

Retraction

Retracted: A Study on the Topic-Sentiment Evolution and Diffusion in Time Series of Public Opinion Derived from Emergencies

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] M. Cai, H. Luo, and Y. Cui, "A Study on the Topic-Sentiment Evolution and Diffusion in Time Series of Public Opinion Derived from Emergencies," *Complexity*, vol. 2021, Article ID 2069010, 23 pages, 2021.

Research Article

A Study on the Topic-Sentiment Evolution and Diffusion in Time Series of Public Opinion Derived from Emergencies

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With the development of the Internet, social media has become an important platform for people to deal with emergencies and share information. When a public health emergency occurs, the public can understand the topics of the event and perceive the sentiments of others through social media, thus building a cooperative communication network. In this study, we took the public health emergency as the main research object and the natural disaster, accident, and social security event as the secondary research object and further revealed the law of the formation and evolution of public opinion through the analysis on temporal networks of topics and sentiments in social media platforms. Firstly, we identified the derived topics by constructing the topic model and used the sentiment classification model to divide the text sentiments of the derived topics into two types: positive sentiment and negative sentiment. Then, the ARIMA time series model was used to fit and predict the evolution and diffusion rules of topics and sentiments derived from public opinions on temporal networks. It was found that the evolution law of derived public opinions had similarities and differences in various types of emergencies and was closely related to government measures and media reports. The related research provides a foundation for the management of network public opinion and the realization of better emergency effects.

1. Introduction

With the development of the economy and the deepening of the social transformation period, social contradictions are further aggravated, and the frequent occurrence of emergencies has become a severe test faced by social governance [1]. Based on relevant research, the emergency is defined as the event that poses a serious threat to human life, health, property, and safety and is further divided into four types: natural disaster, accident, public health, and social security event [2, 3]. For example, the COVID-19 outbreak in 2020 is a typical public health event, which has brought serious economic losses and human casualties to all countries in the world and posed serious challenges to the governance of social order and the maintenance of social stability. When public health events or other types of emergencies occur, people will carry out heated discussions on social media around the relevant events and try to obtain information

related to the event and understand the situation related to the event with the convenience of social media, to reduce the impact brought by the uncertainty [4]. However, the immediacy of emergency makes the response of the government and media lag, which cannot meet the explosive demand of the public for the information related to the event, often leaving the public in the situation of lack of information and psychological anxiety. At this time, the public is vulnerable to the influence of false information and tends to form negative emotions, which makes emergency management more complex, weakens social cohesion, impacts social order and social stability, and finally causes social crisis [5].

In recent years, as an integral part of modern society, social media has penetrated everyone's daily life. According to the statistics of relevant agencies, the global users of social media have exceeded 4.7 billion in 2021, which means that, on average, 6 out of 10 people in the world are using social

media [6]. Through the social network established in the social media platform, on one hand, the public can express their views conveniently, share their experiences and thoughts, and make comments on the event. On the other hand, they can also interact with other social media users through functions such as thumb up, retweet, and comment [7]. The advantages of social media in instant communication and interaction also make it play an increasingly important role in the emergency management of emergencies [8]. Therefore, when an emergency occurs, the public tends to use social media to collect and disseminate information and form a cooperative communication network on the social media platform through the exchange of pictures, texts, and other information, to realize information sharing and the exchange of views [9], which also provides favorable conditions for rescue and management after the occurrence of emergencies.

In addition, the occurrence of emergencies is often not isolated, but there will be further evolution and development in the context of time and space and under the action of the environment derive to other related events. When an emergency occurs, the public's discussion and concern about the emergency itself is usually defined as the original public opinion of the emergency, and the public's discussion and concern about the related events evolved in the context of time and space of the emergency is defined as the derived public opinion [10]. In short, the communication process of emergencies on social media is influenced by various external factors and thus forms other interrelated event contents. Derived public opinions are derived from the public's discussion and attention on related events after the differentiation of emergencies in social networks. The typical characteristic of derived public opinion is the transfer of evaluation object, which is different from the research object of original public opinion. Compared with the original public opinion, the derived public opinion of an emergency is more concealable. In the early stage of an emergency, it hides in the evolution of the original public opinion and is difficult to attract public attention. However, when the original public opinion of the emergency has evolved to a certain stage, or when the control and treatment measures for the emergency are ineffective, the derived public opinion will often break out quickly. On the one hand, it attracts the attention of the public and becomes a hot topic in society, further expanding the scope of impact and the degree of function of the emergency [11]. On the other hand, it will have an impact on the original public opinion, aggravate and upgrade the public opinion, increase the difficulty of public opinion management in the social network, and further impact the social order and social stability [12]. Therefore, the relevant analysis of public opinion derived from emergencies based on public health events is not only conducive to the prediction and emergency management of emergencies but also to reducing the negative impact of online public opinion, which is an important guarantee for the realization of network security governance and the maintenance of social order and social stability.

In this study, we take the public opinion derived from public health emergencies as the main research object and

introduce other types of emergencies such as natural disasters, accidents and disasters, and social security as the secondary research object. Combined with the time series analysis method, this study attempts to explore the topic-sentiment evolution law of public opinions derived from the public health event on temporal networks and further compares the commonality and difference of topic-sentiment evolution law in different types of emergencies. Through the above analysis, this study attempts to answer the following questions:

- (1) What are the characteristics of the topic evolution of public opinions derived from public health emergencies on temporal networks? Are there any differences from other types of emergencies?
- (2) What are the characteristics of the emotional evolution of public opinions derived from public health emergencies on temporal networks? Are there any differences from other types of emergencies?

The rest of this paper is structured as follows. In the next section, the study will review the public opinion derived from emergencies and the related studies on topic-sentiment evolution. The third part introduces the method of this paper, mainly including the principle and advantages of the model used in this paper. The fourth part introduces the research design of this paper, including data collection and preprocessing, topic model, sentiment model, and time series model. The fifth part shows the research findings of this paper and reveals the topic and sentiment evolution rules of derived public opinions on temporal networks. The sixth part is the research conclusion of this paper, which summarizes the foregoing and puts forward the further direction for the follow-up research.

2. Related Studies

2.1. Research on Public Opinion Derived from Emergencies. Derivative public opinion is formed in the discussion and interaction of social media users on related events under the evolution of emergencies. These related events are often referred to as secondary or derivative events, which evolve from the original events. Among them, original events usually refer to the emergent events that first appear and then evolve and spread, while secondary events and derivative events are a series of related events that evolved from original events under the action of the spatiotemporal situation [10]. The difference between the two is that the secondary event and the original event are consistent in terms of type and cause of the occurrence, with continuity and linkage, while the derivative event is quite different from the original event in terms of type and cause of occurrence [11]. In short, the secondary event is triggered by the original event, acts on the same object as the original event, and is of the same type as the original event. In addition, the derived event is also the event caused by the original event, but the research object has changed and the type is different from the original event. For example, the governance and prevention events caused by public health events are called secondary events, but the changes in stock prices caused by

public health events belong to the derived event. In addition, from the perspective of the content of related events, some scholars believe that related events are reflections of original events from different aspects, and they name related events as subevents [12, 13]. However, there are few studies on the definition and feature description of associated events, and there is a lack of authoritative definition standards and discriminant framework. Therefore, to facilitate the follow-up research work, a series of related events evolving in the context of time and space of emergencies are uniformly referred to as derivative events.

Online public opinion on emergencies refers to the synthesis of attitudes, opinions, and sentiments expressed on social networks around the occurrence and dissemination of emergencies in a certain time and space with social media platforms as communication channels [14]. Derived public opinion refers to the social media users expressing their views, opinions, and evaluations on the derivative events of emergencies through the network platform [15]. Existing related studies that take derived public opinion as the research object mainly focus on the dissemination and prediction of derived public opinion, the evolution mechanism of derived public opinion, the formation and response of derived public opinion, and so on. Among them, the dissemination and prediction of derived public opinion are mainly studied. On the one hand, information mining methods are used to understand the dissemination mechanism of derived public opinion; on the other hand, methods such as machine learning are used to realize the prediction of derived public opinion. For example, some scholars established a digital model to simulate the propagation dynamics of network rumors in social networks, to identify the propagation characteristics of network rumors, a special derivative public opinion, in social networks [16]. In addition, some scholars established a control model and explained the propagation mode of derived public opinion based on the propagation mechanism, to realize the control of derived public opinion [17]. As for the prediction of the derived public opinion, on the one hand, recent studies use machine learning algorithms such as HDP to analyze the text semantics to realize the classification of the derived public opinion [18]. On the other hand, deep learning algorithms such as neural networks are used to realize the prediction of the derived public opinion through the analysis of social media data [19].

At present, the research on the evolution mechanism of derived public opinions mainly adopts the method of case study and analyzes the evolution of derived public opinions in social networks by selecting specific emergencies as research objects. Some studies choose a single emergency event as the research object. For example, based on the investigation of an emergency accident and disaster event, the evolution path and internal logic of derived public opinions are explored from the interaction and game among the government, media, and the public [20]. There are also studies taking large-scale emergent event data sets as research objects. For example, based on the analysis of 101 emergent event data sets, the changes of online public opinion in time and space are explored, providing a rich

research basis for the evolution mechanism of derived public opinion [21]. The third aspect of related research on derivative public opinion focuses on the formation reasons and coping strategies of derivative public opinion and provides theoretical summarization of derivative public opinion from a multidisciplinary perspective. For example, some scholars described the propagation mode of derived public opinions in social networks through the epidemiological model and explained the reason why expert intervention and government action cannot play a role from the perspective of time delay [22]. From the perspective of competitive diffusion, some scholars also proposed network interruption strategy and balance strategy to deal with the spread of derivative public opinions in social networks, to control the derivative public opinions, and reduce the damage caused by negative public opinions such as rumors [23].

To sum up, the emergence of derivative public opinion has attracted the attention of all sectors of society and become a key topic of research by scholars. However, the current research on derivative public opinion mainly focuses on the formation reasons and countermeasures of the derivative public opinion, and there is a lack of sufficient exploration of the evolution of the derivative public opinion in the time scale. Therefore, we introduce the time series model to analyze the evolution law of public opinion derived from emergencies in social networks from the perspective of time series, to make contributions to the governance of public opinion derived from emergencies and the maintenance of network order.

2.2. Topic Research on Network Public Opinion. With the development of the Internet and information technology, people have become accustomed to getting information from social media. However, the complexity and diversity of information in social media make it more difficult for us to find the information we want. Using the topic discovery method to analyze topics from event news can not only help people better understand the occurrence and evolution of the event but also analyze the issues of public concern and understand the public opinion and focus. Therefore, the analysis method of topic discovery has attracted the attention of many scholars and has been widely applied in the related research of online public opinion [24].

At present, the topic research of online public opinion on emergencies mainly focuses on the topic discovery and transmission evolution of online public opinion. Among them, the topic discovery of network public opinion is mainly aimed at the identification of the unexpected event topic in social networks, or the improvement and optimization of the accuracy of the prediction model based on the original model. Cluster analysis and topic models are usually adopted in the research. The former is mainly based on the clustering assumption that the similarity of documents of the same class is large and the similarity of documents of different classes is small, and then the text information is transformed into digital information and processed by the machine learning method. For example, some studies use the large-scale text data in social media to detect the tweet event

monitoring system based on subdivision and, based on considering the frequency distribution and the similarity of information content, detect the tweet segments of emergency events as event fragments and then cluster the event fragments into the events to realize the identification of relevant events [25]. There are also studies on the use of machine learning clustering algorithms to identify topic trends in social media and provide meaningful analysis to synthesize accurate descriptions of each topic [26]. The latter is based on the topic discovery tool widely used in text mining to automatically find the potential hidden topics and model them from the large-scale text data. The most widely used model is LDA (Latent Dirichlet Allocation) model and its improved model [27]. For example, the LDA model is used to detect and classify the evolution of topics in social networks when public health emergencies occur [28]. Based on the LDA model, TS-LDA (Trend Sensitive-Latent Dirichlet Allocation) model is proposed to extract potential topics from text information more effectively [29].

The transmission evolution of network public opinion mainly focuses on the communication mechanism and evolution law of emergency topics in social networks. Through the analysis of large-scale social media data, it tries to depict the communication path of event topics in social networks based on the evolution model. Relevant researches focus on establishing the evolution model of the emergency topic in the social network or realizing it by dividing the evolution life cycle of the emergency topic in the social network. For example, based on the OLDA (Online LDA) topic evolution model, combined with the correlation between topics in different time segments, the topic evolution of online public opinion has been effectively tested [30]. Some studies combine the LDA model with the improved Birch hierarchical clustering method to propose a new text enhancement strategy, to expand the content of social media with short text characteristics, and then extract the topic evolution characteristics of network public opinions [31]. In addition to the research based on topic models such as LDA, some scholars had also introduced social network analysis method to construct topic evolution model based on the network matrix formed by forwarding relationship and further explored the interaction and evolution mechanism of event topics under the influence of environment in the communication of public opinion [32]. In addition, the evolution of the topic of emergencies in the life cycle has also attracted the attention of many scholars. For example, based on the amount of information about the event topic in different periods, the evolution of online public opinion is divided into four stages: initial stage, outbreak stage, decline stage, and end stage [33]. Or based on the nature of the events, such as choosing a public health emergency as the research object, the network public opinion is divided into different stages according to the local evolution of the virus and hot trends [34]. Some studies also analyze the propagation characteristics of emergencies in different life cycle stages, such as propagation period, control period, and stable period, by simulating the time evolution process of multiple emergencies in social networks [21].

To sum up, the topic research of network public opinion is relatively mature and has achieved good results, but few studies take the topic of derived public opinion as to the research object. Given this, we take the derived public opinion as to the research object, explore the propagation evolution law of the derived public opinion topic, and compare and further explore the derived public opinion law of different types of emergencies.

2.3. Sentiment Research on Network Public Opinion. With the development of Internet technology, the public has become accustomed to using social media in their daily life. Through the extraction of users' posts, comments, tweets, blogs, discussions, and other content in social media, we can analyze the opinions and attitudes of social media users and then infer the individual sentimental trends and behavioral preferences [35]. This method of analysis is often referred to as sentiment analysis, sometimes also referred to as viewpoint analysis, opinion mining [36]. As a branch of natural language processing, it is widely used in information retrieval, text mining, and other fields [37]. For example, based on the test set, relevant researchers conduct retrieval evaluation by making use of the correlation judgment of information objects and topics, to verify the validity and reliability of the information collected by the test set in the retrieval evaluation [38]. In addition, there are also studies based on social network analysis methods to conduct sentiment analysis on the large-scale text data of emergencies in social networks, to understand the communication structure and characteristics of event content [39].

Similar to topic research, transmission evolution is also the focus of online public opinion sentiment research. The sentiment research of network public opinion mainly focuses on two aspects, namely the influencing factors of sentiment and the evolution mechanism of sentiment. Based on the analysis of text information, we can not only understand what factors will affect sentiments but also understand the changes of sentiments in different times and spaces, to realize the analysis and prediction of sentiments. Among them, in the field of commercial products, the influence factor analysis of sentiment is most commonly used. For example, some studies divide the review text of mobile phone products on Amazon into emotions such as joy, sadness, trust, and anger, and understand the influencing factors of consumers' emotions through the analysis of the review text, to provide feedback for mobile phone manufacturers [40]. According to the content characteristics of product reviews, some studies are conducted to understand the influencing factors of user preferences in the reviews, to improve the effectiveness of user perception information in the shopping platform, and provide better suggestions for users in the choice of products [41]. In addition to the research on the influencing factors of emotion, we can also use the sentiment of users in social media to analyze the evolutionary transmission mechanism of network public opinion, to realize the prediction of emergencies. For example, based on the transference and infectivity of sentiment, scholars have used social media data to predict

national political elections based on sentiment analysis methods and achieved good results [42, 43]. Some scholars also used opinion mining and sentiment analysis to predict stock price indexes and trends based on public comments and opinions published on social media platforms [44, 45].

Before we can do sentiment analysis, we need to first categorize the sentiments. The commonly used research methods are mainly divided into two categories: sentiment classification based on sentiment dictionary and sentiment classification based on machine learning [46]. The former is mainly based on the meaning of words and phrases in the document to mark the sentimental direction of the document, through manual screening, based on the existing dictionary, or based on the method of corpus construction. For example, NRC Sentiment Dictionary is used to calculate the sentimental performance of news headlines in eight dimensions when an emergency occurs [47], or taking emergencies as an example, the method of point mutual information based on existing sentiment dictionaries is used to construct emoji dictionaries to calculate text sentiments [48]. The latter needs to use supervised, semisupervised, and unsupervised machine learning methods, such as support vector machine, Naive Bayes, and neural network, to classify sentiments based on labeled data as the training set. For example, SVM is used as a classifier to classify text data sets by mapping emojis and word vectors into sentiment space [49], or N-gram is used as the text feature and Naive Bayes as the classifier to identify the sentimental types of netizens [50]. With the development of deep learning technology, more and more studies use deep learning models as a classifier to replace the traditional machine learning model for sentiment analysis of short texts. For example, through the sentimental data analysis framework, the convolutional neural network is used to realize the recognition of different sentimental types on text, video, and other data [51], or based on the cyclic neural network, the long and short memory model (CLSTM) is introduced to make the cyclic neural network better store the sentimental information [52]. These studies have achieved good results, making deep learning one of the most popular methods in sentiment classification. The success of these studies has made deep learning one of the most popular methods of sentiment classification.

To sum up, the study of online public opinion by using sentiment analysis has always been a hot topic of research. However, the difference of sentimental evolution in the social network by comparing derivative public opinion of different emergencies with derivative public opinion as the research object has received less attention from scholars. Given this, we combine the deep learning method to classify sentiments and attempt to make further study on the sentimental evolution of derived public opinions in social networks based on time series analysis. In addition, we also compare and explore the law of public opinion derived from public health events and other types of emergencies.

3. The Proposed Methodology

In this part, we introduce the research methods used in the study and mainly build three models, namely, the topic identification of online public opinion, the sentiment

classification of online public opinion, and the time series model of online public opinion. In the topic identification model, the research mainly used the Word2Vec word vector model to convert text data into word vectors and then used the clustering method to realize topic identification. In the sentiment classification model, the biLSTM model was mainly used to realize the identification of text sentiment based on the training set, and it was divided into positive and negative sentiment types. In the time series model, the research mainly used the ARIMA model to make topic-sentiment analysis of public opinion derived from emergencies and further compared different types of emergencies, to explore the evolutionary commonalities and differences between the public health event and other types of emergencies on temporal networks. In this section, we will briefly introduce the principle and advantages of the Word2Vec word vector model, biLSTM sentiment classification model, and ARIMA time series model.

3.1. The Construction of Topic Identification Model. Social media provides a convenient channel for people to understand the information related to emergencies. However, the large scale of network data, the large amount of useless information, and the existence of noise make it more difficult to extract effective information. To timely and accurately discover important information, the topic identification method has been widely used in event detection and information extraction of social media [53]. However, in social media platforms such as Twitter and Facebook, which are dominated by short text information, the traditional topic identification model represented by LDA is not applicable, and the effectiveness of topic identification cannot be well guaranteed [54]. As a typical topic model, LDA mainly uses the soft clustering method to cluster documents and, through the study of document matrix, realizes topic clustering by using the cooccurrence relationship of words in documents. However, when the topic model is applied to short text documents, the problem of sparse data often occurs. Specifically, on the one hand, the number of words in short documents is smaller than that in long documents, so it is difficult for the model to distinguish the document semantics by a small number of words. On the other hand, the number of contexts in short texts limits the application of the model, making it difficult for the thematic model to accurately identify the meanings of ambiguous words. To further improve the accuracy of topic recognition, researchers proposed a series of topic identification and text mining methods based on deep learning, among which the most representative model is Word2vec, which can generate word vectors and is represented by a shallow and two-layer neural network structure [55]. Compared with the topic model represented by LDA, Word2vec is mainly expressed as the word embedding model with neural network structure. By learning context-word matrix, words are converted into word vectors, which shows better results in topic recognition of short text information.

Word2vec word vector model can be regarded as a simplified neural network model. Firstly, the text is

processed by using a shallow neural network, and based on using a large data set as a training set, the relationship between words and context is obtained. Secondly, the semantic of the word is mapped to the vector space, and the word is transformed into a distributed word vector by representing it as a similar semantic word [56]. Among them, word vector training of the Word2vec model is mainly completed by the Skip-Gram model and Continuous Bag-of-Words (CBOW) model. The difference is that the former mainly realizes the prediction of the context words through the semantics of the current word, while the latter mainly realizes the prediction of the current word through the semantics of the context. Although the Skip-Gram model is more accurate in obtaining word vectors of all texts after traversing all texts, the CBOW model has been adopted by researchers for its higher efficiency and faster speed in the analysis of large-scale social media data sets [57]. Considering that this paper adopts a relatively large data set, we use the CBOW model to carry out topic analysis on the public opinions derived from emergencies.

As a shallow neural network model, the CBOW model is composed of the input layer, projection layer, and output layer. It is a word bag model formed based on continuously distributed word representation methods [58]. The objective function of the CBOW model is usually expressed as a logarithmic likelihood function, as shown in (1), where C represents the objective function of the model, w is the central word to be studied, and n is a given sequence of training words, which means that n words are taken before and after the central word w .

$$C = \sum_{w \in n} p(w|\text{Context}(w)). \quad (1)$$

The CBOW model is a prediction of the central word based on the context words with a probability of $p(w_i|\text{Context}(w_i))$. Assume that T is the number of training words in the corpus, and $\omega_{w(t)}$ is the t the component value of vector ω . Based on the context information of the central word w_i , the model combined with softmax function for normalization calculation and finally generated the vector value of w_i . The specific calculation is shown in

$$p(w_i|\text{Context}(w_i)) = \frac{\exp(\omega_{w(i)})}{\sum_{t=1}^T \exp(\omega_{w(t)})}. \quad (2)$$

The structure of the CBOW model is shown in Figure 1. Firstly, the model enters the context word of the target word and passes it to the embedding layer initialized with random weights. Secondly, the model transfers the word embeddings of the context words to the lambda layer to obtain the averaged word embeddings. Thirdly, we pass the averaged word vectors to the dense layer and match the predicted words with the target words based on the prediction of the target words by the softmax function. Finally, loss calculation and embedding layer updating are implemented by categorical cross-entropy and back-propagation, respectively.

3.2. The Construction of Sentiment Classification Model.

In recent years, sentiment classification models based on deep learning have achieved good results in tests and have been widely applied [59]. Among them, in natural language processing studies that have requirements on the length of input variables, recurrent neural networks (RNN) have become an important tool in the field of sentiment analysis by the high efficiency of information processing [60]. In this study, a bidirectional long short-term memory model was used to realize sentiment classification based on a recurrent neural network.

The long short-term memory model, as a variant of the recurrent neural network, is widely used in sentiment analysis. On the one hand, it is because the design structure of the model can capture remote dependencies and solve the short-term memory problem of traditional recurrent neural networks. On the other hand, it can not only consider the order of text data but also save or delete information in the training process, so it has a great advantage in the processing of sequential text data. The realization of the model is mainly divided into three stages: selective memory, forgetting, and output stage. Selecting memory is the input stage, selectively recording input information. The forgetting stage is the second extraction of information, forgetting unimportant information and recording important information, to achieve the selection of information recording. The output phase determines what information is ultimately output into the current state.

Corresponding to the implementation stage of the model, the long short-term memory model selects information through the "gate" to realize the selective passage of information. The structure of the model is composed of an input gate, forgetting gate, output gate, and memory unit. The model mainly realizes the selection of information to be forgotten through the forgetting gate, and the specific formula is shown in (3). The symbol of forgetting gate is represented by f_t , σ is the activation function, W_f and b_f , respectively, represent the weight and standard deviation of forgetting gate, h_{t-1} represents the hidden state at the previous moment, and μ_t represents the input of text information at the current moment.

$$f_t = \sigma(W_f h_{t-1} + W_f \mu_t + b_f). \quad (3)$$

The input gate is corresponding to the selected memory stage of the model, which mainly determines the input of text information and realizes the preservation of memory information. The specific calculation equation is shown below, where i_t represents the input gate, \tilde{C}_t represents the temporary memory unit, W_i and b_i respectively represent the weight and standard deviation of the input gate, W_C and b_C respectively represent the weight and standard deviation of the memory unit, and C_{t-1} represents the memory unit of the previous moment.

$$\begin{aligned} i_t &= \sigma(W_i h_{t-1} + W_i \mu_t + b_i), \\ \tilde{C}_t &= \tanh(W_C h_{t-1} + W_C \mu_t + b_C), \\ C_t &= C_{t-1} f_t + \tilde{C}_t i_t. \end{aligned} \quad (4)$$

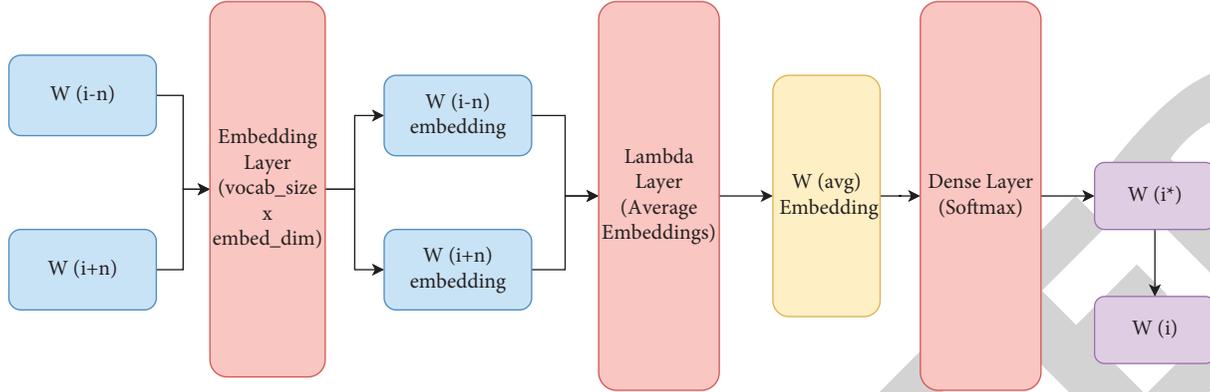


FIGURE 1: The structure of the CBOW model.

Similar to the input gate, the output gate corresponds to the output stage of the model and mainly determines the output of the text information in the memory unit at the next moment. The specific calculation equation is as follows, where the output gate is represented by the symbol o_t , the memory unit is represented by the symbol C_t , W_o and b_o represent the weight and standard deviation of the output gate, respectively, and h_{t-1} and h_t represent the hidden state of the memory unit at the previous moment and the current moment, respectively.

$$\begin{aligned} o_t &= \sigma(W_o h_{t-1} + W_o \mu_t + b_o), \\ h_t &= o_t \tanh(C_t). \end{aligned} \quad (5)$$

Long short-term memory model can effectively process sequential text and solve the short-term memory problem of recurrent neural networks, which has been recognized by many scholars. However, the LSTM also has some defects. It can only process data from the front to the back, ignoring the backward feature of text information and being unable to encode information from the back to the front. Therefore, to further improve the accuracy of the classification effect, we adopted the bidirectional long short-term memory model to achieve the sentiment classification work in this paper. The bidirectional long- and short-term memory model is composed of two forward and backward long- and short-term memory models, including all forward and backward information. It can complete the learning of sequence data from both front and back directions and, finally, get the output results with more accuracy. The model structure is shown in Figure 2 below. Firstly, the model inputs text data in the pretraining embedding layer and transform it into word vectors. Secondly, the forward and backward LSTM models are used to obtain the information before and after the word vectors, and then they are spliced. Finally, the complete information is input into the softmax function layer to output the probability distribution of positive and negative sentiments based on the function prediction.

3.3. The Construction of Time Series Model. Time series is a sequence formed by ordering the observation values of the same object in the order of time. The purpose is to use the

existing historical data to predict future data [61]. To realize the prediction of observations, stochastic and dynamic models based on time series data have been established. Common models include Autoregressive (AR), Moving Averages (MA), and Vector Auto-Regression (VAR), as well as Auto-Regression Moving Average (ARMA) and Auto-Regression Integrated Moving Average (ARIMA) models based on AR and MA models. Compared with other models that directly use the past value to predict the future value, the ARIMA model first weights the past data and corrects the error value, showing a better prediction effect, so it is widely used in time series analysis [62]. Based on existing studies, this study mainly uses the ARIMA model to realize topic-sentiment evolution analysis of public opinion derived from emergencies and then explores the internal formation and propagation rules of public health emergencies and other three kinds of emergencies.

ARIMA model is a composite model based on time series, where AR refers to the autoregressive model, and it mainly makes regression predictions based on the correlation between lag data and observed data. p is used to represent the number of autoregressive items. We refer to Integration and it is expressed as a single integer order. At the same time, it is also the number of times of making the time series stationary and making a difference. The stationarity of the time series is maintained by measuring the observed values in different periods, where the number of differences for the stationary time series is usually represented by d . MA refers to the Moving Averages model which measures the correlation between the observed value and the residual term, where the number of moving average items is often expressed by q . Therefore, ARIMA (p, d, q) is also commonly used in research to represent the autoregressive differential moving average model [63].

The basic principle of the ARIMA model is to approximate the data change of the observed object in time through mathematical methods and realize the prediction of the future based on the fitting of historical data. The general p order Autoregressive (AR) model equation is shown in (6). Among them, the stationary data series is represented by z_t , the autoregressive coefficient is represented by φ_n , ω_t represents the random error term of the time series, also known as the white noise series, and c represents the constant.

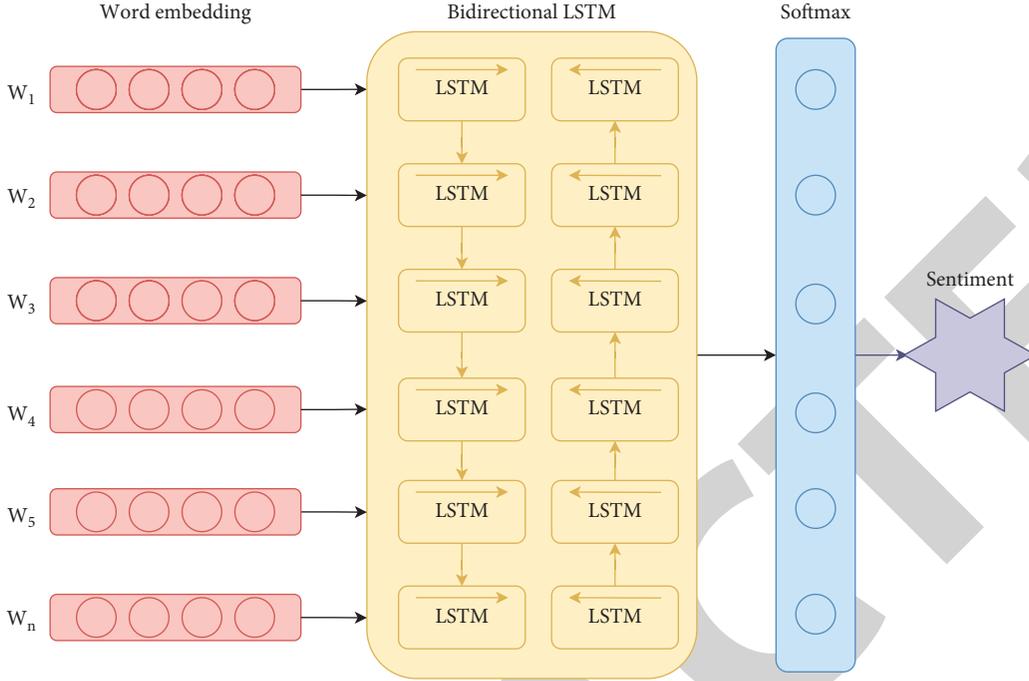


FIGURE 2: The architecture of the biLSTM model.

$$z_t = c + \sum_{n=1}^p \varphi_n z_{t-n} + \omega_t. \quad (6)$$

The Moving Averages (MA) model equation of order q is shown in (7), where β_n represents the moving average coefficient, ω_t represents the white noise process of the time series, and ε represents the expectation of the stationary time series, which is usually assumed to be equal to 0.

$$z_t = \varepsilon + \sum_{n=0}^q \beta_n \omega_{t-n}. \quad (7)$$

ARIMA model is obtained by combining AR, MR model, and difference, and the model equation is shown in (8), where z'_t represents the data series after difference, to convert the nonstationary time into a stationary time series. The parameter p represents the order of the AR model, the parameter q represents the order of the MA model, ω_t represents the white noise sequence, and c represents the constant.

$$z'_t = c + \sum_{n=1}^p \varphi_n z_{t-n} + \omega_t + \sum_{n=0}^q \beta_n \omega_{t-n}. \quad (8)$$

The use of the ARIMA model to analyze the derivative public opinion in the time scale mainly involves the following steps. Firstly, the stability test of the derived public opinion should be carried out. If it is not stable, the non-stationary sequence should be converted into a stationary one using differential transformation or other methods. In this paper, we mainly use the graph method to check the stationarity of time series data. After the production of the time sequence map with the release time of microblog as the

abscissa and the number of texts as the ordinate, it can judge whether the time series data are stable by observing the trend of the derived public opinions on temporal networks. Secondly, the form of the model is determined by the autocorrelation coefficient and partial correlation coefficient, and the parameters of the ARIMA (p, d, q) model are determined according to the fitting degree of the model. Finally, the white noise test is carried out on the residual sequence to judge the effect of extracting useful information from the model, to achieve accurate prediction of derived public opinion.

4. Research Design

In the study, we first captured the public health event as our main research object and then captured the microblog data sets of three different types of emergencies, the natural disaster, accident, and social security event, for comparative analysis. In addition, we complete the text preprocessing by removing stop words, word segmentation, and filtering text content. Secondly, we use Word2Vec and K -means clustering methods to extract the topics of various types of emergencies and divide the identified topics into original topics and derived topics and further obtain the derived topic data sets of each emergency through calculation. Thirdly, based on the training data set, we combined the bidirectional long short-term memory model to realize the sentiment classification of text information and divided it into two types: positive sentiment and negative sentiment. Finally, we use the time series analysis method to model the derived public opinion, explore the topic-sentiment evolution mechanism of the derived public opinion in public health events, draw the evolution map, and make a

comparison with other three kinds of emergencies to understand the commonality and difference of the evolution law. The research framework is shown in Figure 3.

4.1. Data Collection and Preprocessing. The research mainly takes the public health emergency as the main research object and, through the comparison with other three kinds of emergencies, reveals the topic-sentiment evolutionary commonality and difference of public opinion derived from emergencies on temporal networks. Therefore, we selected four representative emergencies in recent years as our case materials and obtained data sources through Sina Weibo. Among them, we selected the case of “virus cruise ship” (the large-scale virus infection in Japanese luxury cruise ships) as our main research object in public health events. This is because it not only involves a massive viral transmission in a confined space, which has captured the world’s attention, but it is also so typical of its relevance to COVID-19. In addition, the forest fire, gold mine explosion, and hostage-taking incident are selected as natural disasters, accidents, and social security cases, respectively.

Sina Weibo is one of the most representative and influential information interaction and exchange platforms in China. Similar to Twitter, Facebook, and other social media platforms, users share their experiences, express their views on events, and interact with each other on Weibo, thus building an information exchange and sharing network. Through the method of limited time and searching keywords, the researchers obtained the event posts and time information of the four types of emergency cases on the platform, which provided sufficient data support for our subsequent research.

Before data analysis, to further improve the efficiency of model operation and the accuracy of results, some data preprocessing steps need to be taken. First, we did a preliminary browsing of the data we obtained to remove invalid posts and filtered the text content through methods such as regular expressions. Second, we used the Jieba tool for word segmentation of Chinese text to solve the problem of lack of space in Chinese text compared with English text. Finally, to further process the invalid words in the text data, we used the HIT Chinese stop word table to label the part of speech and deleted the stop word.

4.2. The Design of Topic Identification Model. Before using the Word2vec model to transform text information into a word vector, we first extract feature words through the TF-IDF model to reduce the interference of useless information and noise in text data. Based on weighted processing, we extract the 20 most important keywords from each text data and use them as corpus sets for word vector transformation. Second, we use the CBOW model in Word2vec to transform the word vector of the data set, convert the text into a word vector, and use the common text mining method k -means to cluster the text. Finally, we divide the extracted topics into different clusters according to the similarity between texts to realize the recognition of text topics.

After using Word2Vec word vector model and K -means clustering method to realize topic identification of text data, we divided the identified topics into original topics and derived topics according to the judgment criteria of derived events. In the existing studies, it is very common to detect derived events based on topic identification based on the clustering method [64]. Considering that the evaluation subjects involved in public opinions of emergencies in social networks are easy to identify, combining with existing studies, we regard the change of evaluation subjects as the criterion for the classification of original topics and derived topics. If the subject of evaluation in the topic has changed, the topic will be identified as a derived topic, and a data set containing the derived topic will be further established for analysis [65].

To analyze the derived public opinion, we need to establish the derived public opinion data set according to the identified topics. First of all, we need to give all text data corresponding topics according to the topic identification model to distinguish the text data of each event and divide it into data sets of different topics. Secondly, we use Q_m to represent the topics identified by the topic model and W_{mn} to represent the keywords of each topic. The sequence number of the topic is m , the sequence number of the keyword is n , and the topic (keyword) is $Q_m (W_{mn})$. For example, the first keyword of the first topic can be expressed as $Q_1 (W_{11})$, and the first keyword of the third topic can be expressed as $Q_3 (W_{31})$, etc. Thirdly, we use K_{mn} to represent the frequency of occurrence of a certain keyword n in topic m , and m values of K_{mn} can be obtained from any text data. Finally, we compare the K_{mn} value among different text data. The higher the value is, the more likely the text data is to belong to a certain topic, to obtain the data sets of the original topic and derived topic. After obtaining the data set of the derived topics, we counted the relationship between the time of microblog posting and the number of microblog postings in the derived topic data set, and then obtained the time-series data that can be analyzed.

4.3. The Design of Sentiment Classification Model. In this paper, we mainly use the bidirectional long- and short-term memory model to realize sentiment classification, but before using the deep learning model for sentiment classification of text data, we need to train and test the sentiment classification model based on the test training set data of Weibo. Combined with the existing research, we use the public data set of microblog sentiment classification evaluation in 2013 and 2014 of the NLPCC International Conference as our model data set. We divide sentiments into two types: “positive sentiment” and “negative sentiment,” among which positive sentiment includes emotions such as love and happiness, while negative sentiment includes emotions such as disgust, fear, anger, and sadness.

The reason why we choose the NLP&CC data set for training and testing is that the NLP&CC data set has been widely used in the training and evaluation of fine-grained Chinese sentiment classification models in recent years and has achieved good results [66, 67]. On the other hand, the

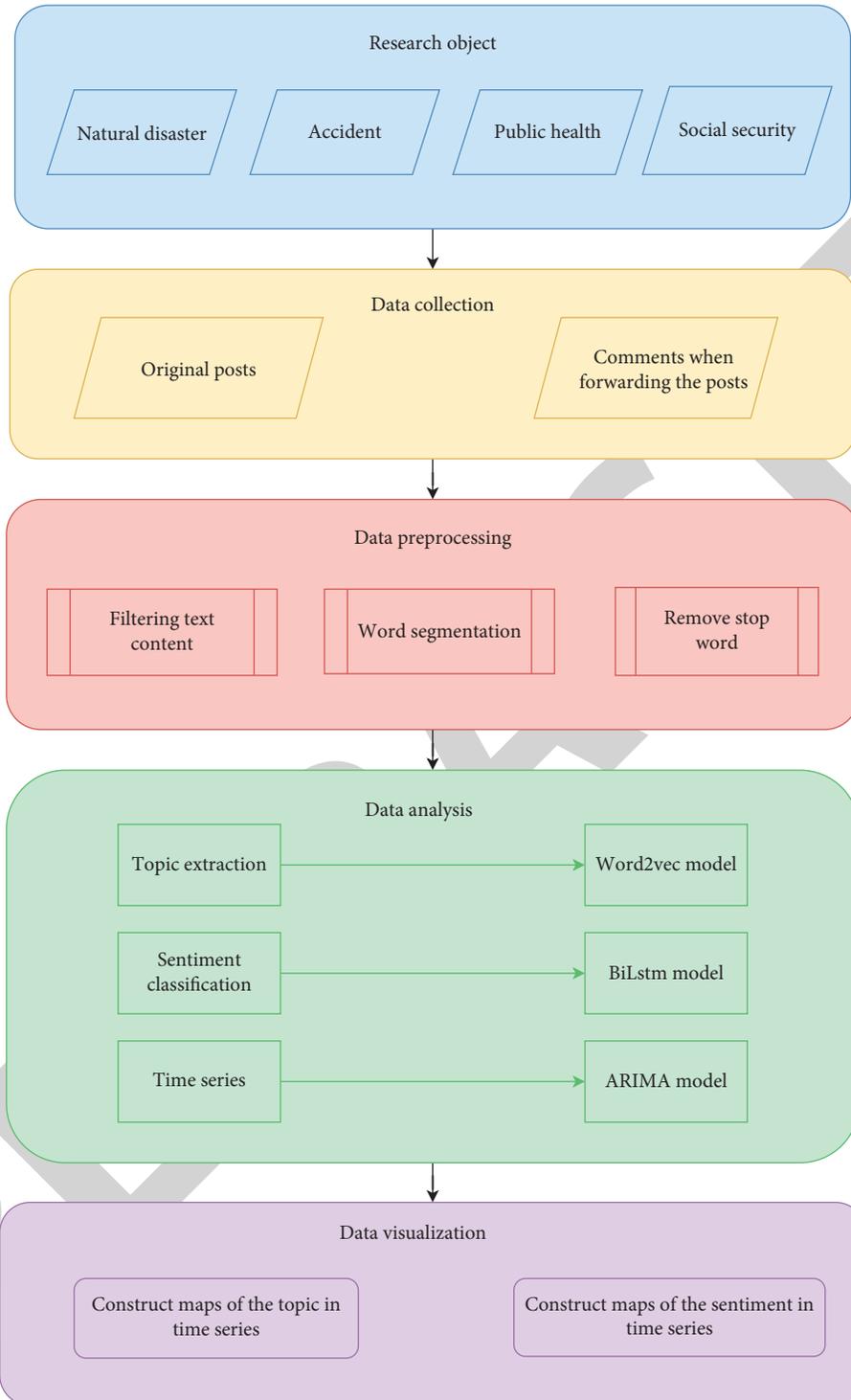


FIGURE 3: Research framework.

NLP&CC data set comes from the Sina Weibo platform, which is consistent with our data sources and is suitable for our sentiment analysis research. At the same time, considering that some new words that were not originally included in the training data set are now widely used, the corpus may change over time. Before adopting the biLSTM model to achieve sentiment classification, we randomly

captured and filtered 200,000 microblogs, carried out pre-training by using the CBOW method, and obtained semantic representation and semantic similarity of words through the pretrained word embedding model. Therefore, when the input statement contains a word that does not appear in the training corpus but appears in the pretraining corpus, the prediction model can also grasp its sentimental meaning and

further improve the prediction accuracy and generalization ability of the model. After the pretraining of the sentiment classification model, we carried out sentiment recognition on the microblog data set, divided the microblog posts into positive and negative sentiment types, and assigned the corresponding sentiment labels to each text data. The accuracy of the model was 0.71, which met the needs of our research.

4.4. The Design of Time Series Model. To realize the topic-sentiment analysis of the derived public opinion on temporal networks, we used the ARIMA model to analyze the derived data set. Based on obtaining the data set of derived public opinion, the research mainly establishes a time graph with the number of texts as the ordinate and the time scale as the abscissa, to observe the evolution of the topic and sentiment of derived public opinion in the time scale. Among them, the steps for obtaining topic-based time series data of derived public opinion are as follows.

First of all, topic clustering of text data is carried out through a topic identification model, and corresponding topic tags are assigned to each microblog. Secondly, we divide the topics identified by the topic model into original topics and derived topics and extract the text data containing all the derived topics according to the calculation method of the derived topic data set. Thirdly, we select a derived topic that needs to be analyzed, filtered, and extracted in the data set and establish the derived topic data set. Finally, we set up a two-dimensional coordinate graph according to the release time and text quantity of the derived topic data set to carry out the time series analysis of the derived topic.

The acquisition method of time series data based on sentiment-derived public opinion is similar to that of topic data. Firstly, sentiment classification is carried out on text data and a corresponding sentiment type is given to each post. Secondly, all text data containing derived topics are extracted according to the computation method of the derived topic data set. Thirdly, according to the needs of analyzing a certain sentiment type, the sentiment data set derived from the event is established by screening and extraction in the data set. Finally, according to the release time and the number of texts in the data set, the coordinate map is established to analyze the change of sentiment derived from public opinion on the time scale.

5. Results and Discussion

5.1. Descriptive Analysis of Data. In this paper, we take public health emergencies as the main research object and further explore the evolution mechanism of public opinions derived from public health events on temporal networks by comparing public health events with natural disasters, accidents and disasters, and social security events. We chose the “Japanese Virus Cruise” as a public health case, which occurred during the COVID-19 transmission. During the period of January and February 2020, 712 people of 3,711 crew members and tourists were infected and many died in an outbreak on a Japanese luxury cruise ship. At the same

time, forest fire (March 30, 2019, to April 10, 2019), gold mine explosion (January 10, 2021, to February 5, 2021), and hostage taking (January 22, 2021, to February 10, 2021) were selected as natural disaster, accident disaster, and social security event cases. After the occurrence of these events, they all attracted the general attention of the public on the Weibo platform. The public carried out relevant discussions around the topic and formed a large amount of text data, which provided abundant analytical materials for our research.

Under the condition of the specified time, we crawled relevant data from the Weibo platform by searching keywords. For example, we crawled posts related to public health events on Weibo between January 19, 2020, and February 21, 2020, based on search keywords such as “COVID-19 virus cruise ship” and “cruise ship outbreak”. The posts included users’ comments on the event itself and interactions with other people’s comments. Finally, the number of complete and valid posts reached 85,551. The number of posts of each emergency is shown in Table 1.

5.2. Derivative Public Opinion Data Set Based on Topic Identification. In this study, the Word2Vec word vector model was used to transform text data into vectors, and the K -means clustering method was used to realize topic identification. Considering that the main object of the study is the formation and development of derived public opinions, we only show the clustering results of public health emergencies in the following Table 2 and realize the identification of derived topics according to the judgment criteria of derived events.

According to the difference of K value, the results of K value clustering will also change greatly. Combined with data volume and data content, we chose the appropriate K value to achieve text clustering. The clustering results are shown in Table 2. The text data of the public health emergency after clustering by the K -means method can be divided into 9 categories. Considering the limited space in the paper, we only show part of the keywords in the table. For example, topics 1 and keywords can be expressed as $Q_1\{W_{12}, W_{13}, W_{14}, W_{15}, W_{16}, \dots, W_{1n}\}$, namely, the topic “police arrest sabotage resistance to disease” by {“eliminate,” “arrest,” “nuisance,” “inspection authority,” “police,” “Jinan Municipal Party Committee,” “playing mahjong,” “industry”} as keywords.

In the topic clustering of the public health emergency, we can find that the topics together form the development vein of public health emergencies. For example, topic 3 “the latest news about a massive virus outbreak on ships” and topic 6 “cruise ship epidemic prevention and control are ineffective, becoming a disaster area” were the beginning of our selected public health events. COVID-19 spreads rapidly in the cruise ships during this period. Then topic 4 “medical personnel are on board to help infected people” and topic 9 “the government held a press conference to give details of the virus outbreak about the ship” represented the government’s concern and response to this public health event. Topic 5 “people prayed for the safe return of those infected” and

TABLE 1: The number of posts of each emergency.

Event types	Microblog entries
Natural disaster	99612
Accident	110505
Public health	85551
Social security	101734

topic 8 “the public accused officials of shirking their responsibility” were not only the public’s care and blessing for the infected people on the ship, but also the evaluation of the behavior of government officials in public health emergencies. Topic 1 “the police arrested those who were obstructing the fight against the epidemic,” topic 2 “people called for a common fight against the epidemic,” and topic 7 “the news media reported the situation of the epidemic” were divided into derived topics according to the judgment criteria of derived events because of the change of evaluation subjects.

Combined with the acquisition method of derived public opinion data sets, we can obtain the data sets of various topics in the public health emergency. For example, there were 2,308, 4,138, and 7,447 data on the topics of “the police arrested those who were obstructing the fight against the epidemic,” “people called for a common fight against the epidemic,” and “the news media reported the situation of the epidemic,” respectively. In addition, we could also calculate the heat of each topic based on the proportion of the topic data set to the total data set. Among them, there were 85,551 data sets of public health emergencies, and the data quantities and heat ratios of each topic are shown in Table 3.

As can be seen from Table 3, among the topics after the clustering of the public health emergency, the topic with the highest popularity was “the latest news about a massive virus outbreak on ships,” which had aroused the most heated attention and discussion in cyberspace. The topic with the least popularity was “cruise ship epidemic prevention and control is ineffective, becoming a disaster area,” and the data set obtained was the least. This phenomenon showed that online public opinion was susceptible to the influence of the event itself in the transmission process, and the initial major progress of the event was easy to attract public attention, but with the passage of time and the impact of other news it had weakened. Among the three topics derived from public opinion, the topic “the news media reported the situation of the epidemic” had the highest popularity, ranking second among all the topics. The topic of “the police arrested those who were obstructing the fight against the epidemic” and the topic of “people called for a common fight against the epidemic” had weakened in popularity, but they also ranked high among all the topics. On the one hand, this confirmed the importance of derivative public opinion, which had a broad scope of influence and a large degree of influence. On the other hand, from the perspective of content, it was also confirmed that derived topics played an important role in propaganda and guidance during the transmission of COVID-19 and lead to the differentiation of content in the transmission process.

To compare the differences between the spread of the public health emergency and other types of emergencies on

temporal networks, we conducted topic clustering for different types of emergencies. In addition, we combined the number of topic data sets in each emergency to calculate the heat of the topic. The topic clustering and heat comparison results of various types of emergencies are shown in Table 4.

According to the transfer of evaluation subjects in the topics, the identified topics could be divided into original topics and derived topics. Considering the differences in the influence of various derived topics on temporal networks, we selected the two derived topic data sets with the highest topic popularity from each emergency for further analysis. The topic data sets derived from the natural disaster event were “guard mountains and rivers and guard homeland” and “salute every hero who carries the burden.” Derived topic data sets of the accident included “a foreign trade dispute arose in the mineral trade” and “improve the system to prevent the recurrence of the tragedy.” The derived topic data sets of the public health event were “the news media reported the situation of the epidemic” and “the public accused officials of shirking their responsibility.” Derived topic data sets of the social security event were “protect fairness and justice and reduce tragedy” and “malignant incident caused the net friend onlookers.”

5.3. Topic Analysis of Derived Public Opinions Based on Time Series. After obtaining the derived public opinion data set, we used the time series analysis method to analyze the extracted derived public opinions on the time scale. Considering that the period of all the data sets of public opinion adopted in the study lasted for about one month, it was not suitable for slicing with the unit of “day.” In addition, to further refine the time scale and more intuitively show the evolution trend of derived public opinions, we finally chose to slice the time data in the unit of “three hours.” The relationship between the release date and the number of posts in the data set was counted, and the analyzable time series data {time, time_number} were finally constructed.

The specific steps of time series analysis were as follows. Firstly, we imported the sliced post publishing time and number data {time, time_number} into the analysis software and observed the stationarity through the observation of the sequence diagram. Secondly, since the acquired data were all nonstationary series, we used the difference method to carry out the first-order difference and the second-order difference respectively to make the data stable. It was found that the second-order difference is more suitable for the data obtained by us, and the data after the difference was transformed into a stationary time series. Thirdly, we carried out autocorrelation and partial correlation tests on the data after difference and determined the values of coefficient p and coefficient q in the ARIMA model by combining ACF autocorrelation diagram and PACF partial correlation diagram. Finally, the results of ARIMA models with different coefficients were compared, and the appropriate coefficients were selected to draw the formation and evolution graphs of each derived topic on temporal networks. The ARIMA model test results of each derived topic are shown in Table 5. The overall fitting effect of the model is represented by

TABLE 2: Topic clustering of the public health emergency.

No.	Topic	Keyword
1	The police arrested those who were obstructing the fight against the epidemic	Eliminate, arrest, nuisance, inspection authorities, police, Jinan municipal party committee, playing mahjong, industry
2	People called for a common fight against the epidemic	Together voice, power, advice, conviction, total amount, complete, colleges and universities, having been square, each way
3	Latest news about a massive virus outbreak on ships	Latest news, docked, new coronet, passenger, infection, confirmed, risk, patient, crew, institute
4	Medical personnel are on board to help infected people	Unknown, number, critical, patient, CDC, team healing, sea, deterioration, body
5	People prayed for the safe return of those infected	Home country, thanks, family members, science, coping, disaster, crisis, family, family
6	Cruise ship epidemic prevention and control is ineffective, becoming a disaster area	Hard-hit areas, rescue teams, living hell, high incidence areas, drugs, find out, blacklist, suicide note, location
7	The news media reported the situation of the epidemic	huanqiu.com, TV, cases, reports, people's daily, infected persons, Japan broadcasting association, health department
8	The public accused officials of shirking their responsibility	Shirk responsibility, malpractice, flaunt, show, shine a magic mirror, empty talk, distinguish, hear, post
9	The government held a press conference to give details of the virus outbreak about the ship	Epidemic, media, journalists, proliferation, control, data, acknowledgment, press release, disclosure, epidemic

TABLE 3: Comparison of the number of posts and heat on various topics in the public health emergency.

Ranking	Topic	Microblog Number	The heat of the topic
1	Latest news about a massive virus outbreak on ships	49213	0.575
2	The news media reported the situation of the epidemic	7447	0.087
3	People prayed for the safe return of those infected	6499	0.076
4	The public accused officials of shirking their responsibility	6490	0.076
5	The government held a press conference to give details of the virus outbreak about the ship	6295	0.074
6	People called for a common fight against the epidemic	4138	0.048
7	The police arrested those who were obstructing the fight against the epidemic	2308	0.027
8	Medical personnel are on board to help infected people	1711	0.020
9	Cruise ship epidemic prevention and control is ineffective, becoming a disaster area	1450	0.017

stationary R^2 , and the range of R^2 is 0-1. The closer the value is to 1, the better the fitting effect of the model will be. The information criterion of the model is represented by BIC, and the model is selected according to the fit degree of the model. In addition, the residuals of each model were not correlated, and the residuals of the time series data conformed to the distribution of random series, and there was no outlier, showing a good fitting effect.

According to the test results of the ARIMA model of each derived topic, as shown in Table 5, we established the measured and fitting graphs of the formation and evolution of each derived topic on temporal networks. The curves of actual and predicted values for each derived topic are shown in Figure 4, where the abscissa is the time of posting posts after slicing and the ordinate is the number of posts. Moreover, the red curve represents the actual value, the blue curve represents the predicted value, and the confidence intervals UCL and LCL are represented by the purple curve and the pink curve, respectively. In addition, Figures 4(a) and 4(b) respectively represent the derived topics with the highest and second-highest popularity among the topics of the natural disaster emergency. Figures 4(c) and 4(d) respectively represent the derived topics with the highest and second-highest topic

popularity in the accident event. Figures 4(e) and 4(f) represent the derived topics with the highest and second-highest topic popularity among the public health event, respectively. Figures 4(g) and 4(h) represent the derived topics with the highest and second-highest topic popularity among the social security event, respectively.

As can be seen from Figure 4, the two derived topics of the natural disaster event had an obvious "long tail effect" in the time series, and the heat of the event had an obvious outbreak phenomenon at the beginning of its occurrence, and it gradually flattened out over time. Among them, the mean value of the derived public opinion data in Figure 4(a) was about 514.08, the standard deviation was about 717.463, the maximum value was 3747, the minimum value was 0, the skewness was 2.440, and the kurtosis was 7.033. The data fluctuated violently and had the characteristics of sharp peak and right bias. The mean value of the derived public opinion data in Figure 4(b) was about 42.75, the standard deviation was 64.142, the maximum value was 394, the minimum value was 0, the skewness was 3.057, and the kurtosis was 12.358. The fluctuation of the data was still relatively severe, but it was a little gentle compared with Figure 4(a), and it had more obvious sharp peaks and right-skewed characteristics.

TABLE 4: Topic clustering and heat comparison of various types of emergencies.

No.	Topic	Data	Heat	Is it derivative?
N-1	The list of martyrs was announced	47759	0.480	No
2	Guard mountains and rivers, and guard the homeland	39412	0.396	Yes
3	The forest fire is under control	3816	0.038	No
4	Salute every hero who carries the burden	3424	0.034	Yes
5	Relatives commemorate the martyrs	1833	0.018	No
6	Remember the spirit of serving the motherland	1600	0.016	Yes
7	Internet users have been detained for insulting martyrs	1323	0.013	Yes
8	The citizens bid a tearful farewell to the martyrs	445	0.004	No
A-1	The survival of the trapped miners	47553	0.430	No
2	The public hoped for the safe return of the miners	32346	0.293	No
3	A foreign trade dispute arose in the mineral trade	14782	0.134	Yes
4	There was an explosion at the gold mine site	7545	0.068	No
5	The results of the accident investigation were announced	6342	0.057	No
6	Improve the system to prevent the recurrence of the tragedy	1057	0.010	Yes
7	Carry out the investigation and rectification of risks and hidden dangers	880	0.008	Yes
P-1	Latest news about a massive virus outbreak on ships	49213	0.575	No
2	The news media reported the situation of the epidemic	7447	0.087	Yes
3	People prayed for the safe return of those infected	6499	0.076	No
4	The public accused officials of shirking their responsibility	6490	0.076	Yes
5	The government held a press conference to give details of the virus outbreak about the ship	6295	0.074	No
6	People called for a common fight against the epidemic	4138	0.048	Yes
7	The police arrested those who were obstructing the fight against the epidemic	2308	0.027	Yes
8	Medical personnel are on board to help infected people	1711	0.020	No
9	Cruise ship epidemic prevention and control is ineffective, becoming a disaster area	1450	0.017	No
S-1	A hostage-taking incident took place in Kunming	47288	0.465	No
2	Protect fairness and justice, and reduce the tragedy	21844	0.215	Yes
3	The public prayed for the safety of the injured	15358	0.151	No
4	Details of the hijacking were relayed to the authorities	4876	0.048	No
5	The public discussed the specific circumstances of the hijacking case	4687	0.046	No
6	Malignant incident caused the net friend onlookers	3943	0.039	Yes
7	Formulate policies and improve relevant systems	2991	0.029	Yes
8	Discuss the offender's motive and condemn the offender	747	0.007	No

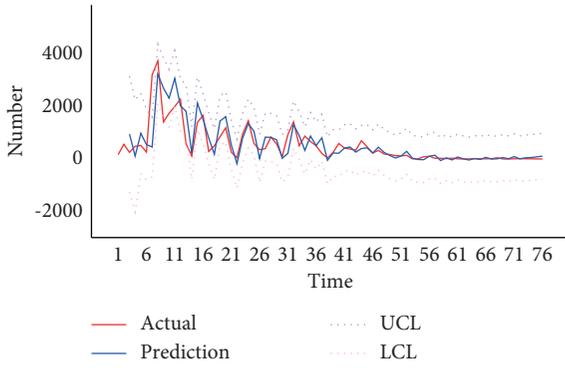
TABLE 5: ARIMA model test results of the topic data set.

Types	Model	Stationary R^2	BIC
N-01	ARIMA (5, 2, 7)	0.712	13.396
N-02	ARIMA (5, 2, 6)	0.686	8.773
A-01	ARIMA (12, 2, 14)	0.778	11.858
A-02	ARIMA (12, 2, 16)	0.819	3.816
P-01	ARIMA (8, 2, 3)	0.684	10.906
P-02	ARIMA (6, 2, 3)	0.682	8.566
S-01	ARIMA (3, 2, 1)	0.651	15.038
S-02	ARIMA (3, 2, 3)	0.475	10.822

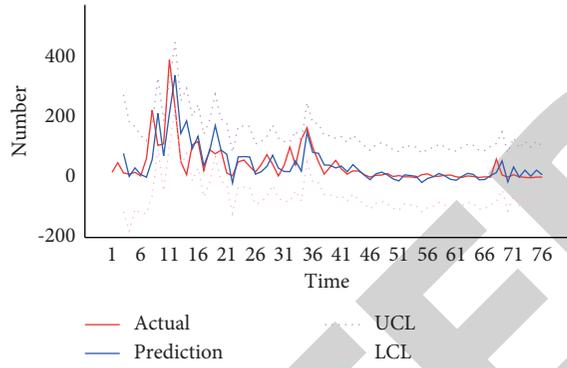
According to the observation of Figures 4(c) and 4(d), it can be found that the derived topics of the accident emergency all passed a stable period before the outbreak, which was also consistent with the development of the event itself. Combined with the text data, the accident did not arouse public attention immediately after its occurrence but took a period of fermentation before it finally aroused public opinion. Among them, the mean value of the derived public opinion data in Figure 4(c) was about 73.97, the standard deviation was about 294.524, the maximum value was 3117, the minimum value was 0, the skewness was 7.673, and the kurtosis was 68.851. Moreover, the fluctuation range of the

data was large, and the characteristics of the peak were very obvious and skewed to the right. In Figure 4(d), the mean value of the derived public opinion data was 1.60, the standard deviation was 0.371, the maximum value was 47, the minimum value was 0, the skewness was 6.505, and the kurtosis was 49.248, showing obvious characteristics of sharp peak and right skewness, but the range of data changes was smaller than that in Figure 4(c).

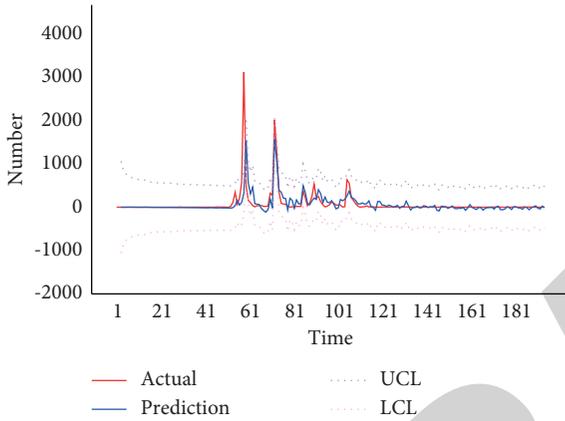
Based on Figures 4(e) and 4(f), the variation of the derived topics of the public health event over time scales was reflected. Compared with other types of emergencies, the time-series images of the public health event showed unique characteristics. According to Figures 4(e) and 4(f), we can intuitively feel the difference in the propagation of derived topics. The former fluctuated more violently and experienced several successive periods of fluctuation, while the latter erupted more gently and discontinuously. Combining the textual data, we found that this was due to the nature of the selected public health event. The frequent occurrence of COVID-19 around the world and its great depredation had attracted more attention and discussion on the derived topic of "the news media reported the situation of the epidemic," and its popularity remained high. The change in the timing trend of the topic "the public accused officials of shirking



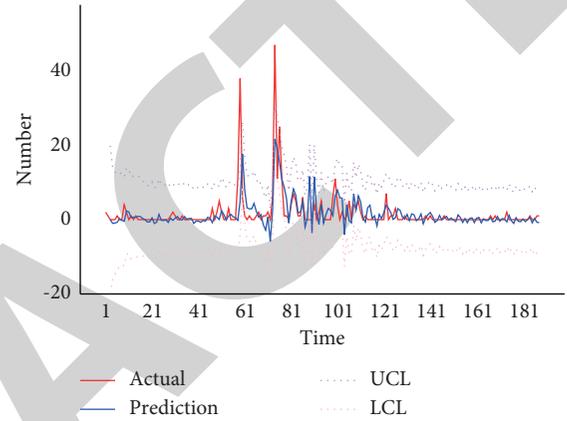
(a)



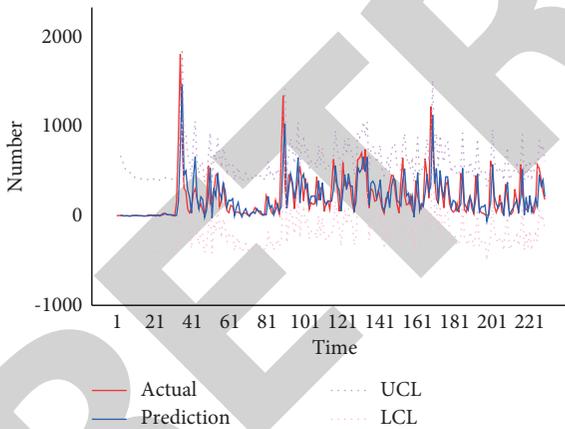
(b)



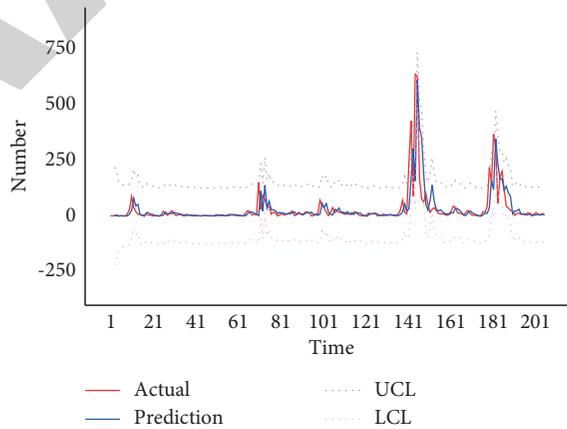
(c)



(d)



(e)



(f)

FIGURE 4: Continued.

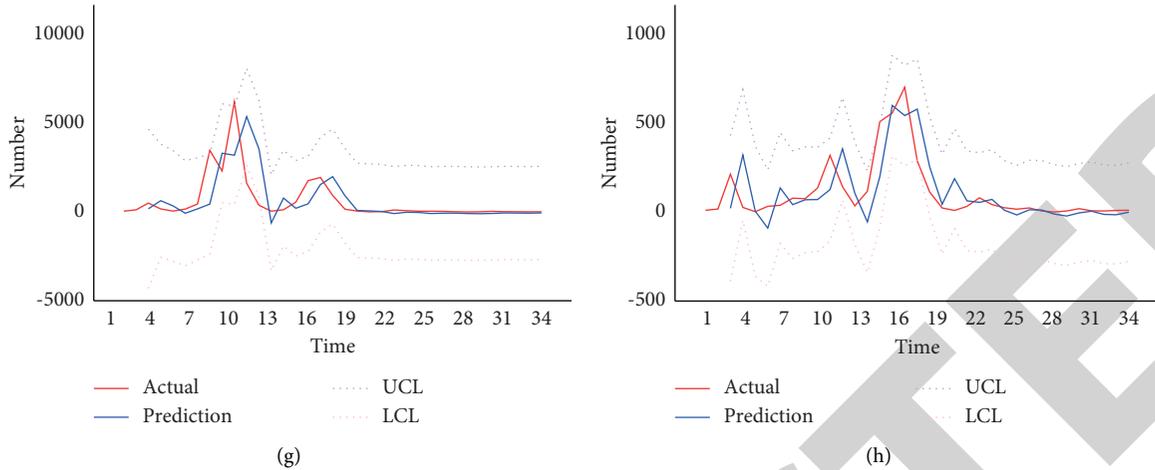


FIGURE 4: Actual and predicted values with ARIMA models in derivative topic. (a) Natural disaster 1. (b) Natural disaster 2. (c) Accident 1. (d) Accident 2. (e) Public health 1. (f) Public health 2. (g) Social security 1. (h) Social security 2.

their responsibility” was due to the influence of the press conference and the improvement of the way to deal with the epidemic, and the popularity did not last and gradually faded. In short, the reason why the opinion dissemination of public health events on temporal networks was different from other emergencies was mainly related to the characteristics of public health events themselves. Different from other emergencies, public health events tended to last for a long time and were prone to drastic changes under the influence of the external environment. In addition, compared with other events, public health events had a wider range of regional impacts, and the extent of impacts varied with the governance measures and environmental differences in different regions. In Figure 4(e), the mean value was 209.21, the standard deviation was 243.799, the maximum value was 1811, the minimum value was 0, the skewness was 2.494, and the kurtosis was 10.211. The data fluctuated sharply, with a large number of peaks, and had obvious right-skewness characteristics. In Figure 4(f), the mean value was 31.16, the standard deviation was 81.708, the maximum value was 634, the minimum value was 0, the skewness was 5.219, and the kurtosis was 31.352. Compared with Figure 4(e), the mean value was smaller and the fluctuation was relatively gentle, but the sharp peak and right skewness were more obvious.

Based on Figures 4(g) and 4(h), we can observe the changes of the derived topics of the social security event on temporal networks. Both of them experienced relatively intense fluctuations at the beginning of the event, and as time goes on, the heat gradually cooled down and the curve gradually became flat. In Figure 4(g), the mean value of the data was 140.55, the standard deviation was 646.252, the maximum value was 6208, the minimum value was 0, the skewness was 6.929, and the kurtosis was 55.914. The fluctuation of the data was relatively violent, and the feature of the peak was especially obvious, and it was right-skewed. In Figure 4(h), the mean value of the data was 7.511, the standard deviation was 92.606, the maximum value was 703, the minimum value was 0, the skewness was 5.319, and the

kurtosis was 30.702. Compared with the mean value of Figure 4(g), the fluctuation of the data was relatively gentle, and the characteristics of sharp peak and right skewness were not obvious.

5.4. Sentiment Analysis of Derived Public Opinions Based on Time Series. After sentiment classification of public opinion data sets by the biLSTM model, we gave each text data the corresponding positive sentiment or negative sentiment label and established a derivative public opinion data set through data screening. Then, we extracted the positive sentiment data set and negative sentiment data set from the derived public opinion data sets respectively and established the ARIMA model to analyze them on temporal networks. Among them, the ARIMA model test results of the sentiment data set derived from public opinion are shown in Table 6. In addition, we selected appropriate model coefficients to draw a map of the evolution of positive and negative sentiments derived from public opinion in the time series. The fitting degree of the selected model was higher than that of other coefficient values, which achieved better results, and also met the conditions that the residual sequence was uncorrelated and the outlier value was 0.

After determining the coefficients of the time series models of positive and negative sentiments, we drew the corresponding time series maps of public opinions derived from emergencies. For example, the evolution trend of positive sentiment derived from public opinion over time is shown in Figure 5. The legend was consistent with the time series of the topic. The red and blue curves represent the actual and predicted values, and the purple and pink curves represent the upper and lower limits of confidence intervals, respectively.

It can be seen from Figures 5(a) and 5(b) that the public opinion derived from the type of the natural disaster event had a relatively obvious positive sentiment fluctuation at the initial stage of the event, and it was relatively gentle as time goes on. Combined with the text material, it mainly came

TABLE 6: ARIMA model test results of the sentiment data set.

Types	Positive sentiment			Negative sentiment		
	Model	Stationary R^2	BIC	Model	Stationary R^2	BIC
N-01	ARIMA (6, 2, 16)	0.677	12.001	ARIMA (5, 2, 10)	0.707	12.862
N-02	ARIMA (6, 2, 3)	0.660	6.588	ARIMA (5, 2, 6)	0.656	8.026
A-01	ARIMA (12, 2, 14)	0.776	11.891	ARIMA (8, 2, 1)	0.707	2.717
A-02	ARIMA (12, 2, 16)	0.805	3.655	ARIMA (4, 2, 1)	0.717	1.086
P-01	ARIMA (10, 2, 8)	0.691	10.900	ARIMA (8, 2, 10)	0.694	6.378
P-02	ARIMA (8, 2, 1)	0.688	8.302	ARIMA (8, 2, 3)	0.676	4.906
S-01	ARIMA (4, 2, 2)	0.711	13.463	ARIMA (3, 2, 2)	0.650	13.907
S-02	ARIMA (3, 2, 1)	0.549	10.362	ARIMA (3, 2, 3)	0.450	7.313

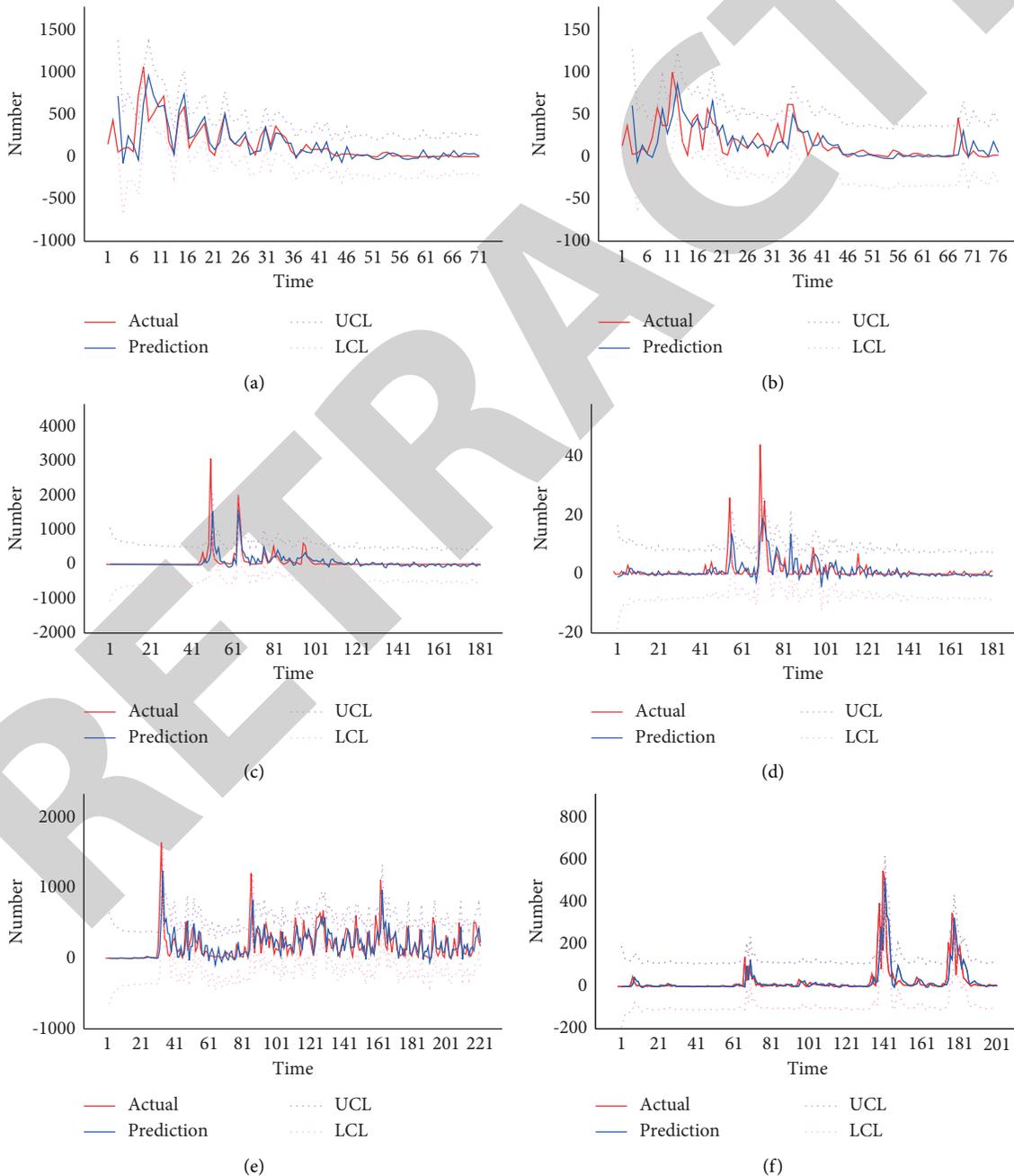


FIGURE 5: Continued.

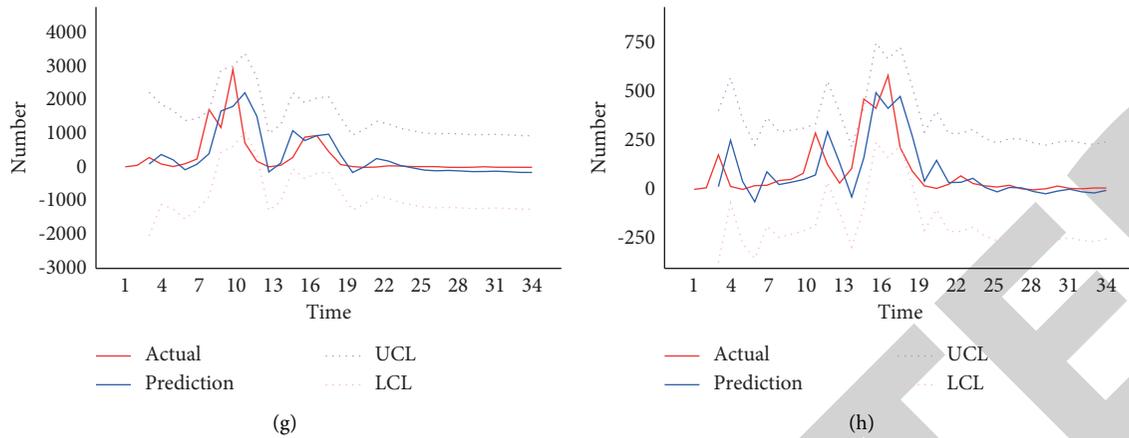


FIGURE 5: Actual and predicted values of ARIMA model in positive sentiment. (a) Natural disaster 1. (b) Natural disaster 2. (c) Accident 1. (d) Accident 2. (e) Public health 1. (f) Public health 2. (g) Social security 1. (h) Social security 2.

from the public's respect and love for the heroes that emerged at the beginning of the event. Compared with Figure 5(a), the positive sentiment in Figure 5(b) formed a wave peak again at the end of time and became the focus of people's attention. This was because the announcement of the list of heroes suffering in emergencies at this time caused people to spontaneously form respect and gather positive sentiment.

According to Figures 5(c) and 5(d), it can be found that the sentimental evolution of public opinions derived from the accident was similar to the topic evolution map, both of which realized rapid outbreak after fermentation. Combined with the materials, the positive sentiment gathered at this time was mostly from the recognition of the emergency management department's handling speed and handling methods, as well as the admiration of the disaster victims' tenacious will to survive.

Based on Figures 5(e) and 5(f), we can observe the evolution of positive sentiment of the public health event in time series. The former formed a continuous outbreak of fluctuations in the transmission process, and the sympathy and encouragement of people around the world for the victims of the disaster became the mainstream of communication on social media. The latter had undergone a period of fermentation. It was not until the specific ways and arrangements of the event emerged that positive sentiment emerged from the public, which mainly focused on the prayers and wishes for the victims.

According to Figures 5(g) and 5(h), we can observe the evolution process of the positive sentiment of the social security event in the time series. The fluctuation trend of the two was relatively similar, both of which presented inverted "U" fluctuation at the initial stage of the outbreak of the event. The content of the material focused on the hope that public justice can be protected and the relevant system can be improved. Meanwhile, it was also the joy of the success of rescuing hostages and the recognition of rescuers.

When an emergency occurs, the distribution of negative sentiment derived from various public opinions in the time series is shown in Figure 6. From Figures 6(a) and 6(b), it can

be found that the negative sentiment change of public opinion derived from the natural disaster event in the time series presented an "M" shape and had a long tail effect. The burst curve of negative sentiment was similar to that of positive sentiment, both rising sharply at the onset of the event, but the difference was that the duration of negative sentiment was shorter than that of positive sentiment. Combined with the text, it may be related to the media propaganda content. At the initial stage of the event, relevant media publicity focused on the economic losses and human casualties caused by the natural disaster, but after the outbreak of the event, it focused on paying tribute to the heroes emerging from the emergency and praising the people's spirit of protecting their homes, which gathered more positive sentiment rather than negative sentiment.

Figures 6(c) and 6(d) show the change of negative sentiment in the time series of public opinions derived from the accident, which were similar to positive sentiment. The outbreak of negative sentiment was mainly concentrated in the intermediate stage after the occurrence of the accident, which was related to the lag of public attention caused by the accidents. With positive sentiment being different, negative sentiment also produced intense fluctuation change but far less than on a change in positive sentiment. This may be because, after the event, the rescue workers searched the relevant locations of the victims in time and made supplies, which weakened the formation of negative emotions such as anxiety and fear.

According to Figures 6(e) and 6(f), we can observe the negative sentiment change of public opinion derived from the public health event in the time series, and the trend of curve change was consistent with the positive sentiment. The curve of negative sentiment in Figure 6(e) fluctuated up and down continuously, while the curve of negative sentiment in Figure 6(f) formed a sharp outbreak trend after passing the lag period in the initial stage. Combined with the text, this may be determined by the nature of the study of the public health emergency. Although COVID-19 had brought heavy disasters to the people of the world, people were also inspired by the heroes emerging from the disasters. In addition, the

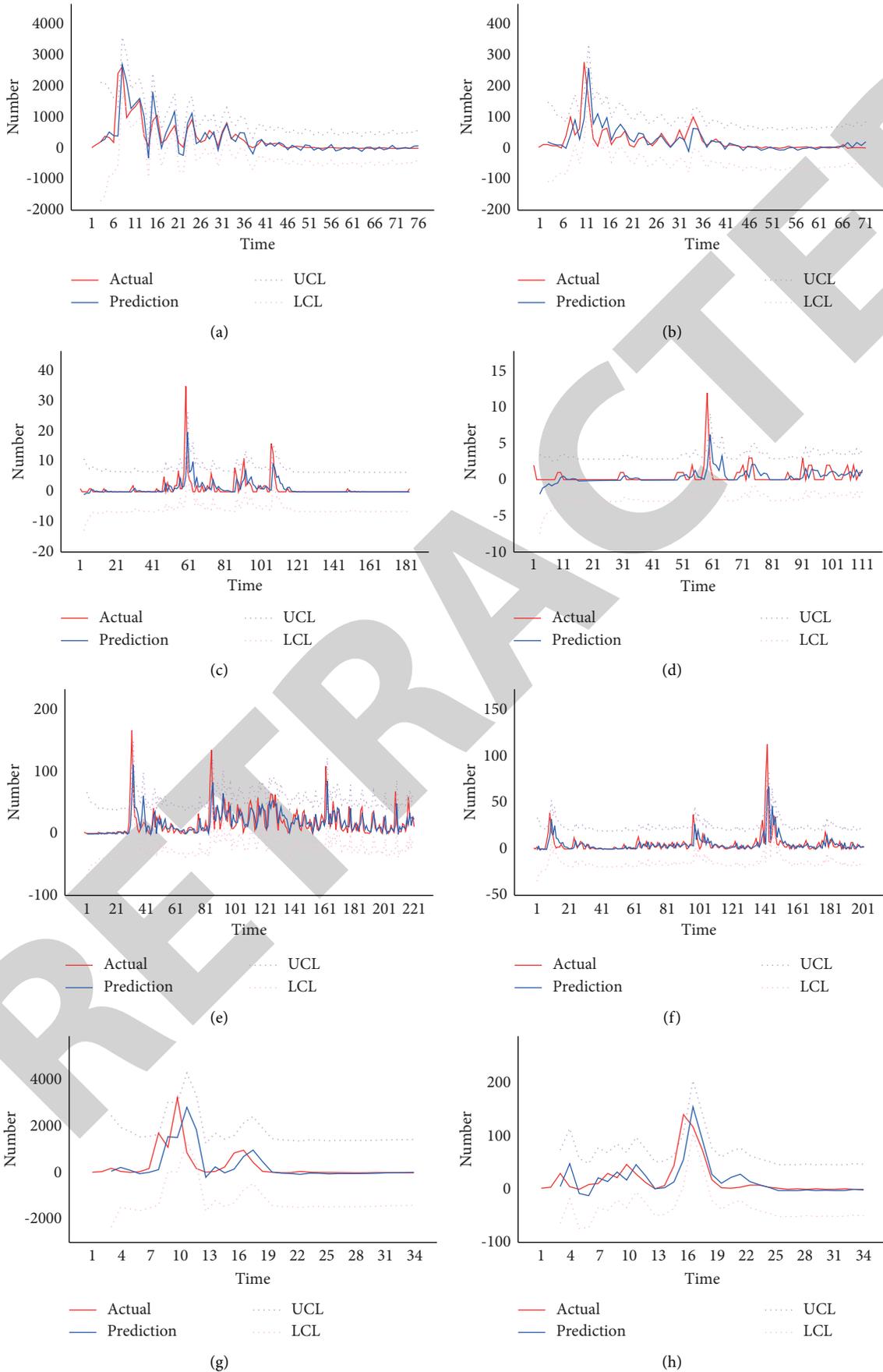


FIGURE 6: Actual and predicted values of ARIMA model in negative sentiment. (a) Natural disaster 1. (b) Natural disaster 2. (c) Accident 1. (d) Accident 2. (e) Public health 1. (f) Public health 2. (g) Social security 1. (h) Social security 2.

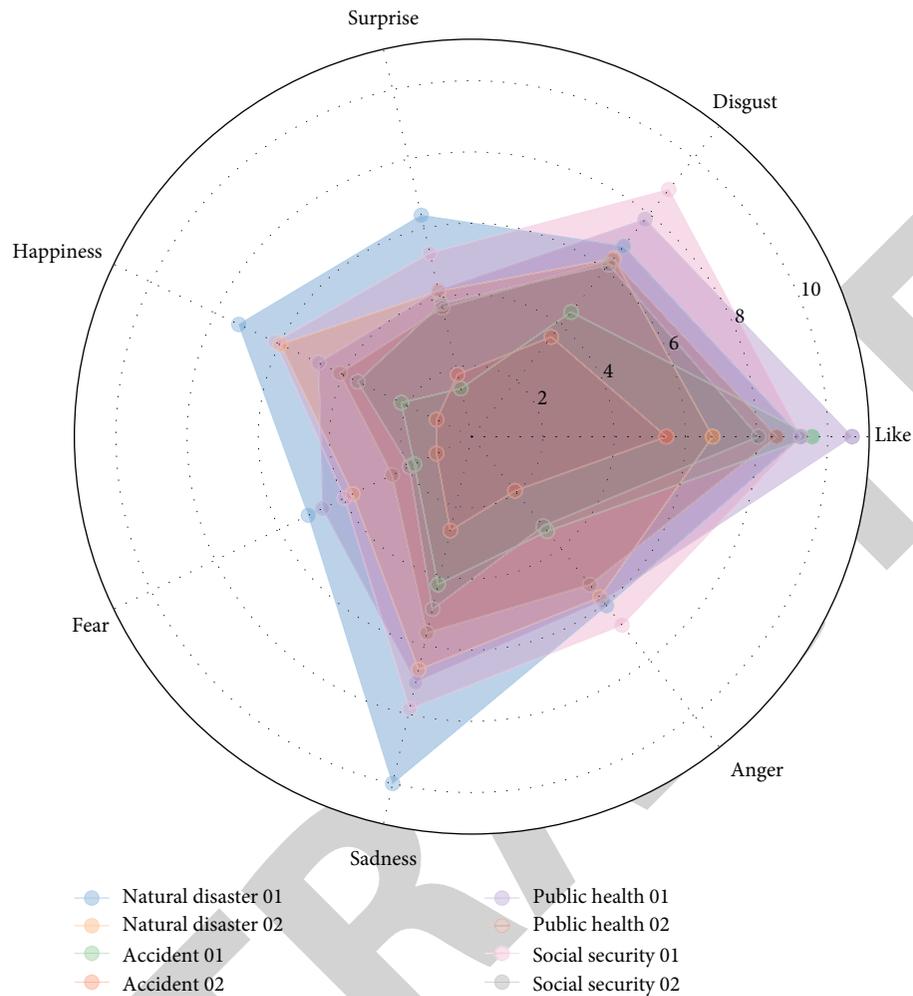


FIGURE 7: Multidimensional emotion radar diagram of public opinion derived from emergencies.

continuous overcoming of the epidemic management difficulties had brought confidence to the people, and positive sentiment and negative sentiment were accompanied by each other.

Based on Figures 6(g) and 6(h), it can be found that the emotional distribution of public opinions derived from the social security event in the time series was similar to positive sentiment, both of which showed an inverted “U” shaped trend. But the evolution curve of negative sentiment was steeper and more dramatic, and it was also associated with the rapid changes of social security events, which were less predictable. When the hostage taker made the corresponding action of threatening the hostage, the negative sentiment of the public was produced sharply and fluctuated accordingly.

Combined with the above analysis, we found that the evolution and distribution of public opinions derived from different types of events were significantly different in time series. Based on the topic analysis, it was found that influenced by the nature of events, the evolution of the derived topics of the public health event in time series was more volatile than that of other emergencies and fluctuated continuously with time. In addition, it also had a certain

continuity. This was also because the public health event was dynamic in time and a long-term process of continuous development. In space, it involved the vast majority of people and had a broader scope of time and space. From the sentiment analysis, it was found that the positive and negative sentiments of the public health event were similar to those of other emergencies, and both had a certain range of ups and downs. But more than any other emergencies, the emotional evolution of the public health event had spiked and revived rather than leveling off over time. At the same time, the occurrence curve of positive sentiment and negative sentiment in the public health event was closer, and the disasters brought by the epidemic caused people to continuously form negative sentiment. However, the formation of negative sentiment was not independent, and the emergence of heroes in the public health event and the good news of overcoming difficulties would also promote the generation of positive sentiment.

5.5. Emotional Distribution of Derived Public Opinion in Emergencies. To have a deeper understanding of the emotional dynamics of public opinions derived from

emergencies in social media, we further subdivided sentiments into seven emotion types: “like,” “fear,” “sadness,” “surprise,” “anger,” “happiness,” and “disgust,” and used the radar chart to describe the distribution of each derived public opinion on different emotions. The details are shown in Figure 7. To facilitate the understanding of the graph, we took the logarithm of the number of microblogs containing different emotions.

As can be seen from Figure 7, in the derived public opinion of various emergencies, the emotion of like occupies a dominant position. Combined with the text materials, the emotion of like mainly came from paying tribute to the heroes who emerged in the emergency. Despite the huge material losses and casualties caused by all kinds of emergencies, the heroic deeds and the spirit of cooperation that emerged in the emergencies also brought hope to the public. Among them, compared with other emergencies, the distribution of public opinion derived from public health events was also in the first place. This may have something to do with the fact that the public health event was larger in scope and involved the largest number of people, resulting in the largest number of heroic acts and acts of resistance. Secondly, disgust and sadness played an important role in the derivative public opinion of all kinds of emergencies. Combined with the text materials, the aversion mainly came from the resistance of the public to the disaster and the resistance to some behaviors of seeking personal interests during the disaster. Much of the sadness came from mourning the loss of life. This finding also corresponds to our previous conclusion that the spread of derived public opinions in social media was accompanied by the spread of different emotions, and the distribution of emotions also helped us to further understand the influence of derived public opinions.

6. Conclusion

In this paper, the main research object of our study was the public health emergency, and through the comparison with the natural disaster, accident, and social security emergency, we revealed the evolution law of public opinion on temporal networks. Firstly, we used the topic clustering method to construct the topic model of emergencies and divided the identified topics into original topics and derived topics. Secondly, we extracted the derived topic data set according to the keywords of the derived topics and used the sentiment classification model to assign the corresponding sentiment labels to the text data. Finally, we used the time series model to analyze the formation and evolution rules of public opinions derived from emergencies and compared the topic-sentiment evolution rules of the public health event with other emergencies in common and different.

It is found that compared with other types of emergencies, the public opinions derived from the public health event had unique characteristics in the evolution of topics and sentiments. In the topic analysis, the public opinion derived from public health events had more obvious dynamic characteristics and fluctuated with time. Through sentiment analysis, it was found that the public opinion

curve derived from public health events had more spikes and did not gradually stabilize over time, but formed a new growth curve. But at the same time, combined with the text materials, it was found that the government’s measures and media reports would deeply affect the fluctuations of public opinion derived from emergencies on temporal networks. The public not only paid attention to the development of original events but also paid great attention to the development of derivative public opinions. Through correlation analysis, we can have a clearer understanding of the propagation characteristics of derived public opinions on temporal networks. At the same time, it can also make a certain contribution to the emergency management of public opinion, reduce the public’s negative emotions, and maintain the network order and society.

By using deep learning methods, we can more easily understand the propagation and evolution of public health events on temporal networks. However, there is still room for further development of the relevant research carried out by the deep learning method in this paper, such as selecting a more appropriate clustering model and classification model and selecting larger data sets for training. We will also take this study as a starting point and carry out further research in the future.

Data Availability

The data of this article are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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