Att model was compared with other classification models.

Table 2 shows that the SVM algorithm performed poorly in sentiment classification, achieving an F1 value of only 0.7275. The two neural network algorithms, BPNN and CNN, also showed moderate performance with F1 values of 0.7914 and 0.8277, respectively. The BiGRU algorithm demonstrated an improvement in accuracy of 0.0202 and F1 value of 0.0226 compared to the BiLSTM algorithm, highlighting the advantage of the BiGRU over the BiLSTM. Furthermore, after introducing the attention mechanism, the BiGRU-Att algorithm achieved an accuracy of 0.9216 and an F1 value of 0.9248, showing an increase of 0.008 and 0.0068 compared to the BiGRU algorithm. This result demonstrated the enhancement effect of combining the attention mechanism on classification performance, indicating that the BiGRU-Att algorithm can effectively differentiate between positive and negative opinions in Weibo text.

To validate the advantages of the BiGRU-Att-KF model for predicting negative public opinion dissemination, it was compared against other prediction models.

Table 3 shows that the traditional GM(1,1) model was less effective in predicting negative public opinion dissemination, as indicated by high RMSE and MAE values. The prediction errors of the BiLSTM and BiGRU

algorithms were lower, and the BiGRU algorithm performed better, showing its good accuracy in prediction. The prediction error of the BiGRU-Att model was further reduced, $R^2 = 0.96$. The RMSE value of the BiGRU-Att-KF model for predicting negative public opinion dissemination was 201.25, the MAE value was 115.62, and $R^2 = 0.98$. This result indicated that the BiGRU-Att-KF model can provide an accurate prediction of future negative public opinion dissemination.

Based on the predictions generated by the BiGRU-Att-KF model for the number of negative public opinions, an early warning line can be established. If the relevant departments determine that the early warning line indicates a high level of negative public opinion, they can proactively deploy resources and formulate countermeasures to mitigate negative sentiments among netizens. Then, public opinion was guided according to the early warning line. If the number of negative public opinions in a certain hour is lower than the early warning line, it proves that the number of negative public opinions is within the controllable range. However, if the number exceeds the warning line, immediate action should be taken to guide public opinion in a positive direction and prevent the situation from escalating.

5 Conclusion

This research paper focused on utilizing Weibo text as a dataset and employed the BiGRU-Att algorithm for sentiment classification of positive and negative public opinions. Subsequently, the harmful public opinion dissemination prediction is carried out using the BiGRU-Att-KF algorithm. Experimental results demonstrate that the BiGRU-Att algorithm exhibits strong classification performance, achieving an F1 value of 0.9248. Moreover, the BiGRU-Att-KF model accurately predicts harmful public opinion dissemination with minimal errors. The findings suggest that the BiGRU-Att-KF model can be effectively utilized for pessimistic public opinion prediction, providing a scientific basis for guiding public opinion in practice.

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Biographies



Jianbao Zhang was born in Jiangsu Province of China in 1982 and graduated from Renmin University as a doctor of philosophy in 2015. He has published more than 20 papers focusing on youth education, which is his lasting interest. He was once awarded the title of “Young Talents of Beijing Universities” and is currently the Vice Professor and Executive Dean of the School of Marxism at Beijing Wuzi University.



Zhengang Li was born in Inner Mongolia Autonomous Region in 1979 and obtained his Ph.D. in sociology from Beijing Normal University in 2016. He is now working in The Institute of Sociology, Chinese Academy of Social Sciences, specializing in social policy research and social big data analysis.

