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Research on Risk Evolution of University Online Public Opinion Based on GWO-LSTM Prediction

Authors: Cao Chao

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Abstract

Research Objective: Improving the accuracy of risk prediction for university online public opinion events holds significant importance for safeguarding national security and social stability. Research Methods: Based on the popularity and comments of university online public opinion events on the Weibo platform, this study proposes a public opinion risk model grounded in event popularity and sentiment analysis results, employing a combination of the Grey Wolf Optimizer and LSTM as the prediction model to analyze the risk evolution of university online public opinion, with validation through case study analysis. Research Conclusions: This paper constructs a full-chain analytical framework for university online public opinion. The model considers more comprehensive factors, exhibits high prediction accuracy and goodness of fit, and can comprehensively reflect the actual risk situation and its changes in public opinion. Prevention and control evolution analysis demonstrates that utilizing the model for public opinion prediction enables timely control of public opinion incidents, preventing continuous escalation. The study shows that the model can effectively reflect and predict the degree and changes in public opinion risk, achieving a mean absolute error of 13.8% in validation events. Simultaneously, the evolution analysis using the model demonstrates the importance and necessity of university online public opinion prediction.

Full Text

Research on the Evolution of University Online Public Opinion Risk Based on GWO-LSTM Prediction

Cao Chao[1], Ling Chunyu[2], Luo Fanglu[3]
[1]Student Work Department, Central South University Party Committee, Changsha 410083, China
[2]Organization Department of Party Committee, Central South University,

Changsha 410083, China
[3]School of Marxism, Central South University, Changsha 410083, China

Abstract

[**Research Objective**] Improving the accuracy of online public opinion event risk prediction in universities is of great significance for maintaining national security and social stability. [**Research Method**] Based on the popularity and comments of university-related online public opinion events on the Weibo platform, this study proposes a public opinion risk model that incorporates both event popularity and sentiment analysis results. The Grey Wolf Optimizer algorithm combined with LSTM serves as the prediction model to analyze the evolution of online public opinion risks in universities, with case-based verification and analysis. [**Research Conclusion**] This paper constructs a comprehensive, full-chain analytical framework for university online public opinion. The model features more comprehensive considerations, high prediction accuracy and fitting degree, and can fully reflect the actual risk situation and changes in public opinion. Prevention and control evolution analysis demonstrates that using the model to predict public opinion enables timely control of public opinion incidents and prevents continuous escalation. The research shows that the model effectively reflects and predicts the degree and changes in public opinion risk, achieving an average absolute error of 13.8% in validation events. Meanwhile, evolutionary analysis using the model demonstrates the importance and necessity of university online public opinion prediction.

Keywords: University online public opinion; Public opinion risk; LSTM; Sentiment analysis; Grey Wolf algorithm; Public opinion evolution
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1. Introduction

With the rapid development and popularization of network information and intelligent technologies, the Internet embodies not only technical attributes but also communication, social, and ideological attributes. People’ s various ideas and opinions are expressed through sophisticated network platforms, with temporal and spatial distances in communication continuously shrinking, making it easy to form “public opinion fields” that endanger social security and stability. Universities, as the frontline of ideological struggle, have always attracted significant social attention. Moreover, university faculty and students, being intellectually active and highly connected to the Internet, make unexpected incidents in universities more likely to become hotspots of online public opinion.

University online public opinion, as a specific type of network public opinion, has its particularities. First, it has a broad audience, relating not only to faculty and students but also involving alumni, parents, and the general public, resulting in wide dissemination scope and significant influence that may evolve into social crisis events. Second, it exhibits high sensitivity—universities, as educational institutions, often see their public opinion closely related to teaching, research, and student management. Once negative public opinion emerges, it can severely impact school reputation, enrollment, and faculty stability. University public opinion often spreads rapidly within short timeframes, posing enormous challenges to institutional reputation and image, disrupting normal order, and affecting institutional development. However, many universities often lack adequate preparation in capturing public opinion information, accurately predicting development trends, and rapidly formulating response plans, resulting in passive management and missed "golden 6 hours" for public opinion handling. This requires universities to promptly identify online public opinion issues, understand internal and external public opinion dynamics, discover potential problems and risks, timely grasp development trends, and anticipate possible crises in advance, thereby formulating appropriate response strategies to minimize crisis impact. Therefore, research on university online public opinion prediction has become a key focus for academia, government, and universities.

In response to these challenges, strengthening university online public opinion governance is not only necessary for maintaining campus security and stability but also essential for providing a clearer growth space for cultivating well-rounded successors with moral, intellectual, physical, aesthetic, and labor education. This paper proceeds from the characteristics and realities of university online public opinion in the network environment to further clarify the occurrence mechanism of university online public opinion and propose effective management and control strategies.

2. Research Status

Due to the complexity, rapidity, suddenness, and interactivity of online public opinion, failure to guide its dissemination and evolution in a timely and correct manner can cause significant impacts on social public security [1]. Therefore, establishing online public opinion prediction models to grasp the risk degree and development trends, predict and handle online public opinion crises promptly and effectively, plays an important role in maintaining social order, improving public satisfaction and social security, and enhancing government governance systems and capabilities [2].

Online public opinion prediction methods are divided into traditional mathematical model prediction and nonlinear time series prediction methods based on machine learning and deep learning [3]. Early research primarily used traditional prediction models such as grey prediction [4], exponential smoothing [5], and statistical methods like Markov chains [6]. These methods are simple and easy to use but often suffer from low prediction accuracy.

With the development of machine learning and deep learning, prediction accuracy has significantly improved. Zhao Lei and Wang Song [7] effectively predicted the trend of online event public opinion heat using time series data combined with BP neural network theory. Huang Yaju, Chen Fuji, et al. [8] improved prediction effectiveness by using a hybrid genetic algorithm and particle swarm optimization to optimize BP neural networks. Lan Yuexin et al. [9] established a public opinion heat model using multi-dimensional Logistic models for prediction.

To further improve online public opinion prediction accuracy and ensure social opinion security, many scholars have adopted combined prediction and deep learning methods. Xu Minjie et al. [1] combined Logistic models, exponential smoothing, and grey prediction for online public opinion forecasting. Li Tong and Song Zhijie [10] used model ensemble theory to integrate ARIMA, neural networks, and support vector machine regression to construct an average ensemble model for predicting Weibo sentiment trends. Zhong Yiyong [11] combined Logistic models, ARIMA models, and LSTM models to predict the evolution of Weibo public opinion. Sun Jingchao, Zhou Rui, et al. [12] proposed a public opinion prediction model based on recurrent neural networks for processing time series, considering that traditional models and different neural networks have poor prediction effects on nonlinear data, thereby further improving model prediction accuracy. In summary, numerous scholars have conducted research on online public opinion development trends from different perspectives, gradually expanding the methods for online public opinion trend prediction.

However, online public opinion data exhibits certain temporal correlations, making it difficult for statistical or traditional machine learning methods to mine the temporal dimensional associations in time series data while also struggling to achieve accurate prediction accuracy suitable for Chinese text data processing. Therefore, further research on using deep learning methods for online public opinion modeling and prediction remains necessary. This study considers LSTM, a deep learning network, as the foundation for public opinion prediction, establishing a network public opinion risk model that focuses more on risk information while incorporating sentiment analysis as a consideration index to better reflect the complexity and harmfulness of online public opinion. On this basis, the Grey Wolf Optimizer algorithm is added to optimize LSTM model parameters, improving model training speed and prediction accuracy to accurately predict the development trends of unexpected event online public opinion heat and risk, providing a basis for timely public opinion prevention measures.

3. Methodology

3.1 Sentiment Analysis Model Principle

SnowNLP is a Python library specifically designed for Chinese natural language processing. It comes with built-in Chinese positive/negative sentiment training sets and can effectively handle Chinese text sentiment analysis. The principle is based on the Naive Bayes classifier [13], implemented as follows:

Assume sentiment analysis has two categories: positive and negative. A segment of comment containing mutually independent words $w_1, w_2, ..., w_n$ is obtained.

The Bayes formula is as follows:

$$P(positive|w_1, ..., w_n) = \frac{P(w_1, ..., w_n|positive) \cdot P(positive)}{P(w_1, ..., w_n)}$$

By the total probability formula:

$$P(w_1, ..., w_n) = P(w_1, ..., w_n|positive) \cdot P(positive) + P(w_1, ..., w_n|negative) \cdot P(negative)$$

Substituting this into the above equation yields:

$$P(positive|w_1, ..., w_n) = \frac{P(w_1, ..., w_n|positive) \cdot P(positive)}{P(w_1, ..., w_n|positive) \cdot P(positive) + P(w_1, ..., w_n|negative) \cdot P(negative)}$$

This is the basic calculation formula for SnowNLP sentiment analysis. This formula indicates that the probability of a comment containing words $w_1, ..., w_n$ being positive can be calculated through a labeled dataset.

3.2 LSTM

LSTM [12] operates fundamentally similarly to RNN, both possessing memory functions. This advantage enables it to consider the dependency relationships between input data, outputting results generated by combining current network input with historical network information, making it more suitable for simulating time series trends [14].

LSTM is structurally similar to RNN, both comprising input layers, hidden layers, and output layers. The difference lies in its solution to the gradient vanishing and gradient explosion problems [15] during traditional RNN training.

[Figure 1: see original paper] LSTM Hidden Layer Structure

Unlike RNN, the LSTM hidden layer has memory units and gate structures, including input gates, output gates, and forget gates. The module composition is shown in Figure 1. Where x_t is the model' s input vector, h_t is the model' s output vector, the previous layer' s output vector can be seen as participating in network construction as input for this layer, and C_t is the memory unit.

The hidden layer forward propagation and gate structure control mechanism are as follows: At time t, the input gate updates the memory unit temporary value based on hidden node h_{t-1} and input data x_t. C_t is obtained by combining the retention degree of the previous moment' s state determined by the forget gate with the input gate's calculation. The final hidden layer state is derived from the output gate in two parts: the first part obtains output state o_t using activation function σ, while the second part consists of C_t processed by activation function *tanh*. Ultimately, output state h_t depends on the previous moment' s hidden layer state h_{t-1} and current moment input data x_t.

Using the LSTM model can effectively capture and process long-term dependencies in time series. For the complexity of network public opinion time series development, it can automatically and effectively learn its important features and handle internal data correlation relationships.

3.3 Grey Wolf Optimization Algorithm

(1) Grey Wolf Algorithm [16] is an optimization search method inspired by grey wolf hunting activities. In nature, grey wolves survive by cooperating and competing to find food resources. The Grey Wolf Optimizer algorithm utilizes this behavioral characteristic by simulating position transformations between winners and losers in the search space within grey wolf populations, gradually improving the fitness value of the entire group to find optimal solutions.

The basic principle is: position transformation and iterative updates are performed based on winners and losers among grey wolf group members. The algorithm includes four basic steps: 1) Initialize the grey wolf group: determine the initial positions of grey wolves and calculate their fitness values. 2) Search process: update each grey wolf' s position and fitness value based on distances and fitness values between individuals. In this model, the fitness function is the mean square error of the LSTM model training set. 3) Select the optimal grey wolf: determine the global winner, i.e., the optimal solution, based on fitness values. 4) Update positions: update each grey wolf' s position based on the optimal grey wolf' s position and other grey wolves' relative positions.

(2) Improved Grey Wolf Algorithm. Since the grey wolf intelligent optimization algorithm was proposed, different scholars have proposed various improvement strategies to balance global and local search and optimize solution quality. This study adopts the mature Improved Grey Wolf Optimizer (IGWO) based on good point set initialization and nonlinear parameter control proposed in literature [17].

Initializing grey wolf individual positions through this method can increase group diversity, improving global search capability to a certain extent and accelerating algorithm convergence speed. Second, parameter A in the GWO algorithm plays a key role in balancing its global search and local exploitation capabilities. The classical grey wolf algorithm' s A value linearly changes from 2 to 0 with iteration count. Research [18] shows that nonlinear transformation of parameter A contributes to better optimization performance. This study uses a trigonometric cosine function for nonlinear transformation of parameter A in the algorithm.

The Grey Wolf Optimizer has advantages including group cooperation, simple implementation, rapid convergence, and strong global search capability, enabling faster convergence to optimal solutions in high-dimensional optimization problems and searching among multiple local optima. This paper uses the grey wolf algorithm to optimize LSTM hyperparameters to find the model' s optimal solution.

4. Model Construction

This model analyzes and explores risk changes in university online public opinion caused by network emergencies. Based on sentiment analysis and LSTM long short-term memory recurrent neural networks, a network public opinion risk evaluation and prediction model is established. The process includes data collection, risk index model establishment, and risk index prediction.

Unlike approaches that predict popularity peaks from the perspective of public opinion heat to provide optimal decision-making moments and early warnings for relevant departments, this model focuses more on the magnitude of public opinion risk, evaluates public opinion risk indices, considers positive and negative public opinion situations, simultaneously uses deep learning models to predict index changes, and provides decision-making recommendations. The process can be divided into three parts: data collection, risk model establishment, and model prediction. First, select specific unexpected network public opinion events as research objects and obtain relevant data through multiple channels; second, process different index data categorically, perform data cleaning, and calculate risk indices; finally, train the model based on LSTM and conduct evaluation and evolutionary analysis. The specific process is shown in Figure 2 [Figure 2: see original paper].

[Figure 2: see original paper] Public Opinion Risk Index Prediction Model Flowchart

4.1 Data Collection and Preprocessing

The "Sichuan University Subway Incident" that occurred in June 2023 is used as the demonstration case. This incident lasted 16 days and 9 hours, experiencing event outbreak, reversal, result announcement, and other stages. Based on university personnel, this public opinion event had significant impact on the university.

This study selects the 3.5-day event reversal period as the dataset for model construction. Weibo posts and comments under the topic "Woman Who Falsely Accused Man of Taking Photos Apologized" are crawled as the first dataset. After cleaning, 6,806 valid comments are obtained, as shown in Table 1 . Time dissemination trend data from "ZhiWei Seeing" is collected as the second dataset.

Using one hour as the time series unit, statistics are compiled for the posting times of 6,806 comments, with public opinion heat changes shown in Figure 3 [Figure 3: see original paper]. The time series runs from 19:00 on June 11 to 24:00 on June 14. The public opinion heat chart shows four major discussion peaks during this 3.5-day period, with public opinion heat reaching its maximum at 4-5 hours after event publication. Additionally, heat data from Weibo and "ZhiWei Seeing" show generally consistent trends. This study adopts a combined weighted approach from both data sources to calculate the network public opinion risk index, making the model more universal and accurate.

Normalization Processing. Considering the evaluation systems and units of data obtained from different platforms, time series data undergoes linear normalization to eliminate dimensional and data range impacts. The same formula is used for sentiment analysis statistics in this study. The formula is as follows:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Principal component analysis is used to interpret the importance of three statistical indicators [19], obtaining weights for the evaluation model as shown in Table 3 . The public opinion risk index is calculated using the following formula and weights:

$$Risk\ Index = \sum_{i=1}^{n} w_i \cdot x_{i,norm}$$

4.2 Sentiment Analysis

SnowNLP is used to conduct sentiment analysis scoring [13] on 6,806 valid comment data, with negative comment counts statistically categorized as shown in Table 2 .

Emotion Analysis of Weibo Comments

Corresponding times for comments are counted, with one hour as the unit, calculating average sentiment scores within each time unit to obtain temporal comment sentiment changes as an important indicator for the public opinion risk index.

[Figure 4: see original paper] Change of Negative Emotion

Using the difference between negative comment counts and remaining comment counts within each time unit as the negative sentiment degree for comparison, as shown in Figure 4. Analysis reveals that during this public opinion development period, negative comment counts always exceeded remaining comment counts in any time unit, indicating obvious negative characteristics of this network public opinion. The negative sentiment degree change trend is generally consistent with total comments—when total comment quantities are high, the negative sentiment degree proportion decreases; when total comment quantities are low, the negative sentiment degree decreases, indicating that sentiment changes have certain positive correlations with network public opinion heat.

4.3 Public Opinion Risk Index

There is no standardized definition for public opinion risk index. This study considers both data sources mentioned above while incorporating sentiment analysis statistics. The advantage of this approach lies in comprehensively considering public opinion heat information from multiple aspects while obtaining positive and negative public opinion information through sentiment analysis results.

Information Weight

Notably, with one hour as the time unit, heat shows obvious periodic changes over time. During late-night periods, public opinion heat significantly decreases. To explore deeper patterns within public opinion changes, this study uses an LSTM deep learning model optimized by intelligent algorithms for prediction, incorporating periodic changes brought by time unit selection.

[Figure 5: see original paper] Change of Network Public Opinion Risk Index

As shown in Figure 7 [Figure 7: see original paper], this public opinion incident reached its maximum risk value 5 hours after outbreak.

4.4 Model Prediction

This study uses the TensorFlow framework in Python to build an LSTM neural network [20], adding an attention mechanism to obtain optimal model results [21]. Based on the network public opinion risk index model constructed above, 77 risk indices in the time series are placed into the model for training, divided into 75% training set and 25% test set.

Finally, overall public opinion development is predicted, with comparison between predicted values and actual real values shown in Figure 8 [Figure 8: see original paper]. Test set prediction errors are shown in Table 4 .

[Figure 6: see original paper] Comparison of Model Prediction

Error Comparison

To evaluate the prediction effect of the established prediction model, representative statistical indicators [20] are selected: MAE (Mean Absolute Error), RMSE (Root Mean Square Error), and their average relative errors as evaluation metrics. The calculation formulas for mean absolute error and root mean square error are:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

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

Smaller evaluation indicator values indicate smaller prediction errors and better prediction effects. Comparison methods and error tables are shown in Table 5 .

Error Comparison Table

The table shows that using the GWO-LSTM model can better train an excellent model. Among numerous prediction models, the trained optimal model achieves the lowest MAE and RMSE on the test set. Meanwhile, compared with LSTM networks without parameter tuning, the parameters obtained by the optimization algorithm reduce MAE by 48% and RMSE by 49%.

4.5 Model Validation and Evolution Analysis

This study selects another topic under this incident, "Sichuan University Subway Incident Student Receives School and Party Probation," to verify model accuracy. Following the above model, a network public opinion risk index model is established for this topic. The trained model from this section is saved to predict public opinion risk indices for the new topic. Results are shown in Figure 7.

[Figure 7: see original paper] Model Prediction Effect on New Topic

Through chart data comparison, black represents actual values and red represents the optimized LSTM model, with the two being closest, achieving an average absolute error of 13.8%. The figure shows that in the test time series, both BP neural networks and LSTM neural networks can relatively accurately predict public opinion change trends, but the PSO-BP network model shows significant gaps with actual values, while the LSTM prediction model optimized by GWO hyperparameters has prediction accuracy almost identical to actual values, with obviously superior prediction effects. This indicates that LSTM neural networks have good adaptability for time series prediction, and the LSTM model optimized by GWO hyperparameters is more excellent in training and has higher prediction accuracy compared to LSTM models with conventional parameters.

Starting from the basic point of researching how university online public opinion risk changes over time, this study focuses on the concept of risk and incorporates sentiment analysis as an important consideration factor, using LSTM to predict trends in public opinion risk index changes and analyzing evolutionary development of public opinion risk under human intervention. Through model validation and evolutionary analysis using recent public opinion examples, prediction results demonstrate the importance of intervention for public opinion control. This research enriches the content of public opinion prediction research and provides references for public opinion control evolution research, offering certain theoretical value. Using this model can effectively identify and respond to public opinion changes, preventing crisis occurrence or enabling rapid action at the initial crisis stage to limit crisis diffusion.

To use this model for evolutionary analysis of university public opinion events, consider human intervention on heat at specific moments. At the second wave peak in the time series, intervention is applied to reduce risk by 70%, 50%, and 20%.

[Figure 8: see original paper] Prediction of The Test Set

As shown in the evolutionary analysis chart under the validation set in Figure 8, when human intervention reduces public opinion heat and its risk value, subsequent public opinion development stabilizes more quickly. Moreover, results show little difference in subsequent stable development between reducing the risk index by 30% and by 70%. However, reducing the risk index by only 30% will have a relatively large impact on subsequent development compared to no intervention. This indicates that timely intervention and control of public opinion development have a certain "butterfly effect" on overall public opinion development, while allowing public opinion to ferment naturally or with untimely control will cause significant social benefit losses.

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Corresponding Author: Ling Chunyu, ORCID: 0009-0008-8214-4388, Email: 44381269@qq.com

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[3] Zhao Xiangkang. Zwsj-data.xlsx. ZhiWei Seeing heat data.

Author Biographies:

Cao Chao (born 1993), Master' s degree, Assistant Researcher. Research interests: university online public opinion, network ideology.

Luo Fanglu (born 1987), Ph.D., Associate Professor, Researcher at Hunan Education Public Opinion and Risk Prevention Research Base. Research interests: national security, network ideology.

Corresponding Author: Ling Chunyu (E-mail: 469190629@qq.com, born 1977), Master' s degree, Lecturer. Research interests: university party building.

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