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Qualitative Prediction and Quantitative Analysis of Events in Educational Network Public Opinion Crisis: a Deep Learning Approach

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Abstract: The crisis of educational network public opinion refers to issues such as public dissatisfaction and trust crisis caused by unexpected events in the field of education. The frequency and scope of the impact of educational network public opinion crisis are gradually expanding, bringing huge challenges to educational management departments and institutions. This article aimed to explore how to use deep learning technology to qualitatively predict and quantitatively analyze educational network public opinion crises. This article adopted experimental and comparative methods to qualitatively and quantitatively analyze the crisis of public opinion in educational networks, and obtained the characteristics of several deep learning methods. Experimental data showed that under the framework of convolutional neural network (CNN), the accuracy of public opinion crisis prediction in the sigmoid function was 99.9%; the loss rate was 0.34%, and the running time was 65 seconds.

1. Introduction

With the popularization of the Internet and the rapid development of information technology, the crisis of educational network public opinion has increasingly become the focus of social attention. The crisis of public opinion in educational networks is a dynamic and changing process that depends on the three main bodies of government, schools, and the public. The occurrence of its public opinion crisis is an extremely complex and unpredictable process, which not only affects schools, teachers, students, and other aspects, but also poses great harm to society. With the participation and discussion of numerous netizens, some social conflicts and hot topics, as well as campus violence incidents, would attract public attention.

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There are many illegal and irregular incidents in schools, as well as news of school events. The Internet has provided new channels for the development of public opinion, making news dissemination faster and the likelihood of public participation greater. Although online learning is crucial for emergency distance learning in most educational institutions, opinions on online learning vary greatly during the current pandemic. Therefore, Andy Ohemeng Asare et al., aimed to investigate the public's perception of online emergency distance learning during the pandemic [1]. Andreas Giannakoulopoulos et al., analyzed tweets about online education to evaluate the types of information disseminated in this article. They believed that two-way discussions between users are more common. This means monitoring the quality of educational information on social media and encouraging the education community to participate more in relevant discussions [2]. Ying Qu et al., believed that in emergency situations, negative public opinion, especially negative endogenous public opinion, on the university internet may seriously affect its reputation. Identifying endogenous negative influencing factors is very important for studying the public opinion communication mechanism of universities and solving public opinion crises in universities. The biggest impact on public opinion dissemination is the supervision and intervention of schools, which can suppress dissemination from the source [3].

This article first elaborated on the basic concept of online public opinion, and also analyzed the technical support for the development of public opinion, the impact of public opinion, and the necessity of paying attention to public opinion. Secondly, a discussion was conducted on the language models in deep learning, which can extract and classify features of comments in public opinion. In addition, this article introduced the application of deep learning frameworks and conducted experiments based on the proposed frameworks, and compared the advantages of the three frameworks through data. This article used quantitative analysis methods to establish a prediction model for crisis events in educational network public opinion.

2. Public Opinion under Deep Learning

2.1 Online Public Opinion

Online public opinion refers to the opinions or criticisms expressed by the public on actual hot topics on online platforms [4-5]. Traditional public opinion is mainly based on traditional media such as newspapers, radio, and television, while current online public opinion mainly relies on the Internet as a platform. The popularization of new media platforms has provided the public with a wide range of channel choices, no longer relying solely on traditional media to disseminate information. On internet platforms, a large amount of information can be obtained, and personal opinions and attitudes can be freely expressed. The content of online public opinion dissemination is rich and diverse, covering a wide range of topics in politics, economy, culture, and other aspects. The theme of online public opinion dissemination is vague, both clear and ambiguous. The dissemination of reporting themes is an important factor in the online dissemination of public opinion [6-7]. Network communication is bidirectional and interactive. On online platforms, people's willingness to participate is relatively high. Discussing, forwarding, and commenting on popular topics on Weibo can generate great enthusiasm, and users in the comment section tend to create interactive scenes. Online public opinion crisis is the sum of negative emotions, attitudes, and opinions of the public towards public events, posing a serious threat and challenge to the legitimacy of the ruling party and the positive image of the government. Online public opinion is more complex than other forms of public opinion, because the internet, as a virtual society and open platform, is active in different groups and ideological trends, and online public opinion crises are frequent [8-9]. Therefore, the Chinese government should attach importance to online public opinion crisis events and establish a working mechanism to control online public opinion to promote the healthy and civilized development of the online public opinion environment. Online data collection is a website that automatically collects public opinion data from various online spaces and generates public opinion through links between websites [10-11].

2.2 Language Model

The language model is mainly responsible for vector representation of vocabulary and probability calculation of sentence sequences. They typically use dictionaries, machine learning, or deep learning methods to convert text into numerical forms that computers can automatically process and store [12-13]. Traditional language models mainly include hotspot models, word band models, and N-gram language models. Although a hotspot model is simple and efficient, there is a problem of dimensional explosion. Although the vocabulary bag model can express text through independent vocabulary, there is also a risk of causing incorrect sentences. The N-gram language model is essentially a statistical model. According to the chain rule, the probability of the existence of sentence X, G(X), is the product of the probabilities of m words:

$$G(X) = G(\mathrm{v}_1\mathrm{v}_2\Lambda\ \mathrm{v}_m) = G(\mathrm{v}_1)G(\mathrm{v}_2|\mathrm{v}_1)\Lambda\ G(\mathrm{v}_m|\mathrm{v}_{m-1}\Lambda\ \mathrm{v}_2\mathrm{v}_1) \quad (1)$$

The parameter space is very complex and the calculation of probability is difficult, so Markov chains are introduced:

$$G(X) = G(\mathrm{v}_1\mathrm{v}_2\Lambda\ \mathrm{v}_m) = G(\mathrm{v}_1)G(\mathrm{v}_2|\mathrm{v}_1)g(\mathrm{v}_3|\mathrm{v}_2)\Lambda\ G(\mathrm{v}_\mathrm{m}|\mathrm{v}_{m-1}) \quad (2)$$

The conditional probability of Bi-gram is:

$$G(\mathrm{v}_\mathrm{m}|\mathrm{v}_{m-1}) = \frac{D(\mathrm{v}_\mathrm{m}\mathrm{v}_\mathrm{m\text{-}1})}{D(\mathrm{v}_\mathrm{m\text{-}1})} \quad (3)$$

$D(\mathrm{v}_\mathrm{m\text{-}1})$ is the frequency of the m-1st word. The language model of neural networks is based on neural networks and mainly consists of a four layer structure [14]. The nonlinear ability of neural networks leads to greater generalization ability in neural network language models, but there are many model parameters, such as vocabulary vectors, hidden vectors, and biases, which can easily lead to insufficient memory [15-16]. The main goal of the Word2Vec model is to generate high-quality vocabulary vectors for integrating vocabulary vectors with high applicability, vector density, and contextual attention, which is more advantageous than traditional integration methods. The attention mechanism is reflected in the calculation of weighting coefficients, where a larger weighting coefficient indicates that the current attention is focused on the corresponding key values.

Data collection is a fundamental element of online public opinion research, and the quality of data collection and processing directly affects the effectiveness of text classification and the accuracy of public opinion trend research. Therefore, choosing the correct data collection method is crucial for online monitoring and analyzing public opinion. The first step in the web crawling process is to send a request, and the next step is to obtain a response; the third step is to analyze the webpage, and the last step is to record the data.

2.3 Deep Learning Framework

LSTM (Long Short Term Memory) is a recurrent neural network structure primarily used for processing sequence data. LSTM stores, forgets, predicts, and outputs information through memory units, forgetting gates, input gates, and output gates. BLSTM (Bilateral LSTM) is an extension of LSTM, which can simultaneously process data in both forward and reverse directions. CNN is a neural network used for processing two-dimensional data such as images and videos.

The crisis of educational public opinion refers to the crisis caused by public attention and discussion in the field of education. These crises can stem from various events, such as educational policies, school safety, teacher behavior, etc. By categorizing these crises, the public's concerns in the field of education can be better understood. LSTM, BLSTM, and CNN all have powerful capabilities for processing complex data. LSTM and BLSTM can capture long-term dependencies in sequence data through memory units and gating mechanisms, while CNN can effectively handle complex data features through local connections and weight sharing. LSTM, BLSTM, and CNN all have good performance in processing sequence data. However, LSTM and BLSTM may face the problem of gradient vanishing when processing large-scale data, which can affect the training speed and accuracy of the model. In contrast, CNN has good efficiency in processing two-dimensional data, but it may limit the model's understanding ability.

3. Online Public Opinion Events in the Field of Education

3.1 Education Network Public Opinion

Education is closely related to people's lives and concerns the significant interests of the public. Especially in recent years, public discourse such as teaching and ethics, educational reform, and educational justice have frequently emerged. Education has become a common area of online public opinion. In the era of new media, netizens, as the discussion center of public opinion in the education industry, have the ability to promote superstructure reform with broad participation from the bottom up. The public opinion content of educational networks covers a wide range of fields, such as educational policies, education system reform, and teacher ethics and conduct. Spreading information on social platforms makes it difficult and complex to spread public opinion online in the field of education. Education public opinion is a hot topic in the field of education, involving teacher ethics and education industry culture. People would express their opinions, attitudes, and emotional expressions.

Currently, many universities and scholars view online public opinion in universities as online public opinion related to their own events, rather than being triggered by certain social contradictions at a specific moment in history. The public opinion crisis consists of two parts: one part is the public opinion crisis, which refers to the sum of the opinions, attitudes, suggestions, and feelings expressed by the public as the main body towards objective events or phenomena. In negative events, this expands the influence of public opinion and gives relevant parties a sense of crisis. The other part is crisis public relations, which refers to strategic and management activities related to crisis response. The purpose of online public opinion in universities should not only solve the crisis of public opinion in schools, but more importantly, cultivate the values, behavioral norms, and ways of thinking of young students and the public.

3.2 Experimental Setup

This article selected data on the education network public opinion crisis in a certain region as experimental data, including characteristics such as event type, occurrence time, involved individuals, and public opinion tendency. Firstly, the data was preprocessed and feature extracted, followed by qualitative prediction and quantitative analysis of events using CNN and LSTM models.

Before the experiment, it is necessary to build an experimental environment that involves the operating system, processor, memory, compilation software, editing language, and deep learning framework. The experimental environment configuration is shown in Table 1.

To ensure the objectivity of the results, the data source for emotional analysis tasks should be representative websites or social media platforms. This article conducted a survey and data extraction of school public opinion on events that have occurred in schools. This dataset contains over 4000 datasets, including four types of emotional labels. Among them, approximately 2000 data were labeled as happy emotion labels, while the other data were labeled as disgust, anger, and depression emotion labels, each with approximately 1000 data. Due to the negative emotional experiences of disgust, anger, and depression, and the relatively similar descriptions of certain vocabulary and phrases, model learning becomes difficult. Based on different emotional trends in the dataset, the labeled elements in the dataset were simplified and reclassified into two emotional directions: positive and negative.

Table 1. Experimental environment configuration

Experimental environment	Specific configuration
Operating system	Window11 32bit
Processor	Inter Core i8-8850H
Memory	12G
Compilation software	Google
Editing language	Python5
Deep learning framework	Keras

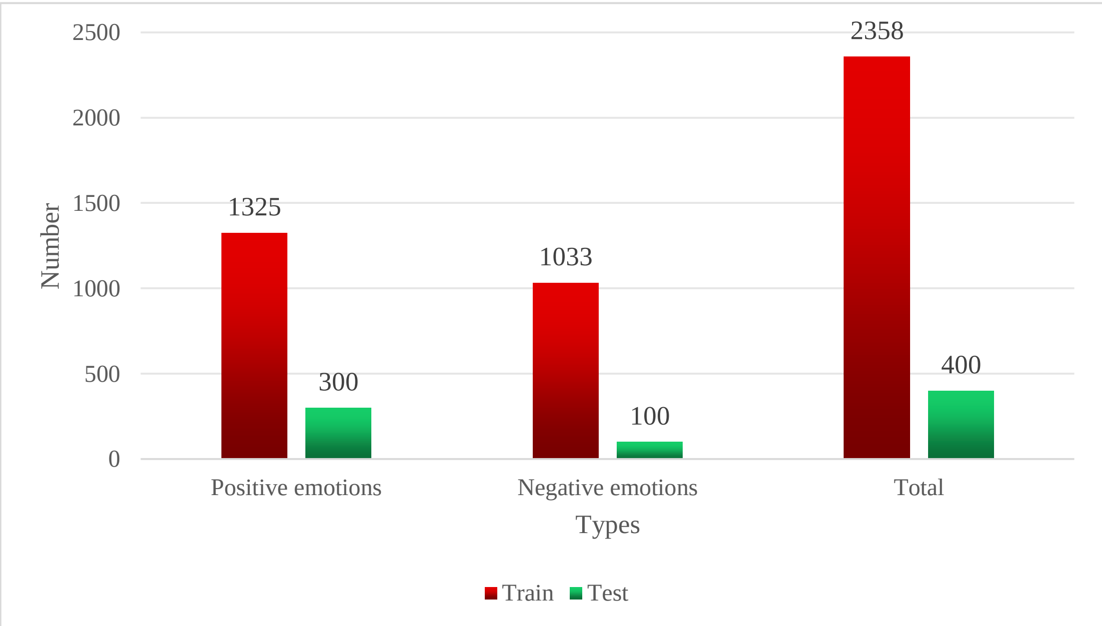

Figure 1. Data distribution statistics

In Figure 1, in the sample data of this article, a total of 1325 positive sentiment data were trained, and 300 test samples were used. The total number of training samples for negative emotions was 1033, and the test sample was 100. A total of 2358 public opinions were included in emotional classification training, and 400 public opinion comments were used as classification test samples.

3.3 Experimental Plan

In the process of predicting online public opinion crises, it is necessary to further analyze the large amount of relevant information studied and collected, and establish a scientific, reasonable, effective, practical, operable, and objective model that can reveal the relationship between regular features and phenomena. On the basis of qualitative prediction of crisis events, a model was established to quantitatively analyze online public opinion crises [17-18]. This method is mainly used to study the probability, intensity, and development trend of events. The weight values were calculated by establishing an event impact degree function. Regression analysis was used to determine the correlation of various factors in the network over time series and qualitative predictions were made. Before qualitative prediction of educational network public opinion crisis events, risk identification is necessary. Distinguish negative public opinion that may occur in online public opinion crises. Based on predictions and assessments of similar situations that have occurred in the past, the level of public opinion risk was constructed and evaluated, and corresponding response measures were developed based on this.

The experimental frameworks used in this article include LSTM, BLSTM, and CNN. They were randomly shuffled during each call, using three activation functions: sigmoid, tanh, and ReLu. When training the data using the model, the activation function and optimizer were adjusted and transformed to observe changes in accuracy. Each model has set data such as loss rate, accuracy, and consumption time to evaluate its performance.

4. Experimental Results of Deep Learning Framework

4.1 LSTM and Improved Classification Results

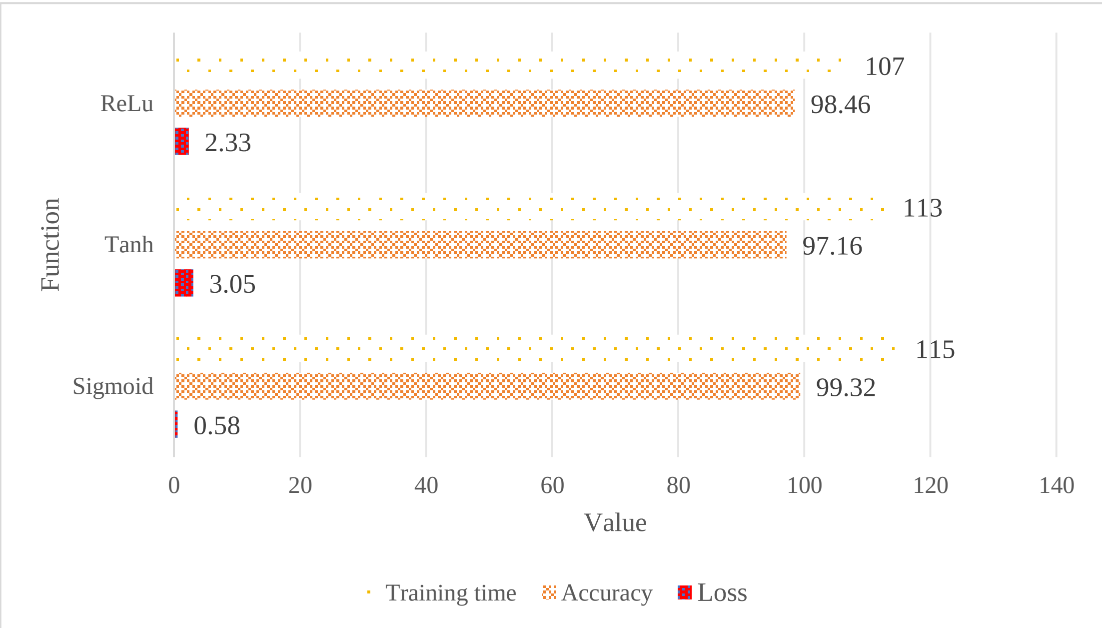

Figure 2. LSTM computational results

In Figure 2, this article can find that in the LSTM deep learning framework, for the classification of educational public opinion emotions, the sigmoid activation function had a loss rate of 0.58%, an accuracy of 99.32%, and a training time of 115 seconds. The loss rate of Tanh activation function was 3.05%; the accuracy was 97.16%, and the training time took 113 seconds. The loss rate of ReLu activation function was 2.33%; the accuracy was 98.46%, and the training time took 107 seconds.

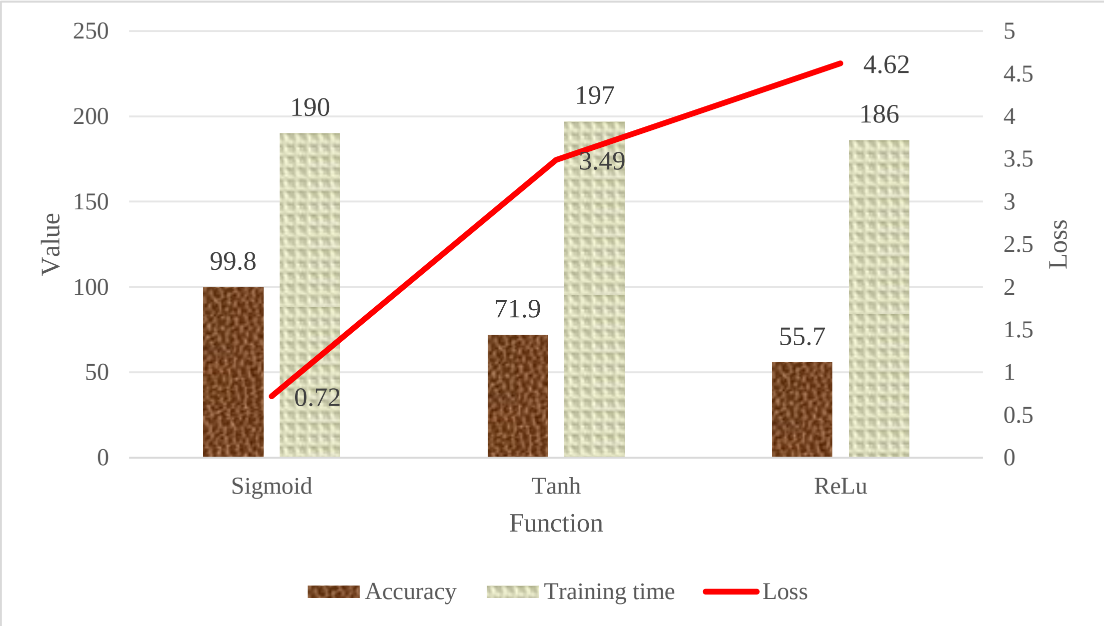

Figure 3. BLSTM computational results

In Figure 3, in the bidirectional long-term and short-term memory framework, the accuracy of educational public opinion sentiment classification also varied among three different activation functions. Among them, the accuracy in the sigmoid function was 99.8%; the loss rate was 0.72%, and the running time was 190 seconds. The classification accuracy in the tanh function was 71.9%; the loss rate was 3.49%, and the running time was 197 seconds. The accuracy in the ReLu function was 55.7%; the loss rate was 4.62%, and the running time was 186 seconds.

4.2 Classification Results of CNN

Figure 4. CNN computational results

In Figure 4, in the CNN framework, the classification accuracy in the tanh function was 51.9%;

the loss rate was 2.92%, and the running time was 66 seconds. The accuracy in the ReLu function was 62.7%; the loss rate was 2.36%, and the running time was 65 seconds. Overall, the CNN framework performed best in classification accuracy and took the shortest time under the sigmoid activation function.

4.3 Qualitative Prediction and Quantitative Analysis of Educational Network Public Opinion Crisis

Qualitative prediction of events refers to the analysis of the characteristics and trends of public opinion events to predict the possible development direction and impact of events. In educational online public opinion, natural language processing and machine learning techniques are used to analyze a large amount of data on social media platforms, news articles, forum posts, and extract information such as keywords and emotional tendencies to clarify the nature and possible development trends of events. Quantitative analysis refers to the in-depth analysis of public opinion events through quantitative means, including the measurement of indicators such as event scale, dissemination speed, social media influence, as well as the statistics and data analysis of event related information. By quantitatively analyzing and quantifying the impact of an event, it is possible to better understand the severity of the event and propose corresponding strategies [19-20].

This article used deep learning technology to qualitatively predict and quantitatively analyze educational network public opinion crises. CNN is used for qualitative prediction of events, and short-term memory and its improved models were used for quantitative analysis. By analyzing the characteristics of public opinion data, CNN models were used to classify event types and analyze the temporal characteristics of public opinion data. The model was used to predict the trend of event development and quantitatively evaluate the degree of impact of the event.

The government should strengthen its guidance on online public opinion crises and provide a good, fair and just public opinion environment for netizens. When conducting information dissemination on the Internet, due to its characteristics of virtuality and anonymity, when negative comments appear, if they may cause adverse effects, schools need to intervene to prevent misleading students. In the crisis of online public opinion, the choice of subjects is an important link. Therefore, the key to guiding netizens to participate in the qualitative analysis of events lies in the government and the media. It is necessary to establish and improve relevant laws and regulations to regulate improper behavior in online public opinion evaluation. By strengthening normative education and moral awareness among netizens, and leveraging the role of news media, positive publicity and reporting can be carried out, forming a public opinion orientation. It is necessary and feasible to establish a network public opinion monitoring platform under the leadership of the public opinion crisis management department. It is necessary to effectively monitor and analyze various news and comments on the internet, and guide public opinion through timely and authoritative warnings issued by relevant departments. By establishing a sound internet technology support system and information security measures, and improving the construction of warning mechanisms, it is possible to strive to control the situation within a controllable range before negative events expand their impact.

5. Conclusions

The occurrence of online public opinion crisis is accidental and uncertain. In qualitative event prediction, it is necessary to construct a model to quantitatively evaluate potential negative news, issues with significant impact, and sensitive topics that may arise. In the event of online public opinion crisis, a complete quantitative analysis model can be established, and relevant data can be collected and organized on this basis. This article used a neural network model for predicting public opinion crises in educational networks. By establishing a model, events in the education network public opinion crisis were predicted, quantitatively analyzed, and validated. This article applied LSTM and CNN frameworks for data accuracy analysis in experiments. The two deep learning methods each have their own advantages and disadvantages, which indirectly indicates that there is also a lot of room for improvement.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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