

# An Analysis of the Evolution of Online Public Opinion on Public Health Emergencies by Combining CNN-BiLSTM + Attention and LDA

Hanlu Lei<sup>1</sup>, Hu Wang<sup>1</sup>, Linli Wang<sup>1</sup>, Yuhang Dong<sup>1</sup>, Jingjie Cheng<sup>2</sup>, Kui Cai<sup>2</sup>

<sup>1</sup>School of Management, Wuhan University of Technology, Wuhan, China

<sup>2</sup>Wuhan Huaxia University of Technology, Wuhan, China

Email: fleihanlu@163.com

**How to cite this paper:** Lei, H.L., Wang, H., Wang, L.L., Dong, Y.H., Cheng, J.J. and Cai, K. (2023) An Analysis of the Evolution of Online Public Opinion on Public Health Emergencies by Combining CNN-BiLSTM + Attention and LDA. *Journal of Computer and Communications*, 11, 190-199.  
<https://doi.org/10.4236/jcc.2023.114009>

**Received:** March 30, 2023

**Accepted:** April 27, 2023

**Published:** April 30, 2023

## Abstract

In this paper, the Foxconn epidemic event in Zhengzhou was taken as an example to analyze the evolution of online public opinion on public health emergencies. In order to improve the performance of online public opinion analysis, based on the life cycle theory and LDA theory, the emotional changes of Internet users in four stages of the Foxconn incident centered on the evolution of inscription were divided. The emotions of netizen speech at different stages are analyzed based on CNN-BiLSTM + Attention model, which uses Convolutional Neural Network (CNN) to extract local features. Bi-directional Long Short-Term Memory (BiLSTM) is used to efficiently extract contextual semantic features and long distance dependencies, and then combined with attention mechanism to add emotional features. Finally, Softmax classifier realizes text emotion prediction. The experimental results show that: compared with TextCNN, BiLSTM, BiLSTM + Attention, CNN-BiLSTM model, the emotion classification model has better effects in the accuracy rate, accuracy rate, recall rate and F value. By analyzing the emotional distribution and evolution trend of public opinion under "text topic", the paper accurately deconstructs the development characteristics of public opinion in public health emergencies, in order to provide reference for relevant departments to deal with public opinion in public health emergencies.

## Keywords

Public Health Emergencies, Emotional Evolution, CNN-BiLSTM, Attention Mechanism, LDA

## 1. Introduction

With the popularization of Internet information technology, social networking

platforms such as Weibo, Wechat, Zhihu and XiaoHongshu have become important ways for netizens to express their opinions and emotions. In recent years, public health emergencies have occurred frequently, especially the outbreak of the novel coronavirus pneumonia in 2019, which caused many online public opinions, not only throughout the whole process of the incident from beginning to end, but also affected social stability and economic development, and even threatened national security. Therefore, the evolution of online public opinion on public health emergencies has become a hot topic in current research. GAO S *et al.* [1] used fuzzy set qualitative comparative analysis to study the rebound of online public opinion that caused multiple public opinion crises in public health emergencies. In order to reveal the phenomenon and rule of online public opinion resonance in public health emergencies, CHENG Q *et al.* [2] explored the relationship between topic relevancy and online public opinion resonance strength based on Langevin's equation. Based on SEIR model and NetLogo simulation analysis, Li L *et al.* [3] analyzed the communication law of online public opinion in major public health emergencies. CAI M *et al.* [4] revealed the formation and evolution of public opinion on public health emergencies through the temporal network analysis of topics and emotions on social media platforms. In the study of online public opinion of public health emergencies, the above scholars mostly focused on the law of transmission and evolution, and also involved emotion analysis and topic classification, but few analyzed the emotional distribution and evolution of public opinion under the "text topic".

As a subtask in the field of NLP, sentiment analysis has also been widely concerned by scholars in recent years [5] [6] [7] [8] [9]. As a key technology in the field of natural language processing, deep learning has a good performance in the field of sentiment analysis, and has gradually replaced traditional machine learning algorithms. Konate and Du [10] used deep learning models and traditional machine learning models to conduct sentiment analysis experiments on facebook multilingual texts, and proved that the single-layer CNN model had the best performance. CNN has multiple convolution kernels of different sizes to extract features, and has achieved good results in text sentiment classification [11]. Qian Q *et al.* [12] proposed that LSTM model can capture the linguistic role of sentiment words, negative words and intensity words in sentiment expression. Liu G proposed [13] a new unified architecture including bidirectional LSTM (BiLSTM), attention mechanism and convolutional layer. This model can capture both local features of phrases and global semantics of sentences, and experiments show that it is superior to other state-of-the-art sentiment classification models.

The specific work of this paper is as follows: 1) 6897(4806) comments on Zhengzhou Foxconn epidemic incident are crawled on Weibo as experimental data for studying public health emergencies; 2) The life cycle of public opinion on Zhengzhou Foxconn epidemic event based on Baidu index divides the event into four stages; 3) Data preprocessing, data cleaning was carried out to retain 4806 valid data finally, and unnecessary components such as stop words and

punctuation were removed from the text data to facilitate subsequent feature extraction and representation. 4) The epidemic dataset of HIT SMP2020 microblog Emotion Analysis Competition is used to train the deep learning model, and the comparison experiment of sentiment classification model is carried out. 5) LDA model and CNN-BiLSTM + Attention model are used to analyze the topic and sentiment of negative public opinion at each stage, and the evolution characteristics of public opinion of this event are explored.

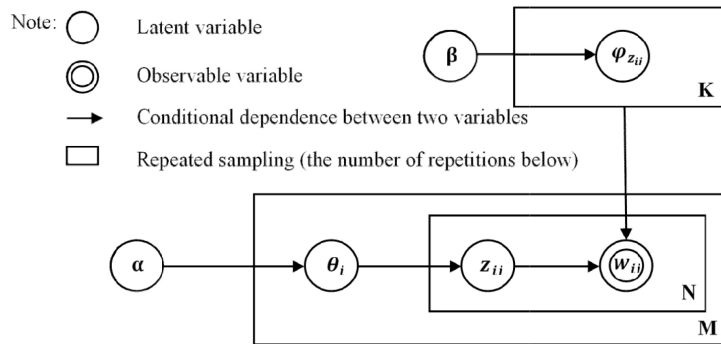
## 2. Related Theory and Model Construction

### 2.1. Life Cycle Theory

In 1986, S. Fink [14], in the field of crisis management, divided the spread of emergency crisis into four stages: incubation period, outbreak period, spreading period and recovery period. In the whole process from the onset to the end of the crisis, each element has different characteristics, and its life characteristics are different in each development stage of the crisis, and the evolution of each stage in the life cycle is also different, which is not a complete linear development. Now some scholars put forward four-stage theory [15], five-stage theory [16] and six-stage theory [17] based on different events. This paper chooses the four-stage division scheme to divide the network public opinion of public health emergencies into latency period, outbreak period, spread period and decline period.

### 2.2. LAD Topic Classification Mode

The LDA model gives the topic of each document in the document set in the form of a probability distribution [18], and then performs topic clustering or text classification according to the topic distribution. The modeling process is shown in **Figure 1**.  $d_i = \{d_{is} | s \in \{1, 2, \dots, S\}\}$  is defined as a set of  $M$  documents;  $d_i = \{d_{is} | s \in \{1, 2, \dots, S\}\}$  is a document consisting of  $S$  sentences;  $w_i = \{w_{ij} | j \in \{1, 2, \dots, N_i\}\}$  is the set of words obtained by tokenizing the document;  $N_i$  is the number of words in document  $d_i$ ;  $N = \sum_{i=1}^M N_i$  is the number of words in document  $D$ ;  $z_i = \{z_{ij} | j \in \{1, 2, \dots, N_j\}\}$  is the set of topics corresponding to the set of words, and  $K = |\bigcup_{i=1}^M z_i|$  is the total number of topics in the set  $D$  of documents.



**Figure 1.** LDA topic analysis model.

### 2.3. Sentiment Classification Model

Based on the relevant research of Chinese and foreign scholars and other classical deep learning experiments. We choose the sentiment classification model of CNN-BiLSTM + Attention. The specific structure is shown in **Figure 2** below. The model uses Convolutional Neural Network (CNN) to extract local features, uses Bi-directional Long Short-Term Memory (BI-LSTM), and uses bi-directional long short-term memory (BI-LSTM) to extract local features. BiLSTM efficiently extracts contextual semantic features and long-distance dependencies, and combines attention mechanism to add emotional features. Finally, the Softmax classifier was used to predict the sentiment of the text.

## 3. Experiments

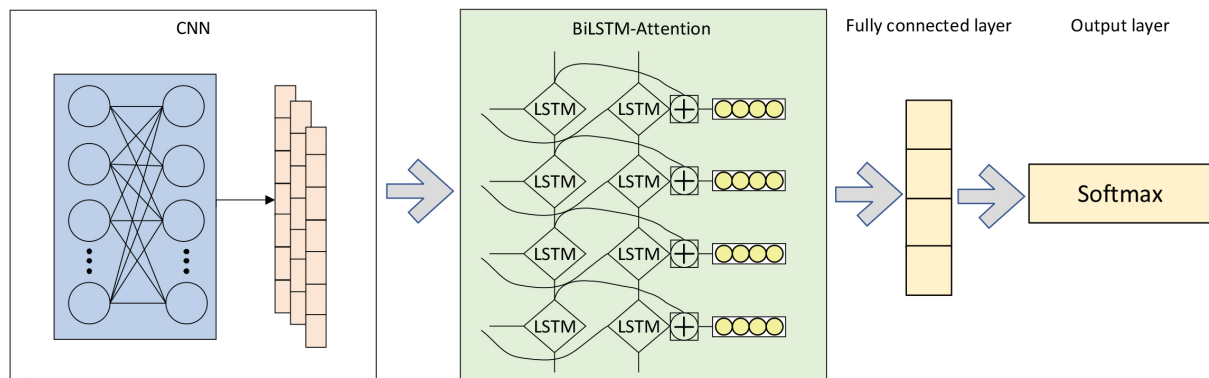
The experiment environment of this paper is Windows11 (64 bit) operating system, processor AMD R7-5800H, memory 32 GB, development tool Anaconda3, programming language python 3.7.

### 3.1. Data Acquisition and Processing

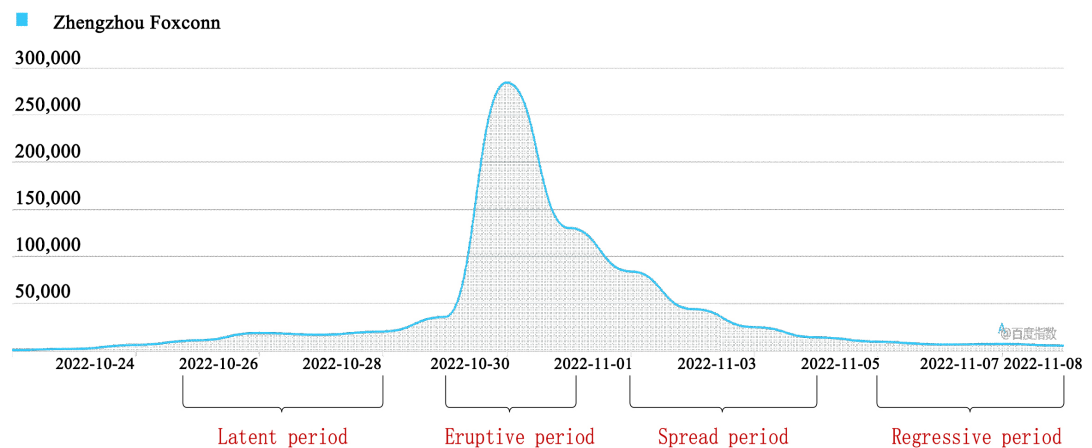
The Foxconn epidemic incident in Zhengzhou in 2022 has attracted wide public attention and caused serious negative social impact and certain economic losses. Although the event period of this public opinion event is not long, due to the low attention in the early stage, rumors are rampant and public opinion is repeated, which is of great research significance as an emergency public health safety case. Therefore, this paper takes the microblog data platform as the source of text data, and collects relevant microblogs with “Zhengzhou Foxconn” as the key word through python custom crawler. The time range of data collection is from October 25 to November 8, 2022. After data cleaning, 4806 valid data were finally obtained.

### 3.2. Life Cycle Division of Zhengzhou Foxconn Incident

Late at night on October 25, 2022, Zhengzhou Foxconn logged on to Weibo for hot search. Soon on October 26, Foxconn issued a statement that the news of “about 20,000 people in Zhengzhou park were diagnosed” was grim and untrue, but many netizens remained skeptical about the matter. Later in the night of October 29, it was revealed that some Foxconn employees could not stand suffering and chose to walk home. The public opinion rose again, and Foxconn responded to respect individual wishes. Finally, on November 2, Zhengzhou government issued 15 policies to care for Foxconn employees, and the public opinion incident entered a period of decline. **Figure 3** shows the life cycle of public opinion about Zhengzhou Foxconn in Baidu index. According to the life cycle theory, the life cycle of network public opinion about Foxconn incident is divided into: 1) Latent period: October 25-28; 2) Eruptive period: October 29-31; 3) Spread period: November 01-04; 4) Regressive period: November 05-08.



**Figure 2.** CNN-BiLSTM + Attention model framework.



**Figure 3.** Life cycle of network public opinion on foxconn incident.

### 3.3. Model Training

By sorting out the data, 646 data were obtained in the incubation period, 1592 data were obtained in the outbreak period, 1063 data were obtained in the epidemic period, and 332 data were obtained in the regression period. Firstly, the document is segmented into words and stop words, and then the LDA model is used to analyze the negative public opinion in each stage. Coherence is used to evaluate the model and determine the optimal topic, and the public opinion topic is summarized by the divided topic words. Then we use the HIT SMP2020 microblog sentiment Analysis Competition epidemic dataset to train the deep learning model, with a total of 18,700 comments. Then the comparison experiment of sentiment classification is carried out.

The dataset is split into training, validation, and test sets in a 6:2:2: random ratio. The distribution is as follows (**Table 1**).

In the preprocessing part, we use jieba tool to import the stop words list and Baidu dictionary for Chinese word segmentation. In terms of neural network parameters setting, batch\_size is set to 16, the number of cnn convolution kernels is set to 256, the size of the convolution kernel is set to 5, the activation function is “relu”, and the number of forward and backward neurons of the BiLSTM model is set to 50, and dropout technology is used to prevent overfit-

ting. Its parameter is set to 0.25. Then the model comparison experiment was carried out, and finally the experimental results as shown in the table were obtained (**Table 2**).

The table shows that CNN-BiLSTM + Att improves Accuracy, Precision, Recall, and F1 values to some extent in the sentiment classification comparison of this dataset. The subsequent analysis trained this model to predict the sentiment of the data.

**Table 1.** Dataset description.

Number	Label	Dataset		
		Train	Val	Test
0	Positive	6090	2030	2030
1	Negative	5130	1710	1710
Total		11,220	3740	3740

**Table 2.** Performance evaluation of sentiment classification algorithms.

Method	Accuracy	Precision	Recall	F1
Textcnn	0.7957	0.8094	0.7957	0.7917
BiLSTM	0.8838	0.8838	0.8838	0.8838
BiLSTM + Att	0.9017	0.9019	0.9017	0.9017
CNN-BiLSTM	0.8958	0.8963	0.8958	0.8959
CNN-BiLSTM + Att	0.9068	0.9068	0.9068	0.9068

### 3.4. Evolution Analysis of Life Cycle Stages of Zhengzhou Foxconn Incident

#### 3.4.1. Analysis of Latent Period Evolution Characteristics

Although this event had a certain degree of popularity in the incubation period, it was not paid attention to by relevant personnel due to the limited scope of dissemination, and the best time for public opinion guidance was missed. The trained CNN-BiLST + Attention sentiment classification model was used to classify the review data at this stage, and 542 negative emotions and 104 positive emotions were obtained. At this stage, the negative sentiment rises rapidly in a short time, but the overall public opinion influence is low due to the small spread range. Through the LAD model, the optimal number of three categories of topics was confirmed, and the topics of public opinion were as shown in **Table 3**, which mainly focused on: 1) When it was revealed that 20,000 people were diagnosed with the disease in Zhengzhou Foxconn, the public felt panic and worried about their own safety and travel problems, so they called on Foxconn to isolate and control. 2) The public appealed to the relevant departments to refute the rumor as soon as possible. 3) Although Foxconn denied the rumor in time, the public still remained skeptical, expressing serious dissatisfaction with Foxconn's management because of the safety issues related to their own lives.

**Table 3.** Topic of latent period.

Number	Subject Words (Part)	Topic generalization
1-1	Zhengzhou, quarantine, epidemic, Foxconn, society, 20,000	The public called for quarantine after it was revealed that 20,000 people had been diagnosed with Foxconn in Zhengzhou.
1-2	Foxconn, epidemic, Zhengzhou, refuting rumors, diagnosis, data, hope	The public has called on Foxconn to dispel the rumors as soon as possible.
1-3	Official, rumor, false, heat, unseal, do nucleic acid, close contact	The public remains skeptical of Foxconn's response.

### 3.4.2. Analysis of Eruptive Period Evolution Characteristics

Since only companies reported on the situation during the incubation period, and the government did not respond, public sentiment intensified as more details emerged. There were 1133 negative emotions and 459 positive emotions in this stage. The negative public sentiment was intensified, and the negative sentiment pushed the heat of public opinion to the highest, but there were still some encouraging remarks to the people of Zhengzhou. Through the LAD model, the optimal number of three types of topics are confirmed, and the topics of public opinion are shown in **Table 4**, which mainly focus on: 1) Although Foxconn has refuted the rumor that 20,000 people were previously diagnosed as false news, it still aroused the public's doubts about Foxconn's enterprise management. The public believes that Foxconn ignores the life safety of employees and only pursues the interests of the company during the epidemic period, and hopes Foxconn to give a response. 2) On October 29, the incident of "Foxconn employees returning home on foot" was exposed on the Internet, which further aroused the public's sympathy for the employees, and believed that Foxconn should protect the life safety of employees and make reasonable arrangements for infected and non-infected employees. 3) After the incident of "Foxconn employees returning home on foot" broke out, Foxconn responded that it absolutely respected the opinions of employees and would protect their lives. Public trust in Foxconn is insufficient, and the Henan government is called to pay attention to this incident. Then, on Oct. 30, the Henan government said it had dispatched a working group to Zhengzhou Foxconn to work with relevant departments to study corresponding measures.

**Table 4.** Topic of Eruptive period.

Number	Subject Words (Part)	Topic generalization
2-1	Foxconn, epidemic, capitalists, Zhengzhou, go to work, employees	There has been public anger at Foxconn for putting the interests of the company ahead of the lives of its workers



**Continued**

2-2	Foxconn, epidemic, homecoming, employees, infection, poor, video	Expressed sympathy for the returning workers and demanded a response from Foxconn
2-3	Zhengzhou, Henan, walking, homecoming, government, attention, employees	He called on Henan province to protect employees who are preparing to return home due to the epidemic

**3.4.3. Analysis of Spread Period Evolution Characteristics**

Foxconn's timely response and the government's support during the outbreak of public opinion made the public opinion gradually stable and the heat gradually decreased, and then the rumor of "death occurred in Foxconn Room 726" appeared on November 1, which aroused the heat again. Through the prediction, 750 negative emotions and 313 positive emotions are obtained. At this stage, the masses have emotional twists and turns, resulting in many negative emotions. The optimal number of three types of topics is confirmed through the LDA model, and the topics of public opinion are shown in **Table 5** below: 1) The previous response from Foxconn and the local policy is still skeptical, and Foxconn is required to publish the real data, do not conceal from the public, and express that the public has the right to know. 2) People are panicked about the current epidemic prevention policies of enterprises in Zhengzhou, and they are worried about the lives of people in Zhengzhou. 3) On November 1, Foxconn was exposed to the incident of "death in Room 726", which aroused public fear and questioned Foxconn again. The occurrence of this incident triggered a second emotional wave when the mood was about to calm down. Then Foxconn once again refuted the rumor that the "Room 726" incident was not true, indicating that someone maliciously forged the video. On November 2, Zhengzhou government issued 15 care policies for Foxconn employees.

**Table 5.** Topic of Spread period.

Number	Subject Words (Part)	Topic generalization
3-1	Foxconn, epidemic, infection, data, information, publication, government	Officials remain skeptical of Foxconn's response and have called for the number of infections to be released.
3-2	Zhengzhou, epidemic, epidemic prevention, terrible, virus, enterprise, government	The public has expressed panic over the current epidemic control
3-3	Foxconn, Enterprise, Room 726, scary, problem	"Room 726" incident was reported on the Internet and raised questions about Foxconn again

**3.4.4. Analysis of Regressive Period Evolution Characteristics**

In the fading period of public opinion on the Foxconn incident, the government and enterprises have made positive responses in the early stage, which also ensured the rights and interests of employees to a certain extent, and the heat of



the incident has gradually decreased. Through the model prediction, we get 150 negative emotions and 182 positive emotions, indicating that the public sentiment has gone to a good trend. The optimal number of category 1 topics is confirmed through the LDA model, and the topics of public opinion are shown in **Table 6** below: It is mainly focused on: At the conference on Covid-19 prevention and control held in Zhengzhou on November 3, it was proposed that there were no severe cases in Zhengzhou Foxconn Science Park, and a small number of people remained skeptical, calling on the government to pay attention to epidemic prevention. Subsequently, the government responded that it has taken a series of prevention and control measures under the guidance of experts, and achieved initial results.

**Table 6.** Topic of Regressive period.

Number	Subject Words (Part)	Topic generalization
4-1	Foxconn, epidemic, severe, enterprise, infection, data, Epidemic prevention, containment, community	The public called on the government to pay attention to epidemic prevention and ensure the normal life of Zhengzhou people.

## 4. Conclusion

Based on LAD topic classification model and deep learning sentiment classification model, this paper analyzes the content evolution of public opinion topics and their emotional tendencies at different stages of public health emergencies, and further judges the characteristics of public opinion at each stage. In the aspect of sentiment analysis, the CNN-BiLSTM + Attention model is selected to train the epidemic-related comments, and the model is verified from four aspects of Accuracy, Precision, Recall and F1, which shows that this model can be well applied to the sentiment classification of public opinion. Through the analysis of the Foxconn incident, it is found that in the development of public opinion on public health emergencies, the timely response of relevant departments is the key factor, which guides the whole public opinion. From this point of view, the relevant departments should set up an effective public opinion early warning mechanism to prevent public opinion.

## Conflicts of Interest

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

## References

- [1] Gao, S., Zhang, Y. and Liu, W.H. (2021) How Does Risk-Information Communication Affect the Rebound of Online Public Opinion of Public Emergencies in China? *Int. J. Environ. Res. Public Health*, **7760**, 14. <https://doi.org/10.3390/ijerph18157760>
- [2] Cheng, Q., Zhang, Y.G. and Li, Y.Q. (2021) Topic Relevance of Public Health Emergencies Influence on Internet Public Opinion Resonance: Simulation Based on

- Langevin's Equation. *Mathematical Problems in Engineering*, **2021**, Article ID: 5818346. <https://doi.org/10.1155/2021/5818346>
- [3] Li, L., Wan, Y.J., Plewczynski, D. and Zhi, M. (2022) Simulation Model on Network Public Opinion Communication Model of Major Public Health Emergency and Management System Design. *Sci. Program.*, **2022**, Article ID: 5902445. <https://doi.org/10.1155/2022/5902445>
  - [4] Cai, M., Luo, H. and Cui, Y. (2021) A Study on the Topic-Sentiment Evolution and Diffusion in Time Series of Public Opinion Derived from Emergencies. *Complexity*, **2021**, Article ID: 2069010. <https://doi.org/10.1155/2021/2069010>
  - [5] Chen, Y. (2015) Convolutional Neural Network for Sentence Classification. University of Waterloo.
  - [6] Liao, S.Y., Wang, J.B., Yu, R.Y., Sato, K. and Cheng, Z.X. (2017) CNN for Situations Understanding Based on Sentiment Analysis of Twitter Data. *Procedia Computer Science*, **111**, 376-381. <https://doi.org/10.1016/j.procs.2017.06.037>
  - [7] Cao, W., Song, A. and Hu, J. (2017) Stacked Residual Recurrent Neural Network with Word Weight for Text Classification. 277-284.
  - [8] Zhang, Y., Meng, J.E., Venkatesan, R., Wang, N. and Pratama, M. (2016) In 2016 *International Joint Conference on Neural Networks (IJCNN)*. 1562-1569 (IEEE).
  - [9] Wang, L., Wang, Z.G. and Liu, S. (2016) An Effective Multivariate Time Series Classification Approach Using Echo State Network and Adaptive Differential Evolution Algorithm. *Expert Systems with Applications*, **43**, 237-249. <https://doi.org/10.1016/j.eswa.2015.08.055>
  - [10] Konate, A. & Du, R. (2018) Sentiment Analysis of Code-Mixed Bambara-French Social Media Text Using Deep Learning Techniques. *Wuhan University Journal of Natural Sciences*, 237-243. <https://doi.org/10.1007/s11859-018-1316-z>
  - [11] Kim, Y. (2014) Convolutional Neural Networks for Sentence Classification. Doha, Qatar, 1746-1751: Association for Computational Linguistics. <https://doi.org/10.3115/v1/D14-1181>
  - [12] Qian, Q., Huang, M., Lei, J. and Zhu, X. (2017) Linguistically Regularized LSTM for Sentiment Classification. Vancouver, Canada, 1679-1689: Association for Computational Linguistics. <https://doi.org/10.18653/v1/P17-1154>
  - [13] Liu, G. and Guo, J. (2019) Bidirectional LSTM with Attention Mechanism and Convolutional Layer for Text Classification. *Neurocomputing*, 325-338. <https://doi.org/10.1016/j.neucom.2019.01.078>
  - [14] Fink, S. (1989) Crisis Management: Planning for the Inevitable. American Management Association, New York.
  - [15] Wu, X.J. (2018) Topic Evolution Analysis of Network Public Opinion Based on Microblog Text. Nanjing University, Nanjing.
  - [16] Xie, K.F., Zhao, S., Chen, G. and Cai, W.J. (2010) Research on the Life Cycle Theory and Cluster Decision-Making of Network Public Opinion Emergencies. *Journal of Wuhan University of Technology (Social Science Edition)*, 482-486.
  - [17] Li, G. and Dong, Q. (2011) Research and Empirical Analysis on the Propagation Process of Enterprise Network Public Opinion under the Environment of Web2.0.
  - [18] Chen, X.M., Gao, C. and Guan, X.H. (2015) The Network Public Opinion Point Extraction Method of LDA Theme Model % J Books Intelligence Work. 21-26.