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Research on College Network Early Warning Based on LSTM

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Abstract

With the development of information technology and the continuous optimization of China's education system, college students have gradually become the main group in the Internet, and college network public opinion events have received increasing attention. By analyzing the constituent elements of university network public opinion, building an early warning indicator system from three dimensions: subject, carrier, and object, and combining life cycle theory, dynamic comprehensive evaluation method, and short-term memory network, constructing a university network public opinion model. Through empirical analysis of 20 university network public opinion events, the experimental results show that the proposed public opinion model has certain feasibility. Corresponding response strategies have also been proposed for different levels of crisis warning, providing a decision-making basis for relevant departments to guide and manage online public opinion in universities.

Keywords

College Network Public Opinion, Dynamic Comprehensive Evaluation, Life Cycle Theory, Deep Learning, Early Warning

1. Introduction

With the development of the information society, the popularity of communication tools such as mobile phones, and the rise of various social platforms, the number of Internet users in China is increasing. The rapid development of social platforms such as Weibo and Tiktok not only facilitates people's daily communication and exchange, but also enables people to obtain news and global emergencies and other information in a short time. As the main body of Internet users, college students are prone to make extreme statements on the Internet due to their group characteristics such as low social experience and susceptibility to incitement in the event of events related to colleges and universities, resulting in the continuous evolution of events on the Internet. At present, unexpected events involving university groups continue to occur and their frequency is also accelerating. These university events spread through the Internet platform, forming university network public opinion events, causing strong social repercussions, and having a certain impact on university reputation and social stability. In today's era, how to effectively manage network public opinion and defend network positions has become an important and urgent task that universities must face.

(Li Jingyi, 2021) believes that college online public opinion is the sum of all statements and emotions related to college affairs or released by college teachers and students. (Wang Di, 2022) analyzed the network public opinion of university emergencies separately, pointing out that the network public opinion generated by emergencies of places or people related to the university is the network public opinion of the university. (Xu & Liu, 2022) analyzed the characteristics of college online public opinion based on big data, and summarized that it has three characteristics: unexpected events, rapid dissemination of public opinion, and group cohesion. (Yang, 2022b) believes that college online public opinion has particularity and collectivity, interactivity and uncontrollability, periodicity and long-term characteristics. By analyzing the development and evolution process of online public opinion, (Yuan et al., 2022) effectively combines the information diffusion process with group polarization behavior, introduces the idea of dynamic network structure into the SIR model, and analyzes the reasons that affect the polarization phenomenon of online public opinion by adjusting parameters. (Peng et al., 2021) fully considers the development and dissemination characteristics of major emergencies, constructs a public opinion indicator system with four primary indicators, and recommends a network public opinion early warning model through GA-BP. Through comparative experiments, the performance of the model has been improved, which can provide reference for Internet governance. Based on public opinion mining and emotional analysis, (Danner et al., 2022) constructed a microblog public opinion emotional knowledge map, providing a theoretical basis for online public opinion early warning. (Yang, 2022a) proposed a BCBL model for emotional analysis from the perspective of attention mechanism. Based on text mining, (Zhang et al., 2021) introduced emotional heat calculation formulas and divided the stages of public opinion to further grasp the development trend of public opinion and achieve early warning of online public opinion.

However, from the existing literature, there is a lack of early warning research on online public opinion in universities. Most empirical analysis studies mainly focus on certain types of emergencies, such as public health emergencies, or summarize the relevant dissemination laws and governance strategies through research on a certain event, with less research on online public opinion involving a specific subject, such as universities.

2. Related Concepts

2.1. The Connotation and Elements of College Network Public Opinion

At present, scholars have done a lot of research on the concept of online public opinion in colleges and universities. Through comprehensive analysis, this paper believes that online public opinion in colleges and universities refers to the sum of opinions, attitudes and emotions publicly expressed by netizens on Internet social networking platforms, such as Weibo, Tiktok, Zhihu, etc., regarding college management, teachers' ethics, education fairness and other issues related to college teachers and students. College network public opinion is only a special type of network public opinion, so this article analyzes the constituent elements of college network public opinion based on the constituent elements of network public opinion, and combines previous research by scholars to divide the constituent elements of college network public opinion into subject, object, and carrier.

1) Subject. The main body of university network public opinion refers to the relevant personnel involved in network public opinion events. Compared to general network public opinion, the main body of university network public opinion mainly includes three groups, namely, universities, governments, and netizens. When public opinion incidents occur in universities, universities are responsible for disclosing the truth of the incident and responding to relevant comments. The main body of public opinion not only includes colleges and universities, but also involves Internet users. The identity of Internet users also varies. If divided by their influence, they are mainly divided into three types: ordinary Internet users, opinion leaders, and "zombie" accounts. The main body of public opinion also includes the government. Even if not all events are directly related to the government, there will always be some netizens who use this event to express their accumulated dissatisfaction with the government.

2) Object. The object of public opinion in university network public opinion events refers to events that cause public opinion in real life, and the object of university network public opinion events refers to events involving universities. The object of public opinion is the foundation, and the basis for netizens to disseminate public opinion on the Internet is the occurrence of corresponding events online and offline. Even rumors are based on the evolution of events that have already occurred, and form online public opinion based on the events that have occurred.

3) Carrier. The public opinion carrier here refers to the total amount of information such as opinions and attitudes expressed by the public opinion subject towards the public opinion object, and also include the methods and channels of public opinion dissemination. In the Internet era, people rely less on traditional media such as newspapers and more on network platforms for information interaction. Internet platforms also provide users with a variety of communication directions, such as text, pictures, videos, and so on.

2.2. Overview of College Network Public Opinion Warning

College network public opinion warning refers to the effective reduction or avoidance of negative impacts on universities, even on social stability, through monitoring, collecting, analyzing, and preventing information related to the event in the Internet space after an event involving universities occurs. In this article, college online public opinion early warning does not rely on certain characteristic indicators to predict before an event occurs, but rather refers to monitoring and warning the possible development trend of online public opinion through comprehensive analysis of data characteristics of public opinion in the short term after the event occurs. In this study, we specifically identify the key influencing factors of college online public opinion, construct a college online public opinion early warning model, and obtain the crisis early warning level of college online public opinion. Universities, governments, and other relevant departments can take corresponding preventive measures based on the crisis early warning level to effectively guide and manage college online public opinion, so that public opinion can be calmed.

3. Early Warning Indicator System of College Network Public Opinion

According to the three principles of high degree of discussion, openness of the truth, and diversity of nature of events, this article selects 20 typical cases of universities with different social influences since 2019 for empirical analysis. The event summary is shown in **Table 1**.

3.1. Construction of Early Warning Indicator System

Based on the previous analysis of the characteristics and influencing factors of college online public opinion, this article analyzes college online public opinion from three aspects: subject dimension, carrier dimension, and object dimension, and serves as a primary indicator of the college online public opinion indicator system. The subject dimension includes three secondary indicators: college, government, and Internet users, the carrier dimension include a secondary indicator for media, and the object dimension also sets a secondary indicator. Each

Table 1. University event selection.

Number	Event name
S1	The Incident of Teachers' Morality and Morality at Sun Yat-sen University
S2	Xi'an University of Electronic Science and Technology
S3	College Students Abuse Delivery Staff to Resign
S4	Henan University Girl Dies Delayed in First Aid
…	…
S5	Wuhan University "Kimono Sakura Appreciation" Event

secondary indicator has also been set up with corresponding tertiary indicators for quantitative analysis. After sorting out and analyzing, see **Table 2**.

3.2. Quantification of Indicator System

The main methods for quantifying influencing factors are entropy weight method and emotional analysis method. The following is a brief introduction. The theoretical basis of entropy weight method is information entropy theory, which was proposed by American scholar Shannon. The information entropy formula for an event is shown in Equation (1).

$$H(x) = \sum_{i=1}^{n} p_i * \log(1/p_i) \tag{1}$$

Emotional analysis is the process of analyzing the text content published by netizens to determine their emotional tendencies and calculate their emotional values. This article selects an emotional polarity analysis method based on an emotional dictionary to analyze the emotions of college online public opinion netizens. Use the above two methods to quantitatively analyze the indicator system, as shown in **Table 2**.

4. Construction of University Network Public Opinion Model

4.1. Comprehensive Evaluation Method Based on Life Cycle Theory

In this study, the dynamic evaluation method is used for comprehensive evaluation of public opinion ratings in universities. Compared to traditional static evaluation, the dynamic evaluation theory considers the impact of time dimensions, making the comprehensive evaluation more objective. (Guo Yajun, 2002) obtains the index weight coefficient by looking for the maximum variance value of the overall system from the perspective of overall differentiation. However, this method does not further consider the state of the same object at different times. As described in the life cycle theory, the development of online public opinion undergoes multiple stages, such as germination, development, maturity,

Table 2. Early warning indicator system of college network public opinion.

Indicator	Name	Quantification method
Subject dimension	College response attitude	$\lambda_1 * mount + \lambda_2 * frequency + \lambda_3 * time$
	Government intervention attitude	$\lambda_1 * mount + \lambda_2 * frequency + \lambda_3 * time$
	Emotional tendencies of netizens	$emotion * adverb$
	Internet influence	$\lambda_1 * Fan + \lambda_2 * AvgL + \lambda_3 * AvgT + \lambda_4 * AvgC$
Carrier dimension	Network public opinion fever	$\lambda_1 * Total + \lambda_2 * Tran + \lambda_3 * Com + \lambda_4 * Like$
	Communication form	$\lambda_1 * P_v + \lambda_2 * P_q, P_v = P_v/P_T, P_q = P_q/P_T$
Object dimension	Event sensitivity	$\{1.0, 0.75, 0.5, 0.25, 0.0\}$
	Event in-depth report	$\lambda_1 complex + \lambda_2 report$

and decline, and the likelihood of public opinion crises erupting at each stage is also different. Therefore, this paper proposes a new dynamic comprehensive evaluation method based on the life cycle theory. The specific process is shown below.

First, construct a temporal and three-dimensional data table of university network public opinion events. The data in the table has undergone data standardization processing, as shown in **Table 3**.

In order to reflect the differences of evaluation targets in different event evaluation indicators, this article defines the comprehensive evaluation function of university network public opinion indicators as Equation (2).

$$y_i = \sum_{k=1}^{T} p_k y_i(t_k) = \sum_{k=1}^{T}\sum_{j=1}^{m} p_k w_j x_{ij}(t_k) \quad k = 1,2,\dots,T; i = 1,2,\dots,n \tag{2}$$

where $p_k = f(x) = \partial_1 \varphi_1(x) + \partial_2 \varphi_2(x) + \ldots + \partial_N \varphi_N(x) = \sum_{i=1}^{n} \partial_n \varphi_n(x)$ is the value of the life cycle fitting function of the research object s_i obtained by the least square method at time t_k. At this time, the variance expression is shown Equation (3).

$$\begin{aligned} \max \delta^2 &= \sum_{i=1}^{n} y_i^{\,2} = \sum_{i=1}^{n} \left(PX_iW\right)^2 = W^T \sum_{i=1}^{n} X_i^T P^T PXW \\ &= W^T \sum_{i=1}^{n} H_i W = W^T HW \end{aligned} \tag{3}$$

Take the maximum value of δ^2 obtained, that is, solve Equation (4).

$$\max W^T HW$$
$$\begin{cases} W^T W = 1 \\ W > 0 \end{cases} \tag{4}$$

4.2. Clustering Analysis of Internet Public Opinion Events

After analyzing the comprehensive evaluation method based on life cycle theory in the previous article, it is necessary to perform cluster analysis on the calculated evaluation scores. Currently, there are more classic K-MEANS clustering algorithms based on distance and DBSCAN algorithm based on density. Considering the data characteristics of this article, K-MEANS clustering algorithm is

Table 3. Time series stereoscopic data table.

	t_1		t_n
	$x_1 \quad x_2 \quad \cdots \quad x_m$	$\cdots$	$x_1 \quad x_2 \quad \cdots \quad x_m$
s_1	$x_{11}(t_1)\ x_{12}(t_1)\cdots x_{1m}(t_1)$		$x_{11}(t_n)\ x_{12}(t_n)\cdots x_{1m}(t_n)$
s_2	$x_{21}(t_1)\ x_{22}(t_1)\cdots x_{3m}(t_1)$	$\cdots$	$x_{21}(t_n)\ x_{22}(t_n)\cdots x_{3m}(t_n)$
$\vdots$	$\cdots$		$\cdots$
s_n	$x_{n1}(t_1)\ x_{n2}(t_1)\cdots x_{nm}(t_1)$		$x_{n1}(t_n)\ x_{n2}(t_n)\cdots x_{nm}(t_n)$

where s_n represents the evaluation object n; x_m represents the evaluation index m; $x_{nm}(t_T)$ represents the standardized value of evaluation object n regarding the m evaluation index at time $t(T)$.

selected to be used, the Euclidean distance is used for calculation, as shown in Equation (5).

$$d = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{5}$$

4.3. Design of an Early Warning Model for College Network Public Opinion

When dealing with problems related to temporal data, most scholars prefer to use the LSTM model. (Hochreiter & Schmidhuber, 1997) proposed the LSTM model, which is similar to traditional deep learning models such as BP neural networks in structure, and mainly consists of three layers, namely, input layer, hidden layer, and output layer. However, the difference is that the innovative LSTM model mentioned earlier introduces the concepts of forgetting gate, input gate, output gate, and cell state update, and applies them to each memory unit, making LSTM have a more scientific and accurate memory function, Therefore, this article builds a college online public opinion early warning model based on the LSTM model.

In order to make the output results of the early warning model more readable, this article fully connects the output layer of the LSTM model to a common BP neural network, as shown in **Figure 1**.

Through the previous analysis, this article finally established an LC-LSTM college network early warning model based on dynamic comprehensive evaluation method and LSTM model. The main process of this model is shown in **Figure 2**. Firstly, the public opinion indicator data and evaluation results are used as the input and output of the experimental dataset for model training, and the trained.

5. Empirical Analysis and Countermeasures

5.1. Determination of Early Warning Grade of Public Opinion Events in Colleges and Universities

Calculate the three-level indicator data, and obtain the corresponding numerical value of the obtained three-level indicator through the specified quantitative

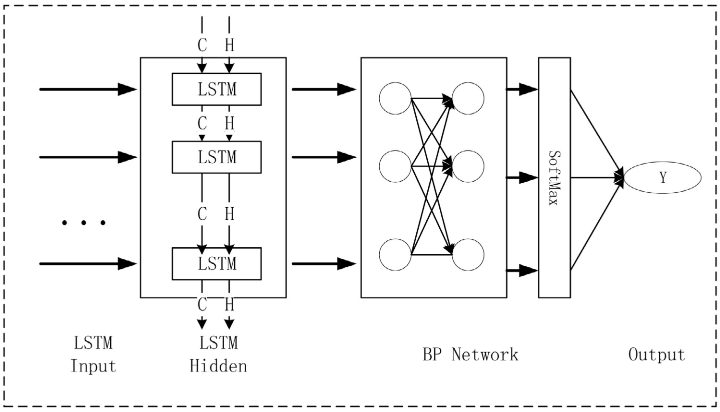

Figure 1. Schematic diagram of LSTM model optimization.

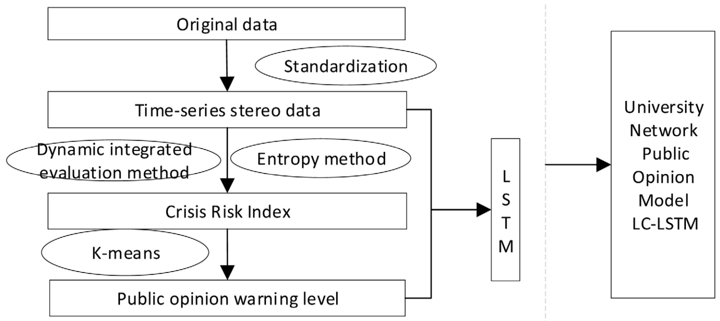

Figure 2. Schematic diagram of university network public opinion model.

method. Conduct dynamic comprehensive evaluation and analysis of various public opinion events according to Equation (4), and divide the public opinion crisis warning level into four levels through K-means clustering analysis, namely, mild level, warning level, dangerous level, and extremely dangerous level. The clustering results are shown in **Table 4**.

It is not difficult to infer that the scope of the four early warning levels is $(0, 0.2203]$, $(0.2203, 0.3997]$, $(0.3997, 0.6026]$, $(0.6026, 1]$.

5.2. Experimental Results and Analysis of Early Warning Model

The parameters of the LC-LSTM early warning model are divided into two types. One is a parameter that does not need to be manually set, such as the connection weight value between various neurons. This value is initially determined through random initialization, and then determined through algorithms such as gradient descent; There is also a parameter that needs to be set before training, also known as a hyperparameter. In order to avoid model overfitting and model computation explosion, hidden layers should not be stacked in multiple layers. After parameter optimization, the model structural parameters are: input layer feature dimension $input\_size = 8$, hidden layer $num\_layers = 2$, hidden layer $hidden\_size = 64$, using the Adam optimization algorithm, initial learning rate $lr = 0.001$, and default parameters for the remaining parameters.

Using a 1:2:7 partitioning rule for the dataset, 2284 samples from 3264 experimental data were used to train the model, 652 experimental data were used to validate the model, and the remaining portion was used for model performance testing. After continuous iterative optimization of the model, the data from the test set that was reserved in advance was input into the trained model to compare the consistency between the expected output and the actual output. Of the 328 test sets, 306 expected outputs were consistent with the actual output, that is, the accuracy of the university network public opinion early warning model optimized based on reward and punishment factors was 93.2%, which proved that it was feasible to apply it to the field of university network public opinion early warning, This article conducts comparative experiments on the unimproved comprehensive evaluation method and the optimized comprehensive evaluation method, LSTM model, and BP neural network model. The experimental results are shown in **Figure 3**.

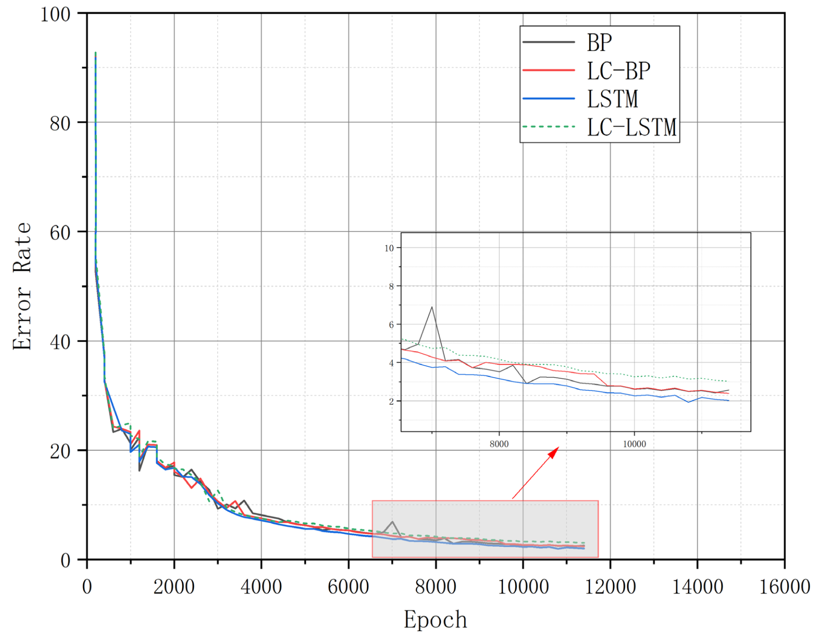

Figure 3. Comparative experimental results.

Table 4. Clustering results of public opinion events.

Risk level	Namely	Mild	Dangerous	Extremely dangerous
Cluster center	0.1802	0.3242	0.5205	0.6388
Event	S5, S9, S12, S14, S17, S19	S3, S6, S7, S10, S11, S15, S18, S20	S1, S2, S8, S16	S4, S13

5.3. Strategies for Coping with College Network Public Opinion

The risk level of public opinion events in colleges and universities with mild concentration is the lowest, which basically does not cause public opinion crises. For such incidents, universities need to pay attention to the details of daily work, strengthen students' understanding of rules and regulations through various channels such as class meetings, listen to various suggestions, and promote the reasonable and rapid resolution of university emergencies.

Warning level public opinion events in colleges and universities are less dangerous and can have a certain range of negative impacts. Universities and relevant departments should pay close attention to such public opinion events. Universities and relevant departments should promote the disclosure of event information, which can effectively avoid the occurrence and development of misunderstandings, thereby avoiding the occurrence of public opinion crises.

Network public opinion events in dangerous universities have a high degree of danger and have a large impact on society. Universities and relevant departments must attach importance to such public opinion events, in addition to timely communicating with students to understand the situation, real-time monitoring of Internet users' discussion data on the event, and reasonable guidance through network opinion leaders at key nodes to control public opinion within a controllable range and minimize the negative impact of the event.

The network public opinion events in extremely dangerous universities have the highest risk level, and have a strong harm to universities and even society. For such events, universities and relevant departments must intervene as soon as possible, continue to follow up the development of the event, take certain measures to cut off the source of public opinion when necessary, avoid the spread of negative public opinion, disclose the information of the event in an authoritative capacity, and avoid the evolution of public opinion.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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