Detection of Negative Emotions and Dpression in Social Networks Based on Bert-LSTM Model

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Abstract. Due to the surge of depression among netizens in China's online society, the problem of social depression has developed seriously. The purpose of this paper is to detect and remind Internet nagative emotions through natural language processing technology.In this paper, the Bidirectional Encoder Representations from Transformer(BERT) and Long Short-Term Memory (LSTM) model can be used to detect depression in certain online comments. Experiments show the performance of the Bert-LSTM model in identifying depressed moods in online comments, and they record and compare the performance changes of the model by changing the learning rate.In this paper, the performance of the Bert-LSTM model in emotion processing is mainly demonstrated, and the advantages and disadvantages of the model in emotion processing are analyzed, and some optimization ideas are provided for subsequent research. This paper takes the negative mood and depression in social network comments as the starting point, hoping to build a function for social media platforms to monitor emotional problems in a timely manner through the combination of natural language processing and interdisciplinarity and make a contribution to ensuring people's mental health.

Keywords: Natural language processing, Bert-LSTM, Sentiment detection.

1 Introduction

With the rapid development of society, the emerging social media platform provides a virtual place for people to discuss, communicate, and communicate. According to relevant statistics, the lifetime prevalence of depressive disorders in adults in China is 6.8%, of which depression is 3.4% [1,2]. The number of people suffering from depression in China is 95 million, and about 280,000 people commit suicide every year, of which 40% suffer from depression. The group suffering from depression is becoming younger and younger [3].

Currently, the number of users of social media platforms is huge, and natural language processing and machine learning technologies are becoming increasingly sophisticated. Interdisciplinary research is receiving increasing attention from the academic

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community [4,5]. This kind of research topic has been widely discussed at home and abroad by collecting user speech data on social platforms and combining it with computer technology.The combination of natural language processing technology with machine learning and neural networks to construct a model for analyzing and detecting different emotions is also a hot topic in natural language solutions.Classification and detection of emotions in a certain field through basic text classification models such as BERT and Transformers[6], and the combination of Bidirectional Encoder Representations from Transformers(BERT) and Long Short-Term Memory(BiLSTM) models to fine-tune the model to achieve the detection of depression, such projects even provide some new ideas for the medical treatment of depression. Nowadays, there is still a lot of research on the integration of computer technology and psychology in China, and natural language technology has also provided some more practical and effective help for the treatment of depression, but the number of domestic studies on depression among Internet users through real-time data such as text, pictures, and voice in social media platforms, combined with natural language processing technology, is relatively limited. So, the network data is updated quickly, the information is time-sensitive, the Chinese social media research can not completely apply the methods of foreign social media research, and the projects related to this research in China still have some limitations in feature selection, data set and other aspects, and the practicability and effectiveness still need to be tested for a long time.

The purpose of this paper is to reveal the psychological state of Internet users on social platforms through natural language processing technology and to infer whether people's negative emotions contain depressive tendencies in time.To achieve the goal, this paper first crawled many comment datasets about sentiment on social media platforms such as Weibo and Zhihu, then manually annotated the datasets. Then, the dataset was pre-trained under the natural language processing model based on Bert-LSTM. Second, the data run by the model is grouped, the changes in the data results are compared, and their meaning is analyzed. Finally, whether the model has practical value for the objectives proposed in this research paper is evaluated.

2 Data and methods

2.1 Sources and characteristics of data sources

This study is based on the Bert-LSTM model of textual analysis of negative emotions on the Internet, so the Chinese language is chosen as the relevant corpus for this study, and this study collects about 2,000 pieces of negative emotions in length and content from major social platforms, short-video platforms, as well as major libraries and search platforms related to emotions on the Internet to form the relevant dataset for the current study. This dataset is characterised by the fact that the text content is all about negative emotions and depression on the Internet, and has undergone a series of text processing and annotation. In this paper, we use the relevant preprocessing methods to facilitate the prediction and learning of the model, and the preprocessing process is to segment the Chinese text corpus, embed the relevant content words, and add the relevant special labelling forms to form the identification of the relevant model for the binary classification task in the present study, so that the model in the present study can make the judgement on the common negative and depressive moods.

2.2 Bert-LSTM model

In today's artificial intelligence field, for the upstream task of entity recognition language preprocessing, designing a good preprocessing model has always been an indispensable topic in the study of natural language processing. BERT is the best language preprocessing model, which can not only set up high-quality word vectors, but also be more conducive to the downstream task of entity recognition for entity extraction and classification[2]. The overall structure of the BERT-LSTM model proposed in this paper is shown in Fig. 1, divided into two main modules. Firstly, the preprocessed corpus is pre-trained by BERT to obtain the corresponding word vectors, and then the word vectors are fed into the LSTM module for further processing to complete the whole process of Chinese corpus entity recognition.

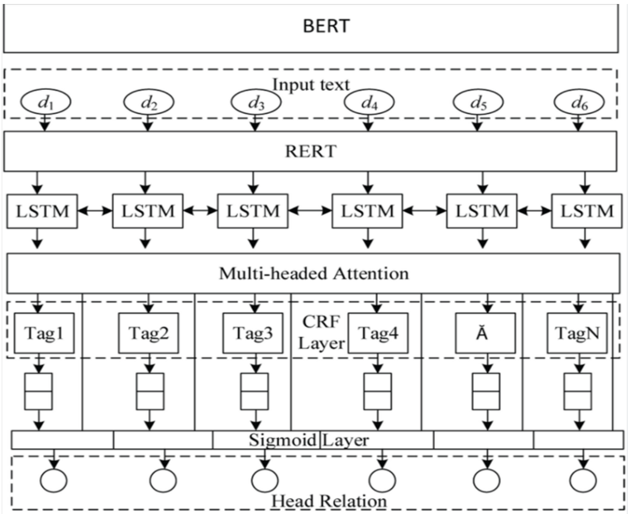

Fig. 1. Diagram of the Bert-LSTM model.

Bert model This study is based on the Bert-LSTM model, which is the core model of the Bert model. The LTSM neural network is added on the basis of the Bert model to enhance the prediction, classification, and processing ability of the Bert model, in which the Bert model is the most perfect and excellent pre-training model under the fine-tuning strategy. The core of the Bert natural language processing model is the Transformer as the main architecture, and its structure is shown in Fig. 2. The core of Bert natural language processing model is the Transformer as the main architecture, its structure is shown in Fig. 2, based on the traditional neural network model, the classification of text semantics has been improved, Bert in the Transformer's architecture has been improved in the feature strategy and fine-tuning strategy to complete the downstream task characteristics.

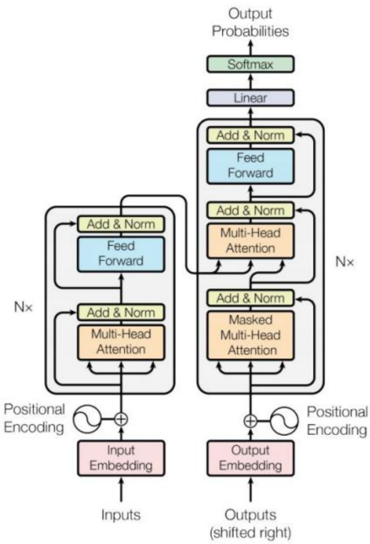

Fig. 2. Transformer operation structure diagram.

LSTM This study is based on the Bert model as the core of the text classification processing model. This study in the use of the Bert model for text processing found that the Bert model in the case of a large amount of data, in order to prevent the emergence of large-scale catastrophic forgetting phenomenon, the study in the Bert-based model to add the LSTM neural network, in order to solve the general neural network of the common long-term dependence on the problem, and effective transmission and expression of useful information in a long sequence of problems, but also to solve the general neural network of gradient disappearance and gradient explosion related to problems. The most important core structures of LSTM are Forget Gate, Input Gate, Output Gate and Memory Cell. Forget Gate work together to filter the useless information and pass the useful information to the next moment[3]. Fig. 3 shows the structure of LSTM.

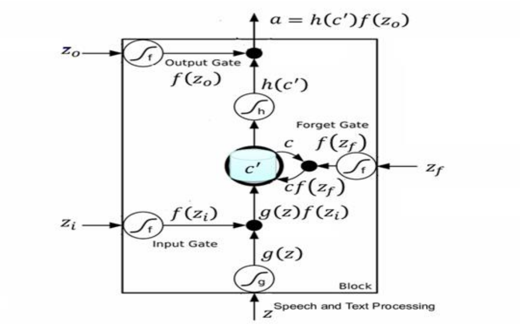

Fig. 3. LSTM cell structure.

2.3 Indicators for model evaluation

This study is to use the common dataset text annotation system, in the dataset with 0 labels to mark the relevant text with negative emotions and with 1 label to mark the relevant text with depressive tendencies in the emotions.

This study is carried out to unfold the research with the Bert model binary classification task, and the performance of the model in this study is evaluated using the precision rate P , the recall rate R, and the F1-value, where the definition of a denotes a positive prediction value[3], i.e., the number of correct entities that the model really identifies.Definition T denotes a fixed predetermined value, i.e., the number of total entities identified by the study, and definition I denotes an array of negative predictions, i.e., the number of entities identified by the model. Each of the metrics evaluated by the algorithm of this study is calculated as follows:

Precision (Precision) is also known as the rate of checking accuracy under common evaluation criteria, which indicates the probability that the model actually predicts as accurate and the probability weight of all predicted as accurate [2].

$$P = a/I \times 100\% \tag{1}$$

Recall (Recall) in the common evaluation criteria, also known as the rate of checking the whole rate, represents the probability that the model is actually predicted as accurate and the proportion of all predicted entities [2].

$$R = a/T \times 100\% \tag{2}$$

F1-score is the output of the model combining precision and recall [2].

$$F1 = 2PR/(P + R) \times 100\% \tag{3}$$

where precision, recall, and F1-score are all in the range 0-1, with 0 being the worst precision and 1 being the best precision.

3 Experimental results and analysis

In this study, a total of 1000 pessimistic speech data sets were selected from various platforms, and the Bert-LSTM model was used for multiple training sessions The valid data were selected and drawn into a line chart. The experimental results are shown in the Fig.4.

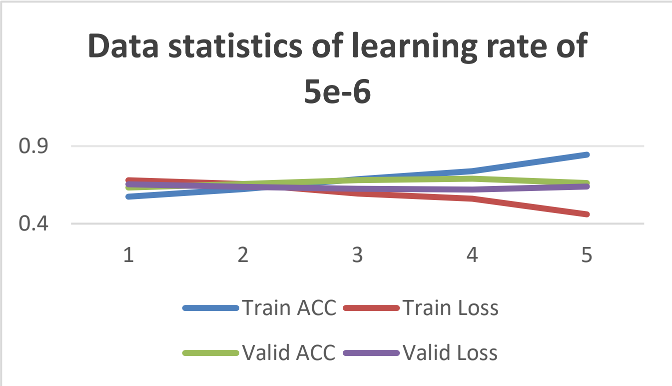

Fig. 4. Data statistics of learning rate of 5e-6.

Fig. 4 shows the data statistics with a learning rate of 5e-6, from which it can be seen that with the increase of training times, on the whole, Valid ACC is increasing and Valid Loss is decreasing, Train ACC is obviously increasing, and the corresponding Train Loss is significantly decreasing. It accords with the basic expectation of model training.

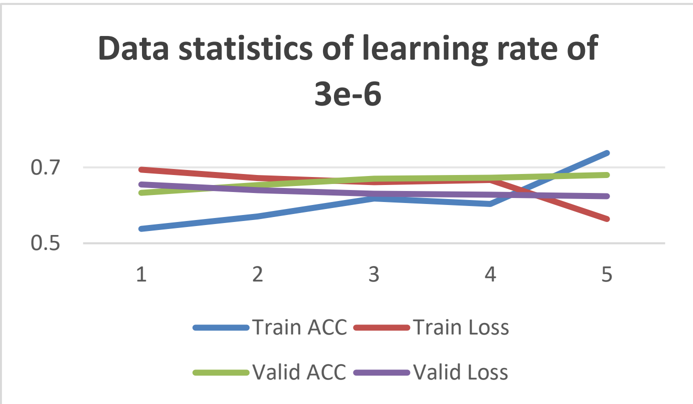

Fig. 5. Data statistics of learning rate of 3e-6.

Fig. 5 shows the statistics of various data with a learning rate of 3e-6, with slight twists and turns, but on the whole, it still conforms to the normal evolution. It can also be seen that Valid ACC and Valid Loss and Train ACC and Train Loss correspond closely, both of which increase the accuracy rate and decrease the loss rate. This also reflects the relatively good performance of the model.

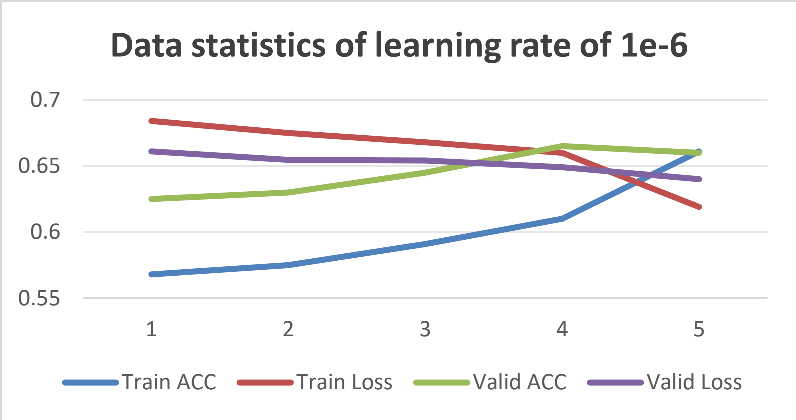

Fig. 6. Data statistics of learning rate of 1e-6.

Fig. 6 shows the statistics of the data with a learning rate of 1e-6. This study can see that the overall change trend of the four data items is similar to that of Fig. 4 and Fig. 5. The difference is that the values of the four data items differ greatly at the beginning, while the differences are small later, but it is still obvious that the accuracy and loss rate correspond closely.

In this study, it can be found that under three different learning rates, with the increase of training times, the overall Train ACC gradually increases and the Train Loss decreases. Accordingly, the overall Valid ACC reaching between 60% and 70%, and the overall Valid Loss decreases. A model with a better detection rate of pessimistic statements with depressive tendencies was obtained. But at the same time, this study also found that with the increase of Train ACC, the rise of Valid ACC was small, and sometimes the situation was flat or even slightly decreased, which may mean that the model has problems in generalization ability[7], which may be due to the overfitting phenomenon of the model paying too much attention to the details of the training data during the training process. As a result, the predictive power of validation data is limited.

It is concluded that when the learning rate is 5e-6, the model shows a fast convergence rate at the early stage of training. But, the performance improvement on the verification set is not significant, and the improvement of Train ACC is far greater than that of Valid ACC. This may be because the large learning rate makes the model pay too much attention to the noise and details during the training process, while ignoring the inherent laws and patterns of the data. With the decrease of the learning rate (such as 3e-6 and 1e-6), the performance of the model on the validation set is improved, and the improvement amplitude of Train ACC is relatively close to that of Valid ACC, but the improvement amplitude is still limited. This suggests that there may be other factors besides the learning rate may affect model performance.

In order to gain a deeper understanding of this phenomenon, this study further analyzed the prediction results of the model. This study found that in some cases, the model was weak in recognizing pessimistic statements with complex emotions and expressions. This may be because the depressive tendencies in these statements are not clearly expressed, or are influenced by other factors, such as culture, emotional intensity, context, and so on. Some of these statements require context to understand their meaning. Therefore, in future research, how to improve the model's ability to recognize these complex statements is a problem that this study needs to focus on.

4 Optimization strategy and discussion

First, in order to improve the performance of the model, the pessimistic statement dataset can be further optimized. First, the size of the increase dataset to collect more samples of pessimistic statements with different levels of depressive tendencies. Secondly, this study also needs to conduct more stringent screening and labeling of the data set to ensure the quality and accuracy of the data, so as to make the identification of depression-prone statements in pessimistic statements more accurate. In addition, this study can also consider introducing more characteristic information, such as cultural background, historical remarks, customs, etc., and adopting data enhancement methods to expand the data set, such as generating more training samples through synonym substitution, random insertion or deletion of words, etc., in order to enrich the dimensions of the data and increase the model's ability to discriminate against diverse data.

Secondly, the possibility of structural optimization of Bert-LSTM model can be further explored. This study will try to adjust the number of layers and the number of hidden units of the model to find the most suitable model complexity for the task at hand. Advanced techniques such as attention mechanisms are introduced to help the model better capture key information in the text. In addition, this study considers combining with other deep learning models, such as Transformer,etc. to build a more powerful hybrid model to improve performance and enhance model discrimination[8].

In addition, in order to prevent the model from overfitting, regularization techniques can be used to constrain the complexity of the model. For example, add L1 or L2 regular terms to the loss function to limit the size of the model parameters. dropout technology[9] is also an effective way to prevent overfitting, and it reduces the model's dependence on specific features by randomly dropping a portion of the network connection during training. These measures help to improve the generalization ability of the model and reduce performance degradation on unseen data.

Finally, in order to further improve the comprehensive performance of the model, the method of ensemble learning can be considered. By training multiple different models and combining their results to make predictions[10], it can not only reduce the instability of a single model,but also improve the overall performance of the prediction, and enhance the accuracy of data detection. In this study, multiple Bert-LSTM models with different parameters or structures will be trained, and then their prediction results will be voted or weighted average operations to get the final prediction results, so that the results are more secure.

5 Conclusion

In this study, the performance of Bert-LSTM model in the detection task of pessimistic speech depression tendency was analyzed, and the effect of learning rate on the performance of the model was discussed. The experimental results show that with the increase of training times, the performance of the model on the training set is gradually improved, but the improvement on the verification set is limited. To solve this problem, this paper proposes some possible optimization strategies, including data set optimization, model structure optimization, regularization and overfitting prevention, ensemble learning and model fusion. This study should also note that while the current model has achieved some success in detecting depression-prone speech, there is still room for improvement.

In the future, this study will further study the detection of pessimistic statements with depressive tendencies, and explore more effective feature extraction methods and model structure to improve the detection performance of the model. The generalization ability of the model can be enhanced by collecting more and richer data, so that it can better cope with a variety of complex scenarios. At the same time, this study will also pay attention to the development trend and technical progress in related fields, in order to apply new methods and technologies to research in a timely manner. It is believed that with the continuous deepening of the research and the continuous progress of technology, this research will be able to better solve the problem of detection of pessimistic speech depression tendency. At the same time, this research plans to combine the efficient detection model with the big data platform, and add a function to the social media software frequently used by people that can remind users of mood changes. Send prompt messages to people who often make depression-prone statements in time, and guide them positively and optimistically. It is also hoped that it can provide some new ways to detect people's psychological trauma under major disasters, provide better protection for people's mental health, and make greater contributions to the development of the mental health field.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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