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# Analyzing Public Opinion Bias through Social Media Using a Hybrid RoBERTa-BiGRU-DPCNN Sentiment Analysis Framework

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*During the development of public opinion, effective guidance through social media is conducive to the formation of a positive public opinion bias, while incorrect guidance may lead to a further loss of control over public opinion. This paper designed a sentiment analysis algorithm called robustly optimized bidirectional encoder representations from transformers pretraining approach-bidirectional gated recurrent unit-deep pyramid convolutional neural network (RoBERTa-BiGRU-DPCNN) to analyze the sentiment categories of texts. The algorithm first used RoBERTa-wwm-ext to obtain the vector representation of a text, then employed BiGRU and DPCNN to extract features, and finally classified sentiment through a softmax layer. Then, the guiding effect of social media was analyzed based on changes in sentiment categories in public opinion events. The sentiment classification performance of the algorithm was evaluated using the SMP2020 dataset, which contains 22,019 samples in the training set and 4,010 in the test set. The Micro F1 value was used to measure the classification performance. It was found that the RoBERTa-BiGRU-DPCNN algorithm achieved a micro F1 value of 73.58%, outperforming algorithms such as TextCNN. The algorithm was applied to analyze two public opinion events, and it was found that the social media guidance effect was poor and failed to form a positive public opinion bias. These results verify the effectiveness of the proposed algorithm in reflecting the guiding effect of social media indirectly.*

*Povzetek: Študija predstavlja napreden model za analizo sentimenta, ki omogoča ocenjevanje vpliva družbenih omrežij na oblikovanje javnega mnenja.*

## 1 Introduction

With the development and rapid popularization of the Internet, the number of netizens has grown rapidly. More and more people are expressing their opinions on social media platforms such as Douyin and Sina Weibo, making the scope and speed of public opinion dissemination wider and faster. Against this background, potential public opinion risks have received widespread attention. In the handling of various emergencies, attention should be paid to the guidance of social media and the formation of public opinion bias [1]; otherwise, issues such as the spread of false public opinion, surges in negative emotions, and a decline in government credibility may arise, which is not conducive to the construction of a healthy online environment. Therefore, studying the monitoring and management of online public opinion is particularly important [2]. Li et al. [3] proposed a cross-network public opinion propagation model in a double-layer online social network. Their numerical simulation analysis revealed that the network promoted the dissemination of public opinion. The researchers pointed out that regulatory authorities should intervene promptly during the early stages of public opinion dissemination. Chu et al. [4] collected Weibo texts related to suicide from WeiboReach between 2015 and 2020 and found that public reports on suicide in online media were emotional and irrational, which was detrimental to public mental health and suicide prevention. Bodrunova et al. [5] pointed out that social media has become a primary platform for most grassroots political discussions. They analyzed the discussions of the Belarusian opposition on YouTube and found through correlation analysis and cluster analysis that users exhibited two mutually exclusive patterns of expression. Fei et al. [6] explored the impact of changes in online public opinion on corporate brand value. Through a study of several Chinese corporate cases, they found that managers could take timely action by analyzing online public opinion. With the development of natural language processing technology, an increasing number of text processing methods have been applied to public opinion analysis [7], and the sentiment analysis algorithm is one of them. Through sentiment analysis algorithms, managers can better understand the emotional tendencies of netizens and changes in tendencies [8], thereby assessing the guiding effect of social media on public opinion bias. In order to improve the accuracy of sentiment classification in Chinese social media texts, this paper first designed a sentiment analysis algorithm based on deep learning techniques and then used this algorithm to analyze the sentiment changes of netizens during public opinion events, thereby evaluating the guiding effect of social media. This paper aims to provide some theoretical support for public opinion management.

## 2 Related works

Currently, there are still relatively few studies on multi-modal emotional features. Single CNN and recurrent neural network (RNN) models can only extract single features. However, emotional expressions are hierarchical. Using a single feature extractor limits the model's ability to capture multi-level emotional features simultaneously. In this paper, we choose to integrate RoBERTa, BiGRU, and DPCNN to achieve hierarchical extraction of emotional features, thereby providing richer joint representations for emotion classification and more effectively solving complex emotion classification problems.

Table 1: Related works.

| | **Model** | **Dataset** | **Result** |
|---|---|---|---|
| **Reference [9]** | TextCNN | Message80W, a Chinese short message service dataset | The model showed varying degrees of improvement in terms of classification accuracy, precision, recall rate, and F1 score. |
| **Reference [10]** | RNN | DEAP dataset | The model was quite robust when performing sentiment classification tasks. |
| **Reference [11]** | Long short-term memory | Indonesian Tweet data | The performance of the single-layer bidirectional long short-term memory model had a statistical significance with that of the two-layer stacked model. |
| **Reference [12]** | BiGRU | DEAP dataset | This model demonstrated more robust classification performance than the baseline model and improved the accuracy and robustness of electroencephalogram-based emotion classification. |

## 3 Sentiment analysis algorithm based on deep learning

Traditional sentiment analysis algorithms require building large sentiment dictionaries and determining the sentiment polarity of texts through statistical analysis of sentiment words, which consume a lot of manpower and resources and have relatively poor classification results. Machine learning-based methods rely on manually selected features [13]. In contrast, deep learning-based methods can automatically extract text features [14] and have achieved significant performance improvements over the previous two methods. Therefore, this paper uses deep learning techniques to design a sentiment analysis algorithm named robustly optimized bidirectional encoder representations from transformers pretraining approach-bidirectional gated recurrent unit-deep pyramid convolutional neural network (RoBERTa-BiGRU-DPCNN). The vector representation of a text is obtained using RoBERTa with whole word masking extended (RoBERTa-wwm-ext). Then, the text features are extracted using BiGRU and DPCNN, and finally the sentiment category is determined through a softmax layer. The architecture of the algorithm is shown in Figure 1.

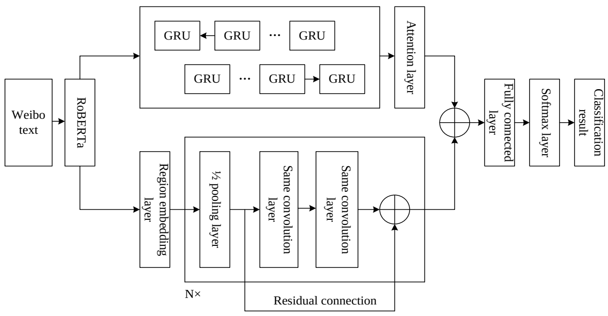


Figure 1: RoBERTa-BiGRU-DPCNN sentiment analysis algorithm.

According to Figure 1, first, word embedding is performed using the RoBERTa-wwm-ext pre-trained language model [15], which is an improvement of the BERT model. Using the WWM method, it has better performance in Chinese text processing. For a Weibo text with a length of $L$, $S=\{x_1,x_2,\cdots,x_L\}$, it is input into RoBERTa-wwm-ext to obtain word vector matrix $A_{L\times N}$ ($N$: word vector dimension, $\mathrm{N} = 768$):

$$A_{L\times N}=a_1\oplus a_2\oplus\cdots\oplus a_L. \quad (1)$$

Recurrent neural networks and their variants have very wide applications in text processing [16], where gated recurrent units (GRUs) have low computational complexity and perform better in extracting context features, but GRUs can only extract one-way information and cannot reflect the influence of the following text on the previous text. Therefore, for feature extraction, this paper uses BiGRU [17]. Taking $A_{L\times N}$ as input, global semantic feature $F_G = [h_1, h_2, \cdots, h_{L-1}, h_L]$ in BiGRU are extracted, whose dimension is $[L, hidden\_size * 2]$ and where $h_i$ is the concatenation result of the forward GRU and backward GRU outputs.

$$h_i = [\vec{h}_i, \overleftarrow{h}_i]. \quad (2)$$

Adding an attention layer after BiGRU is to focus on semantic features that are more important. Weight $\alpha_i$ allocated to each feature vector is calculated as follows:

$$\alpha_i = \frac{exp(e_i)}{\sum_{t=1}^{T} exp(e_i)}, \quad (3)$$

$$e_i = a(h_i), \quad (4)$$

where $a$ is the learning function. The final feature after BiGRU processing is represented as:

$$f_g = \sum_{t=1}^{T} \alpha_i h_i. \quad (5)$$

The dimension of $f_g$ is $2 * hidden\_size$.

DPCNN, which combine TextCNN and ResNet [18], perform well in text classification tasks. Therefore, in addition to BiGRU, DPCNN is used to extract deep semantic features. $A_{L\times N}$ is taken as the input and passed through the region embedding layer. After entering the 1/2 pooling layer, the length of the input sequence is reduced by half; then, through two layers of same convolution, feature dimension $[250, L-2]$ is output. The results of these two steps are residually joined. The process is repeated until the sequence length is 1. Feature representation $f_d$ processed by DPCNN is obtained and is concatenated with feature representation $f_g$ obtained by BiGRU to form final vector representation $F$, whose dimension is 250. Through the fully connected layer,

$$y = dropout(WF+b), \quad (6)$$

where $W$ and $b$ are the weight and bias of the fully connected layer.

Finally, each value in $y$ is mapped to the range of 0-1 through the softmax layer to obtain the classification result:

$$Y = softmax(y). \quad (7)$$

The input is text S = $[x_1,...,x_l]$, and the output is sentiment probability P. The pseudocode of the RoBERTa-BiGRU-DPCNN algorithm is as follows.

```
1. A ← RoBERTa(S)            # word vector [L×N]
2. H ← BiGRU(A)              # bidirectional feature [L×2H]
   α ← softmax(tanh(WaH))    # attention weight
   fg ← Σαihi                # weighted feature [G]
3. fd← DPCNN(A)              # convolutional feature [D]
   # DPCNN: Conv→Pool→residual loop
4. y ← W·concat(fg, fd) + b  # full connection
   P ← softmax(y)            # classification probability
```

# 4 Results and analysis

## 4.1 Performance analysis of sentiment classification

The experiment was conducted in a software environment running the Windows 10 operating system and a hardware environment consisting of an NVIDIA 1080 Ti graphics processing unit (GPU) and 128 GB of memory. PyTorch and Transformer software toolkits were used, and the programming language was Python 3.6. The hidden layer dimension of RoBERTa-wwm-ext was 768, composed of 12 Transformer layers. The hidden layer dimension of BiGRU was 300. The hyperparameter settings are shown in Table 2.

Table 2: Hyperparameter setting.

| Hyperparameter | Value |
|---|---|
| Epoch | 20 |
| Batch size | 8 |
| Optimizer | Adam |
| Learning rate | 2e-5 |
| Warmup rate | 0.3 |
| Dropout rate | 0.1 |
| Weight decay | 0.005 |
| Loss function | Focal loss |
| Activation function | ReLU |

Note: ReLU: Rectified linear unit.

The performance of the designed sentiment analysis algorithm was evaluated using the SMP2020 dataset. All data in the dataset were from the Sina Weibo platform, and those without sentiment were emoved. The category distribution of the experimental dataset is shown in Table 3.

Table 3: Experimental dataset.

| | **Training set** | **Test set** |
|---|---|---|
| **Anger** | 8,344 (37.89%) | 1,508 (37.61%) |
| **Positive** | 5,379 (24.43%) | 1,018 (25.39%) |
| **Sadness** | 4,990 (22.66%) | 900 (22.44%) |
| **Fear** | 1,220 (5.54%) | 210 (5.24%) |
| **Amazement** | 2,086 (9.47%) | 374 (9.33%) |
| **Total number** | 22,019 | 4,010 |

First, the original data was cleaned using NLTK and Regex tools. Next, Chinese word segmentation was implemented with the LTP word segmentation tool. Finally, stop words were removed using a stop word list, and the processed word sequence was input into the word embedding layer to obtain its word vector representation. Since there was an imbalance in the class distribution of the dataset, the StratifiedKFold training method was used, which employed stratified random sampling with K set to 5.

The evaluation of sentiment classification performance was conducted using the confusion matrix shown in Table 4.

Table 4: Confusion matrix.1

| | | **Classification result** | |
|---|---|---|---|
| | | **Positive case** | **Negative case** |
| **Actual result** | Positive case | TP | FN |
| | Negative case | FP | TN |

Macro F1 value (MF1): For a dataset with an imbalanced category distribution, MF1 can effectively measure its performance:

$$MF_1=\frac{\sum_{i=1}^{N} F_1^i}{N}. \quad (8)$$

where $F_1^i$ refers to the F1 value of category $i$ and $N$ is the total number of categories. The F1 value is calculated as follows:

$$F_1=\frac{2\times Precision\times Recall}{Precision+Recall}, \quad (9)$$

$$Precision=\frac{TP}{TP+FP}, \quad (10)$$

$$Recall=\frac{TP}{TP+FN}. \quad (11)$$

The RoBERTa-BiGRU-DPCNN algorithm was compared with several other commonly used text sentiment analysis algorithms.

Table 5 shows the TextCNN algorithm performed poorly in sentiment classification, likely because it did not take contextual information into account and inadequately captured the relationships between texts. In comparison, the RNN-based algorithms showed better classification performance, with the order being RNN < LSTM < GRU. Both LSTM and GRU algorithms alleviated the vanishing and explosion of gradients, thereby showing improved performance. The GRU further simplified the results compared to the LSTM algorithm and performed better in sentiment classification. The comparison between BiGRU and GRU showed that the bidirectional approach can capture more features than the unidirectional one, resulting in superior sentiment classification. The proposed method combined BiGRU with DPCNN to further enhance its feature extraction capabilities, achieving the highest MF1 value among all methods. The results demonstrate the effectiveness of the proposed algorithm.

Table 5: Comparison of sentiment classification performance.2

| Sentiment analysis algorithm | MF1/% |
|---|---|
| **TextCNN** | 61.58 |
| **RNN** | 64.56 |
| **LSTM** | 66.77 |
| **GRU** | 68.32 |
| **BiGRU** | 70.16 |
| **RoBERTa-BiGRU-DPCNN** | 73.58 |

The performance of the proposed algorithm was further analyzed through an ablation experiment.

Table 6: Results of the ablation experiment.3

| | MF1/% |
|---|---|
| **Word2Vec-BiGRU-DPCNN** | 67.45±5.45 |
| **BERT-BiGRU-DPCNN** | 68.56±5.77 |
| **RoBERTa-BiLSTM-DPCNN** | 71.24±6.12 |
| **RoBERTa-BiGRU** | 72.06±6.33 |
| **RoBERTa-BiGRU-DPCNN** | 73.58±6.46 |

In Table 6, the Word2Vec-BiGRU-DPCNN and BERT-BiGRU-DPCNN algorithms were created by replacing RoBERTa in the model with Word2Vec and BERT, respectively, to analyze the role of RoBERTa. The comparison shows that using RoBERTa to generate word vectors yielded better results in sentiment classification than Word2Vec and BERT, with improvements of 9.13% and 5.02%, respectively. The RoBERTa-BiLSTM-DPCNN algorithm was developed by replacing BiGRU in the original model with BiLSTM, and the MF1 was decreased by 2.34%, demonstrating that BiGRU outperformed BiLSTM in feature extraction. For the RoBERTa-BiGRU algorithm, the MF1 decreased by 1.52%, demonstrating that combining DPCNN with BiGRU was effective and improved sentiment classification performance.

## 4.2 An analysis of the guiding effect of social media

The RoBERTa-BiGRU-DPCNN algorithm mentioned above was employed to analyze the guiding effect of social media in public opinion events. Changes in the number of relevant sentiment texts related to these events were calculated to reflect the degree of bias in public opinion after guidance. Two public opinion events were taken as examples for analysis. The timestamps of the collected texts were standardized; each text originally had its own timestamp, which was uniformly converted to Beijing time and then categorized by calendar day. To avoid the influence of data volume deviation on the analysis results, a hierarchical time-balanced sampling method was used to prevent peak-hour data from dominating the overall trend. To ensure the analysis reflected genuine user sentiment, content from suspected non-human accounts was filtered out. After manual random inspection and verification, the proportion of content from real users exceeded 93%.

(1) Event 1: The distribution of materials by the Red Cross Society of Hubei Province

On January 31, 2020, the Red Cross Society of Hubei Province was exposed for having an uneven distribution of pandemic supplies, which drew widespread attention from netizens. The proportion of texts of different sentiment categories during the period from January 31, 2020, to February 15, 2020, was calculated (Figure 2).

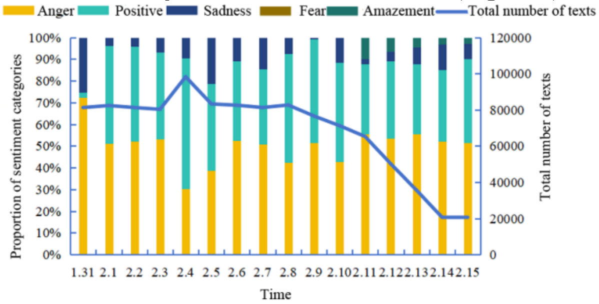


Figure 2: Analysis of Event 1.

1

On January 31, 2020, the Red Cross Society of Hubei Province issued a statement regarding the use of materials.

However, the statement referred to the issue as a work error and failed to provide a reasonable explanation for the distribution of supplies questioned by netizens. The clarification effect was extremely poor, resulting in a predominance of anger in Weibo posts that day. This outcome showed that although social media responded to the incident promptly, the response had the opposite effect, intensifying negative public sentiment. From February 1 to 3, the Red Cross Society of China investigated the incident. During this period, anger levels remained high but did not increase, as netizens awaited the investigation results. This result indicated that a rapid response and transparent information disclosure by official social media can help guide public opinion in a more positive direction and is effective for managing public opinion. On February 4th, the Hubei Provincial Commission for Discipline Inspection announced the penalties for the relevant leaders of the provincial Red Cross Society. On that day, positive sentiment exceeded 60% for the first time, becoming the dominant category. These results suggest that timely and effective information disclosure can, to some extent, curb the negative tendencies of public opinion. Subsequently, some netizens concerned about the incident left the scene, and the volume of related posts began to decline. However, the subsequent rectification measures and the specific distribution of supplies were not made public, and netizens' trust in the Red Cross Society of Hubei had not been returned, so anger continued to dominate. After February 8, the Society began disclosing daily information on the flow of supplies, and the proportion of positive sentiment began to rise.

Overall, social media showed a limited ability to guide public opinion. Although relevant social media responded relatively quickly in the early stages of the incident to prevent further deterioration of public opinion, their subsequent responses were somewhat inadequate and failed to guide public opinion in a more positive direction.

(2) Event 2: Torrential rain in Henan on July 20

On July 20, 2021, heavy rain hit Henan Province. As of July 28, it had affected 13.6643 million people and caused direct economic losses amounting to 88.534 billion yuan. The proportions of texts across different emotional categories during the period from July 18 to July 28, 2021, were calculated (Figure 3).

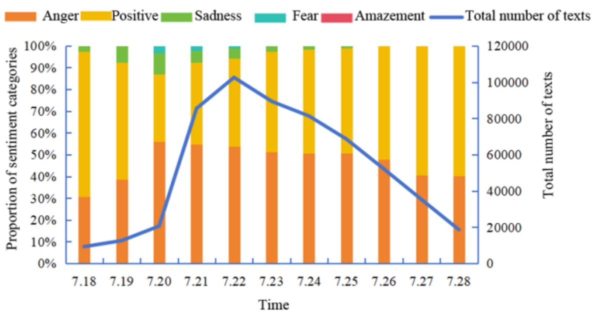


Figure 3: Analysis of Event 2.

2

On July 18, although the meteorological station had issued a rainstorm warning, it received little attention. At that time, the public opinion was still in its early stage. On July 19, the rainstorm began to intensify, and most online complaints about the rainstorm remained within a manageable scope. On July 20, public opinion erupted dramatically, with the number of discussions about the event surging and the proportion of anger rising significantly. Although the government used social media to provide some positive guidance, negative emotions gradually increased as casualties from the rainstorm mounted, traffic was paralyzed, and communication and power services were disrupted. The proportions of anger, sadness, and fear increased. The proportion of positive emotions has decreased, netizens have focused on discussions about the government's slow response and inadequate preparedness for disaster relief. It was only after the government made efforts to share its work on social media and publicize the touching stories during the disaster that the proportion of positive sentiment rebounded. However, many netizens continued to question the rescue efforts and the post-disaster reconstruction efforts. Although public outrage gradually subsided, the underlying anger persisted.

Overall, the guiding effect of relevant social media during this incident was also mediocre, failing to promptly and effectively steer public opinion in a positive direction. In the early stage of the event, social media platforms did not adequately guide public opinion, failed to anticipate potential reactions from netizens, and responded slowly after the rainstorm disaster occurred. This lack of timely and effective countermeasures further fueled the spread of negative emotions. Firefighters, police, and rescue teams and material assistance from various sources served as important contributions to positive sentiment during the incident, helping to foster a favorable public opinion bias. The analysis of these two incidents reveals that, in the handling of similar events in the future, the government should attach importance to the guiding role of social media, monitor public opinion trends promptly, and take proactive steps to prevent negative developments.

# 5 Discussion

The RoBERTa-BiGRU-DPCNN algorithm designed in this paper achieved better performance than the baseline methods on the SMP2020 dataset, which verified its reliability in the sentiment classification task. Compared with the baseline methods, the bidirectional structure of BiGRU can simultaneously capture the forward and backward semantic dependencies in texts and more accurately grasp the complete context of emotional expression. DPCNN constructs a pyramid-shaped feature abstraction structure to capture sentiment features more deeply. The pre-training model used also provides rich linguistic knowledge for the model. Therefore, it obtained better performance in sentiment classification. Similar to traditional public opinion analysis, the research in this paper also verified that the spread speed of negative sentiment is usually faster than that of positive sentiment and captured sentiment changes more deeply. In the application context of public opinion guidance, sentiment analysis technology may be used for public opinion manipulation and targeted emotional marketing.

Moreover, the black-box characteristic of deep learning models may lead to a lack of transparency in sensitive applications such as public opinion guidance, which needs to be paid more attention to in practical applications.

The public opinion field is a typical complex dynamic system, and the guidance of social media can be regarded as the control input to this system. In future work, the idea of adaptive control theory can be introduced into the design of sentiment analysis models. In the field of control engineering, an adaptive system can dynamically adjust its parameters through real-time feedback to deal with unknown disturbances. Therefore, in sentiment analysis tasks, the idea of adaptive control can be borrowed. A lightweight online update module can be added to enable the model to quickly adapt to new sentiment tendencies. External signals, such as the intervention of authoritative media and government announcements, can be introduced as the feed-forward input of the model to improve the response speed to emergencies. The introduction of these adaptive mechanisms can enhance the classification robustness of the model in scenarios of sudden public opinion changes, endow the sentiment analysis model with the theoretical support of dynamic systems, promote the transformation of sentiment analysis from static classification to dynamic adaptation, and enhance the reliability and interpretability of the model in the real and complex public opinion environment.

In addition, based on the current research results, practical applications can be expanded in the following aspects:

(1) Study the cross-platform adaptability of the model and consider the model's performance in sentiment analysis of texts from social media platforms other than Sina Weibo;

(2) Discuss the sentiment analysis effects of the model on different types of events, such as public emergencies and ongoing social issues;

(3) Analyze the real-time sentiment flow detection effect of the model and the multi-granularity warning mechanism to provide decision-making support for intelligent guidance.

In general, in future work, a real-time monitoring system with adaptive capabilities can be developed, an opinion guidance decision-making framework including ethical constraints can be established, and cross-platform and cross-cultural model generalization solutions can be explored.

# 6 Conclusion

This paper presents a sentiment analysis algorithm called RoBERTa-BiGRU-DPCNN. The effectiveness of the proposed method was evaluated using the SMP2020 dataset through comparative and ablation experiments, achieving an MF1 value of 73.58%, which demonstrates the reliability of the method in sentiment classification. The algorithm was then used to analyze the guiding role of social media in two public opinion events, demonstrating its usability in public opinion management.

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