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Deep Reinforcement Learning-based Risk Control Mechanism in Natural Disaster Public Opinion Management

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Abstract With the rapid development of social media platforms, the dynamics and complexity of online public opinion have posed serious challenges to disaster emergency management. In this paper, we propose a risk control framework based on deep reinforcement learning, which realizes structured modeling and dynamic control of public opinion evolution by constructing a spatio-temporal decomposition meta-model of public opinion event scenarios, decoupling the events into three types of characteristic elements, namely, location, type of public opinion, and subject of public opinion, combined with knowledge meta-theory, and designing the Weisbuch-Deffuant viewpoint aggregation rule that takes into account the heterogeneity of the individuals and time lag of the environment. In order to realize the structural modeling and dynamic control of opinion evolution. For sensitive text classification, a heterogeneous graph construction method is proposed to integrate text, words and sensitive entities in the public opinion domain, and graph convolutional networks are utilized to enhance semantic association and risk feature extraction. The "2023 Beijing-Tianjin-Hebei Heavy Rainstorm" event is used as an empirical case to analyze the sentiment, influence and stage evolution of public opinion. The experiment shows that the classification accuracy of the risk warning model based on Weisbuch-Deffuant network reaches 99.36%, and the root mean square error (RMSE) is 0.0079, which is 6.46% and 1.97% lower than that of the traditional BP and GA-BP models, respectively. The risk level analysis shows that most of the public opinion events are concentrated in medium risk (C level), which verifies the effectiveness of the model in dynamic prediction and precise warning.

Index Terms natural disaster public opinion management, deep reinforcement learning, risk control, Weisbuch-Deffuant, heterogeneous graph construction

I. Introduction

China is one of the countries with the most serious natural disasters in the world, with many types of disasters, widely distributed geographically, occurring frequently and causing heavy losses, and various types of safety risks and hazards are intertwined and superimposed, and production safety accidents are still prone to occur frequently. Sudden natural disasters, as events with great impact, not only cause life casualties and property losses, but often also cause strong public opinion reactions [1], [2]. Especially due to the current widespread use of emerging short-video new media, sudden natural disaster public opinion events are more likely to attract the attention of netizens and spread [3], [4].

The complexity of online public opinion on major natural disaster outbreaks poses a great challenge for the government to respond to natural disasters efficiently [5]. The outbreak of a major natural disaster quickly attracts a high degree of public attention, a huge amount of information is mixed with each other, risk factors spread, and the event quickly ferments, giving rise to a huge online public opinion arena [6], [7]. Negative emotions are gathered, group emotions are polarized, social conflicts are intensified, and the public's judgment decreases in the mixed information field, which makes them more susceptible to emotional infection and incitement, and is not conducive to the development of post-disaster mass work [8]-[10]. The hazardous nature of major natural disaster emergencies themselves, the multiplicity of online opinion users, and the repetitive nature of online opinion evolution make online public opinion complex and volatile, which hinders real-world rescue and relief operations [11]-[13]. In highly uncertain crisis situations, it is more likely to ferment into a major public opinion-affecting event, threatening the security and stability in the real society [14], [15]. Therefore, it is necessary to pay attention to the online public opinion of major natural disaster emergencies, to prevent the development and escalation of negative public opinion, and to take strong measures to create a healthy public opinion environment and resolve the crisis [16], [17].

In this paper, we propose a multi-dimensional fusion of public opinion event scenario modeling and risk evolution analysis based on the deep reinforcement learning framework, aiming to achieve accurate identification and dynamic regulation of disaster public opinion risk through structured modeling, optimization of viewpoint aggregation rules, and mining of sensitive information. The article constructs a "public opinion event scenario meta-model" based on spatio-temporal decomposition. By introducing the knowledge meta-theory, the model decouples public opinion events into three types of characteristic elements, namely, location, type of public opinion and subject involved in public opinion, and defines the smallest scenario unit based on spatio-temporal attributes, so as to reveal the multi-scenario coupling mechanism in the evolution of the events. The model abstracts complex events into computable structured expressions. Further focusing on the design of opinion viewpoint aggregation rules. Combining the Weisbuch-Deffuant model and the dynamic characteristics of social networks, we propose an aggregation algorithm that takes into account individual heterogeneity and environmental time lag. By introducing the convergence coefficient distribution and trust threshold, we optimize the viewpoint interaction rules, and propose the "Matthew effect plus edge" strategy for the characteristics of big data platform. On this basis, we propose a heterogeneous graph construction method to meet the sensitive text categorization needs of online communities. By fusing three types of nodes and multidimensional relationships among text, words and sensitive entities, and combining them with the knowledge graph in the field of public opinion to enhance the semantic association, the sparsity problem of short text features is effectively alleviated. The heterogeneous graph construction utilizes graph convolutional networks to capture discontinuous co-occurrence information, and enhances the opinion risk features by embedding sensitive entities, which ultimately improves the domain adaptability and accuracy of the classification model.

II. Deep Reinforcement Learning-based Scenario Modeling and Risk Evolution Mechanism for Public Opinion Events

II. A. Meta-modeling of public opinion event scenarios

It is widely recognized in the academic community that "scenarios" provide a comprehensive and systematic description of the entire process, all aspects of rules and patterns, and a panoramic view of events and their possible consequences based on real-world situations. Focusing on the decision-making needs of public opinion incident management, this paper argues that the "scenarios" of public opinion incidents should be evolving and updated real-life scenarios faced by decision-makers, covering the current state of the incident and possible future developments, with both spatial and temporal attributes. In terms of space, the scenario involves different locations and individuals participating in the public opinion event, and in terms of time, the evolution of the scenario is the whole process of the event.

Therefore, this paper addresses the fact that public opinion events are spatially clustered, temporally clustered, and character-directed, and the evolution of events is a result of the mutual coupling of different scenarios. Combined with the temporal and spatial attributes of the situation, this paper introduces the knowledge element theory to express the event, so as to put forward the concept of "public opinion event scenario element", and believes that the "public opinion event scenario element" is the smallest unit that constitutes the current scenario of the network public opinion event, which is the meta-event state of different time, place and subject elements, combined with the corresponding category of public opinion event. Figure 1 shows the relationship between scenario elements and event scenarios based on spatiotemporal decomposition.

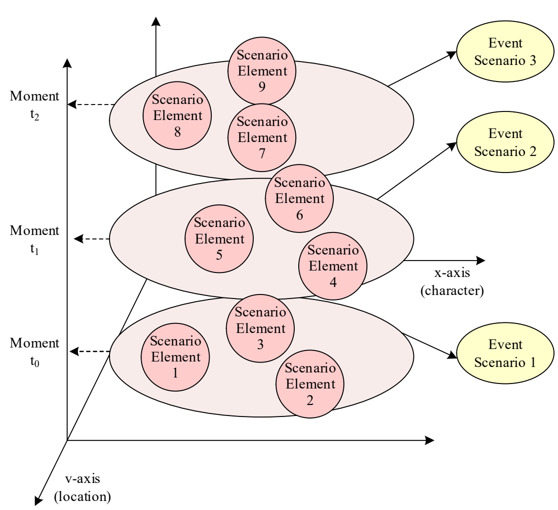

Figure 1: The relationship between the situation element and the event situation

The plane composed of x-axis and y-axis represents the location of the public opinion event and the subject involved, i.e., it is used to judge the relevance to the subject of public opinion decision-making, and represents the collection of the "state" of the public opinion event at a certain moment; the x-axis is the time of the event's evolution, which is the evolution of different scenarios over time, and represents the "momentum" of the development of different public opinion events. The axis is the event evolution time, which is the evolution of different scenarios over time, indicating the development of different public opinion events in terms of "momentum".

Therefore, an online public opinion event will go through multiple "scenarios" from the beginning to the end of the event, and different scenarios correspond to different event dynamics. Therefore, the OE of an online public opinion event can be composed of multiple event scenarios S and governance activities A at specific moments, and the evolution is shown in Figure 2.

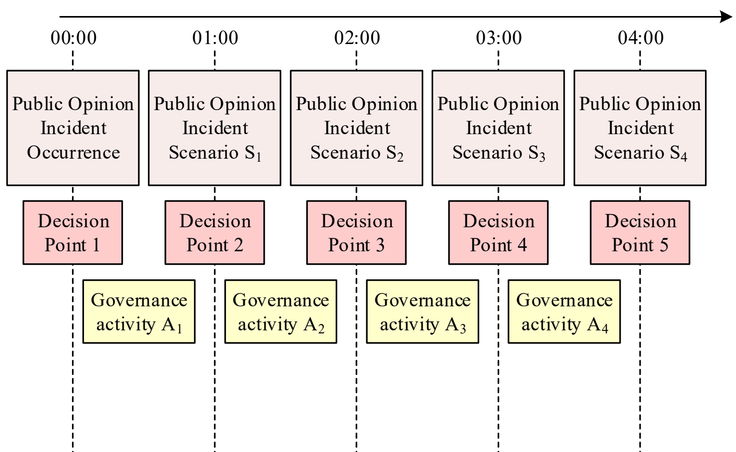

Figure 2: Evolution of event scenarios

Denote it as:

$$OE = \{\langle S_1, A_1\rangle, \langle S_2, A_2\rangle, \cdots, \langle S_t, A_t\rangle\} \tag{1}$$

Where $t = 1,2,3,\cdots,n$ denotes the online public opinion events and governance activities under the moment t and satisfies the condition $S_n \prec S_{n+1}$, $\prec$ is a sign of precedence, which means that the time when S_n occurs is earlier than S_{n+1}.

Characteristic elements are attribute elements that reflect the essence of things and distinguish them from other things. Based on the knowledge element theory, on the basis of analyzing the characteristics of online public opinion events, and combining with the actual needs of public opinion governance decision-making, the scenario element of the event S_n is defined as a collection of 3 types of feature elements, namely, location element (P), public opinion-causing type element (E), and public opinion-involved subject element (M).

$$S = \{P, E, M\} \tag{2}$$

By representing the online public opinion event scenario element S_n through the knowledge meta-model, then the following online public opinion event scenario meta-model can be constructed:

$$S = \{K_P, K_E, K_M\} \tag{3}$$

$$K_P = \{K_{Pa} | \ a = 1,2,3,\cdots x\} \tag{4}$$

$$K_E = \{K_{Eb} | \ b = 1,2,3,\cdots y\} \tag{5}$$

$$K_M = \{K_{Mc} | \ c = 1,2,3,\cdots z\} \tag{6}$$

Among them, K_P is the knowledge element of location, K_E is the knowledge element of type of public opinion, and K_M is the knowledge element of subject involved in public opinion. K_P consists of x location element knowledge meta-instances, and K_{Pa} denotes the a th location element knowledge meta-instance; K_E consists of y instances of knowledge meta-instances of opinion-related type elements, and K_{Eb} denotes the b th instance of knowledge meta-instances of opinion-related type elements; K_M consists of z instances of knowledge meta-instances of opinion-involving subject elements, and K_{Pc} denotes the c th instance of knowledge meta-instances of opinion-involving subject elements.

II. B.Rule Setting for Web Public Opinion Aggregation

Based on the decoupling of spatio-temporal features in situational meta-modeling, the dynamic evolution of public opinion events needs to further quantify the impact of viewpoint interactions. To this end, this section will focus on the aggregation rule setting of online public opinion viewpoints and reveal the mechanism of individual heterogeneity on risk propagation by introducing a social network dynamics model.

Based on the collection of online opinion views obtained above, the Weisbuch-Deffuant model is used to set the rules for aggregation of online opinion views as a basis for the aggregation of online opinion views. The specific process is shown below.

Neglecting the loss in the aggregation space of network opinion views, the network size is set to be M , and the social network constituted by each individual in it is denoted as $G(M,E)$, where E denotes the number of edges in the network.

Random individuals in the social network are denoted by i , and the value of the opinion about a certain network opinion event at moment t is denoted by O_i^t , whose range is $[0,1]$. In the process of network public opinion viewpoint interaction, the time lag of viewpoints and other environmental factors lead to the fact that the viewpoint interaction behavior is often not an in-depth key exchange between individuals, but mainly an individual's response to the viewpoints of other individuals, and a certain degree of modification of the individual's viewpoints based on the specific situation. Therefore, in the process of constructing the risk evolution model of online public opinion, the individual's viewpoint is set to change with time, which is expressed as

$$\begin{cases} O_i^{t+1} \sim \left\{ O_i^t, O_k^t \right\}, i \neq k \ and \ ik = 1 \\ O_i^{t+1} \sim \left\{ O_i^t, O_j^t \right\}, k \neq j \ and \ kj = 1 \\ \qquad\qquad \cdots \end{cases} \tag{7}$$

where k denotes a random node in the social network of individual i ; $ik = 1$, $kj = 1$ denotes a direct connection between i,k and k,j respectively.

In online opinion viewpoint aggregation, the degree of individual interaction is characterized by non-sufficiency and heterogeneity, and the degree of acceptance of others' viewpoints by individuals is also different. In the process of network opinion viewpoint aggregation, the convergence coefficient is mainly a variable that describes the degree of acceptance of other people's viewpoints by individuals, and its different values directly affect the effect of viewpoint aggregation. Therefore, it is not reasonable to set the convergence coefficient to a fixed value. In this section, the distribution of the convergence coefficient $f(\mu)$ is used instead of the convergence coefficient. In addition, the trust threshold is introduced with the viewpoint distance, which satisfies the following equation

$$\Delta O_{ik}^t = \varepsilon * O_k^t - O_i^t \tag{8}$$

where O_{ik}^t denotes the viewpoint distance; ε denotes the trust threshold.

According to the above formula, the general rule of network opinion viewpoint aggregation is obtained as

$$\begin{cases} if \left| \Delta O_{ik}^t \right| \leq \varepsilon, O_i^{t+1} = \chi \cdot O_i^t + \mu_i \Delta O_{ik}^t \\ else, O_i^{t+1} = O_i^t \end{cases} \tag{9}$$

where ε is a fixed value on the value domain $[0,1]$.

However, in real life, the network belongs to a big data platform, and when aggregating opinion viewpoints, the individuals at a certain moment are subject to large changes. Assuming that the number of online opinion viewpoints is M when $t=0$, the size of the social network is $C\left(M, E_M\right)$, and the initial viewpoint value of an individual is $\left\{O_1^0, O_2^0, \cdots, O_M^0\right\}$, and the corresponding acceptance of his/her viewpoints is $\left\{\mu_1, \mu_2, \cdots, \mu_M\right\}$. In order to guarantee the accuracy of network opinion viewpoint aggregation, there are two main ways to link the newly added individuals with other individuals, as follows:

Way 1: Randomly adding edges. It is mainly based on the probability of randomly selecting among the network individuals, so that the newly joined individuals and their connections are established;

Way 2: non-equal probability of adding edges based on degree weights. It is mainly based on the "Matthew effect" of the network connection to connect the newly joined individuals with the existing individuals, and the probability of which is

$$\Pi_i = \frac{k_i}{\sum_j k_j} \tag{10}$$

At the same time, there is a celebrity effect in the network, and it is more in line with the actual situation to perform adding edges in way two. Therefore, the process of network opinion viewpoint aggregation under big data platform is obtained as shown in Figure 3.

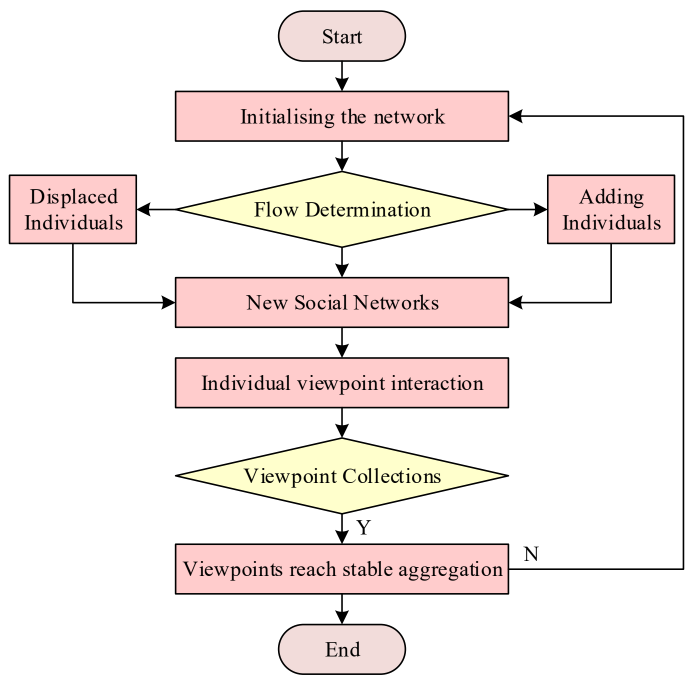

Figure 3: The process of aggregating online public opinion viewpoints

The above process completes the setting of the rules for aggregation of online public opinion viewpoints and the aggregation of viewpoints to prepare for the calculation of the risk factor of online public opinion.

II. C.Heterogram Construction of Sensitive Texts in Online Communities

After completing the theoretical construction of viewpoint aggregation rules, how to extract sensitive information from massive text and realize accurate classification becomes a key part of risk identification. In this section, we will combine the heterogeneous graph construction and domain knowledge fusion to propose a feature enhancement method for sensitive text, which provides high-quality risk feature input for deep reinforcement learning models.

Graph Convolutional Networks are used to update the representation of nodes through the relationships between nodes in the graph, and the weights of different relationships also affect the influence effect between nodes. Constructing heterogeneous graphs on the whole corpus can establish the connection between texts and texts, obtain the discontinuous co-occurrence information between texts, in addition to enriching the features of texts.

Sensitive texts in online communities have two significant features compared with ordinary texts. The first is that the text structure is different and the long and short texts are mixed. In the past research on graph construction for graph neural network text classification, TextGCN utilizes documents and words to construct graphs, obtains global word co-occurrence information, and easily adapts to graph convolution, and this method achieves good results on long texts. For short text categorization, previous studies have utilized various methods to enrich the semantics of short texts, such as potential topics in the knowledge base and external knowledge (entities). Based on this HGAT utilizes text, entities and topics to construct a heterogeneous graph and considers semantic relational information such as entity relationships to achieve better results. The entity used in the above study is a concept in knowledge mapping, which refers to a distinguishable and independent existence of something abstracted from a word in a piece of text. For example, a person, a city, a plant, a commodity and so on. In the knowledge graph, entities will be associated with each other through attribute information, which can be utilized in machine learning tasks such as text classification to enrich domain knowledge and expand text semantic information.

In addition to sensitive text has sensitive features. Sensitive text is based on ordinary text, through the identification of sensitive keywords, as well as a series of other operations (e.g., sentiment analysis) to obtain a special text. If its sensitive information can be utilized, the similar features of sensitive text in the field of public opinion can be fully explored to improve the effect of classification. Many existing researches utilize domain prior knowledge to improve the text classification effect, such as utilizing the additional knowledge of Chinese medicine knowledge graph for graph construction.

Therefore, we propose a graph construction method for the characteristics of sensitive text, which utilizes text, words and sensitive entities to construct a graph. Among them, text is the text obtained from the original corpus after preprocessing; words are the meaningful words obtained by word splitting in the text; sensitive entities are the entities involved in the field of public opinion extracted from the text by entity linking, for example, flood, fire, etc. These sensitive entities are different from the words and belong to the juxtaposition in the heterogeneous graph, the words are the ones that the text separates from the semantic level, and the entities are the ones obtained by the text associated with the external knowledge. Adding these entities to the heterogeneous graph can enrich the information of the original text and help the graph neural network learn text features better. And the sensitive entities contain prior knowledge in the field of public opinion, which is more suitable for the purpose of categorizing sensitive text than ordinary entities. In other words, in the classification task of sensitive text, additional information involving the opinion domain can produce better results compared to ordinary external information.

This graph construction method can alleviate the differences between long and short texts, and enrich the textual information with opinion a priori knowledge to make full use of the sensitive features of the text, thus improving the model's classification effect on sensitive texts in online communities.

As shown in the example heteromorphic graph in Figure 4, we construct a heteromorphic graph $G=(V,E)$ containing the text $D=\{d_1,\cdots,d_m\}$, the words $W=\{w_1,\cdots,w_n\}$ and the sensitive entity $S=\{s_1,\cdots,s_k\}$ as a node, i.e., $V=D\cup W\cup S$, and the number of nodes in the heteromorphic graph $|V|$ is the number of documents (corpus size) plus the number of unique words in the corpus (vocabulary size) plus the number of unique sensitive entities. The set of edges E represents their relationships. The construction process of the heterogeneous graph is described in detail below.

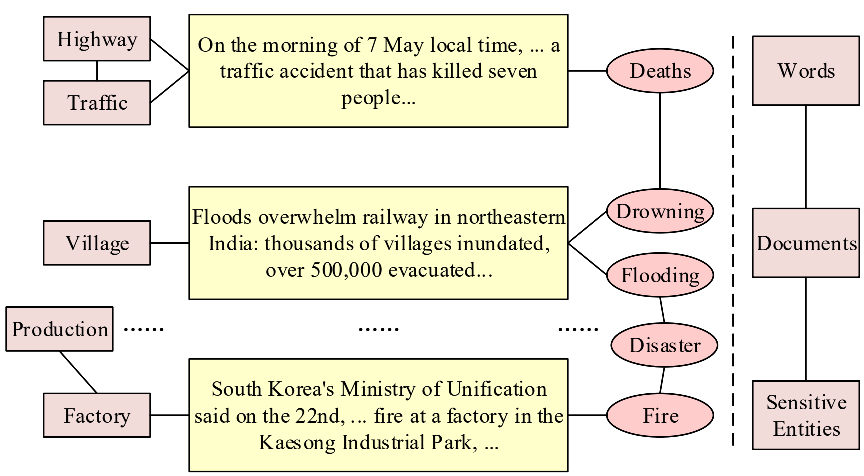

Figure 4: Example of heterogeneous graph

We consider two scenarios to establish links between texts (1) two texts have the same and similar words and (2) two texts have the same or related sensitive entities. Therefore, we create four types of edges in the graph, including document-word edge, word-word edge, document-sensitive entity edge and sensitive entity-sensitive entity edge, based on the occurrence of words in the document, the co-occurrence of words in the whole corpus, the occurrence of sensitive entities involved in the document and the co-occurrence of sensitive entities involved in the corpus.

First, we discover the word W in the document D using Chinese word segmentation, remove the noise and meaningless words, and build a corpus-wide word collection. If the document contains words, we build an edge between the document and the words, and the weight of the edge is the word frequency-inverse text frequency index (TF-IDF) of the words in the document. We utilize a sliding window to count the occurrences of words across the corpus as a way to get global word co-occurrence information. The edge weights between words and words we compute using Pointwise Mutual Information (PMI), which is a commonly used metric to measure the association between two words. If the PMI between two words is greater than a threshold value of 0, an edge between the words is created.

Second, we use the entity linking tool to identify the sensitive entities E involved in a document D based on the knowledge graph in the field of online opinion. If the document contains a sensitive entity, the edge between the document and the sensitive entity is constructed, and the weight of the edge is the TF-IDF value of the sensitive entity in the document. To further mine the sensitive features between texts, we consider the relationship between sensitive entities, and we map a sensitive entity to Chinese Wikipedia to get its description information. We take a sensitive entity and its description as a whole word and learn the embeddings of sensitive entities using BERT based on the Wikipedia corpus. Based on their embeddings, if the cosine similarity score of two sensitive entities exceeds a threshold g, edges between sensitive entities are established. Overall, the weight of an edge between node i and node j is defined as:

$$A_{ij} = \begin{cases} PMI(i,j) & i,j \text{ are words}, PMI(i,j) > 0 \\ TF\text{ - }IDF_{ij} & i \text{ is document}, j \text{ is word or entity} \\ Similarity(i,j) & i,j \text{ is an entity}, Similarity(i,j) > \delta \\ 1 & i = j \\ 0 & \text{Other} \end{cases} \tag{11}$$

By adding sensitive entities in the process of constructing heterogeneous graphs, the prior knowledge of sensitive texts of network public opinion is introduced, and the sensitive information is enriched. Because of the existence of a large number of sensitive entities and edges between them and text in heterogeneous graphs, graph convolutional networks will pay more attention to sensitive information when learning, which is helpful for them to better complete the classification task. For example, the text "Floods in Northeast India Wash Railways: Thousands of Villages Flooded, More Than 500,000 People Evacuated" reinforces sensitive features through the physical relationships between sensitive entities "drowning" and "floods" and "floods" and "disasters", and is complemented by prior knowledge of online public opinion. Therefore, it can be correctly classified as a category of "disasters" with a high degree of credibility.

III. Research on Evolutionary Analysis of Public Opinion on Natural Disasters and Early Warning of Cyber Risks Based on Heterogeneous Graphs

Under the deep reinforcement learning framework proposed in Chapter 2, through the theoretical construction of public opinion event scenario meta-model and viewpoint aggregation rules, this chapter will carry out the empirical analysis of public opinion evolution based on heterogeneous graphs in the context of the actual case of “2023 Beijing-Tianjin-Hebei Heavy Rainstorm”, and design the Weisbuch-Deffuant network warning model to realize the closed-loop verification from theoretical modeling to actual risk warning. We will also design the Weisbuch-Deffuant network warning model to realize the closed-loop verification from theoretical modeling to actual risk warning.

III. A. Empirical Analysis of Natural Disaster Online Public Opinion Evolution Based on Heterogeneous Graphs

Based on the construction of the natural disaster online public opinion isomorphic map, comprehensive analysis of the causal transmission paths, emotions, influence, duration, etc. of various types of events in the process of development can play a multifaceted role: through the construction of the public opinion isomorphic map, the process of the development of the natural disaster online public opinion events and their causal relationships can be clearly presented, which can help to understand the evolution and influence of the events; through the analysis of the causal transmission paths By analyzing the causal transmission paths, key factors and potential risk points in the event can be identified, so that risk assessment and response strategies can be formulated in a targeted manner; and by comprehensively analyzing the development process, emotions, influence and other factors of the public opinion event, it can provide decision-makers with more valuable reference information to assist in formulating natural disaster policies and responding to natural disaster public opinion, and so on.

III. A. 1) Data acquisition

This study analyzes the "2023 Beijing-Tianjin-Hebei Heavy Rainstorm" as an empirical example, and the data come from user comments on the microblogging platform. We used python to crawl the microblogs posted by users on several topics related to the "2023 Beijing-Tianjin-Hebei Heavy Rainstorm" event on the microblogging platform, referring to the Baidu Index's public opinion search index for the event, and selected the crawling dates from 2023-7-20 to 2023-8-2, and obtained the relevant fields, including the number of likes, comments, microblog text, microblog posting time, retweet, and retweets, The relevant fields include: number of likes, number of comments, microblog text, microblog posting time, number of retweets, device source, microblog links, user nicknames, etc. The crawled data is written into a json file. After de-weighting, a total of 7620 pieces of valid data were obtained. The figure shows an example of crawling information. Another selected in the event of the larger number of comments in the microblog crawl netizen's comments, access to the relevant fields include: comments published events, comments, user nicknames, the number of replies received by the comment, etc., a total of 10,236 crawling comments, the crawling data will be written into the csv file.

III. A. 2) Analysis of the evolution of the emotional dynamics of the event

Through the analysis of the crawled data, it is found that the number of microblogs actively published by ordinary netizens about the event is much lower than the number of comments made by netizens under the microblogs of famous media or KOLs, and the latter is more abundant in terms of text information and richness, and the sentiment analysis of which is more representative of the sentiment tendency and evolution trend of netizens in the process of public opinion evolution.

The distribution of IP provinces of comments on this public opinion event is shown in Figure 5.

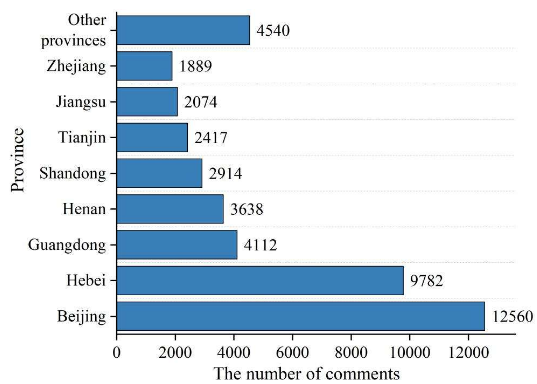

Figure 5: The provincial distribution of comment ips on public opinion events

In the analysis of the content in the comments and their IP affiliation, it was found that more than 50% of the comments were from Beijing and Hebei, the Beijing-Tianjin-Hebei region where the event took place, with 12,560 and 9,782 comments, respectively, reflecting a high degree of participation by netizens from the affected areas; in addition, active discussions in non-affected provinces, such as Guangdong and Henan, reflected the nationwide impact of the event.

III. A. 3) Evolutionary analysis of the impact of events

The evolution of an event's influence refers to how an event's influence changes at different stages over time. Generally speaking, when an event has just occurred, its influence is relatively small, but as time passes, the influence of the event may gradually increase or decrease. This depends on a variety of factors, such as the nature of the event, the people involved, the location, the time, and so on, as well as the degree of public concern and emotional tendency towards the event. Here, the five most representative key sub-events in the course of the event are selected - the release of meteorological warnings, urban flooding and subway shutdown due to heavy rainfall, the official activation of the emergency response, civil mutual aid and Internet rumors, and post-disaster reconstruction and donation disputes. Crawl the netizens' comments under several microblogs with the highest comment volume of the five sub-events. According to the formula, the influence index of each sub-event of the "2023 Beijing-Tianjin-Hebei Mega Storm" public opinion and the influence of each event at different times are calculated and analyzed, and the evolution of the influence of the sub-events of the “2023 Beijing-Tianjin-Hebei Mega Storm” public opinion is shown in Figure 6.

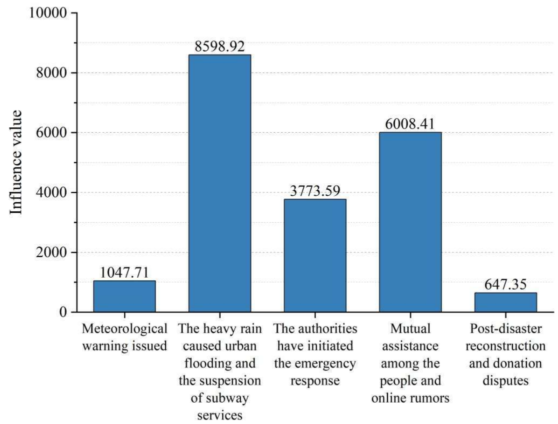

Figure 6: The evolution of the influence of public opinion sub-events

According to the figure, it can be found that the evolution of the influence of sub-events is characterized by the following features: firstly, sub-events show rapid diffusion and often spread rapidly within a very short period of time after the event is released on the Internet, forming a huge influence. Secondly, sub-events show stage changes, the influence of sub-events in different stages is different, in the event just occurred, the public may only be a preliminary understanding of the situation, the influence of the event is relatively small, such as the beginning of the “weather warning release” influence is only 1047.71; With the further development of the incident, the public's attention to the incident may gradually increase, and the influence of the incident may also gradually expand, the influence of the “heavy rainfall causing urban flooding and subway suspension” reached 8598.92; After a period of time, the public gradually lost their attention to the event and shifted to other contents, and the influence of the event gradually decreased, for example, the influence of the event's “post-disaster reconstruction and donation controversy” only amounted to 647.35 in the end. Thirdly, complexity and uncertainty, sub-event influence evolution is a complex process, influenced by a variety of factors, especially by the compound influence of the preceeding sub-events, and the influence evolution process of each sub-event is not the same, which makes the sub-event influence evolution uncertain and unpredictable.

III. A. 4) Stage evolution analysis of public opinion events

The number of microblogs related to the “Beijing-Tianjin-Hebei Heavy Rainstorm” event in 2023 is counted and time-labeled, which can be more intuitive to see the change of netizens' attention to the event in different time periods, and Fig. 7 is the temporal change of the number of posts drawn according to the crawled data.

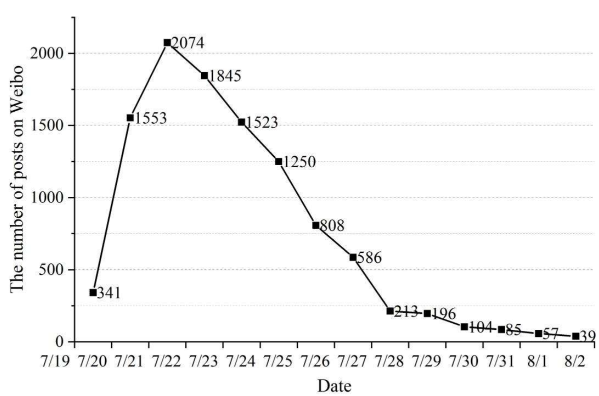

Figure 7: The sequential changes in the number of Weibo posts

The attention of the incident shows significant stage characteristics. From July 20 to August 2, 2023, the number of articles posted by netizens showed an evolutionary trend of “rapid rise - high level shock - continuous decay” with the development of the event. Specifically: the initial outbreak stage (July 20-22): after the Central Weather Bureau issued the red rainstorm warning on July 20, the number of posts was only 341 on the same day; with the intensification of the rainstorm disaster, flooding and subway shutdowns and other secondary disasters occurred in many places in Beijing on July 21, the number of posts rapidly surged to 1,553 on the 21st, and peaked at 2,074 on the 22nd, which reflected the real-time concern and information dissemination needs of the public for the disaster; the high-level shock - continuous decay. The high shock phase (July 23-25): the official launch of the Level II emergency response (July 23) and civil mutual aid, the proliferation of rumors on the Internet (July 24-25) drove public opinion to continue to ferment, and the number of posts fell from the peak, but remained high, with 1,845 on the 23rd, 1,523 on the 24th, and 1,250 on the 25th, indicating continued public discussion on the progress of the rescue and the dynamics of the disaster. This shows the public's continuous discussion on the progress of rescue and the dynamics of the disaster; Decay and recession phase (July 26-August 2): With the discussion on post-disaster reconstruction, netizens' attention dropped significantly, and the amount of posts decreased day by day, with 808 posts on the 26th and only 39 posts on August 2nd. This trend is closely related to the weakening of the actual impact of the event and the shift of public opinion hotspots, especially the donation controversy and other later sub-events that did not trigger large-scale secondary communication.

III. B. Natural Disaster Public Opinion Risk Early Warning Based on the Weisbuch-Deffuant Model

III. B. 1) Experimental setup

On the basis of constructing the natural disaster online public opinion crisis risk index and determining the risk level of natural disaster public opinion, the Weisbuch-Deffuant network early warning model is further constructed to predict the natural disaster online public opinion crisis risk index and realize the early warning of natural disaster online public opinion risk.

In this paper, a natural disaster online public opinion early warning model based on Weisbuch-Deffuant is constructed, with the 16 risk assessment indicators in the optimal index system for natural disaster online public opinion risk assessment as inputs to the model, and the crisis risk indexes of natural disaster online public opinion events as the predicted outputs, and the entire structure and parameters of the natural disaster

(1) A three-layer BP neural network structure with a single hidden layer is used, the number of input nodes is 16, and the number of output nodes is 1. The parameters a are tested one by one, and the early warning model works best when a=5, when the number of nodes in the hidden layer is 9. The transfer function of both the hidden layer and the output layer is set to be a sigmoid function, and the training function to be Traingd, the maximum number of times of the network's training is 1,000, and the training target error is 1×10-5 and the learning rate is 0.05.

(2) Setting the population size as 45, the initial crossover probability Pc1 and variation probability Pm1 are 0.6 and 0.05 respectively, the maximum number of genetic generations is 100, and the real number coding method is adopted, according to the structure of natural disaster online public opinion early warning model of Weisbuch-Deffuant network, it can be seen that: the values of the parameters of W1, B1, W2, and B2 are 144, 9, 9, and 1 respectively, and it can be calculated to get the coding length R is 163.

From the natural disaster public opinion event case base, 80% of natural disaster online public opinion events are used as the training set and 20% as the test set, and the Weisbuch-Deffuant network warning model is constructed to predict the crisis risk index of natural disaster online public opinion. The initial weights and thresholds of the network are first optimized using adaptive genetic algorithm, and the best weights and thresholds are obtained after 49 generations of genetic evolution, and the network training is carried out until the error of Weisbuch-Deffuant network reaches the training target error.

III. B. 2) Data sets

The source of experimental data is Weibo platform, and the public opinion data of 932 natural disaster events within 24 hours from January 1, 2020 to January 1, 2025 were obtained by crawler for analysis and labeled, containing a total of 842,271 pieces of data. The risk level is categorized into 4 grades: D (low), C (medium), B (high), and A (extremely high), and the risk level definition table is as follows:

Grade D: Crisis Risk Index (0-0.30), public concern is low, and the Olympic situation is at low risk.

Grade C: Crisis Risk Index (0.31-0.59), with some public concern, the OSI is at medium risk.

Grade B: Crisis Risk Index (0.60-0.79), high public concern, Austrian situation at high risk.

Level A: Crisis Risk Index (0.80-1.00), public concern is very high, and the Austrian situation is at very high risk.

III. B. 3) Prediction results of different neural network warning models

In this paper, the results of the Weisbuch-Deffuant network early warning model are compared with the results of the traditional BP neural network and GA-BP neural network, and the results of the crisis risk index early warning of the test samples in some test sets are shown in Table 1.

Table 1: Comparison of warning results of online public opinion crisis risk indices

Test sample	Expected output of the crisis risk index	BP		GA-BP		Weisbuch-Deffuant	
		Actual output	Relative error	Actual output	Relative error	Actual output	Relative error
1	0.4099	0.3793	7.47%	0.4224	3.06%	0.4053	1.13%
2	0.6683	0.6275	6.10%	0.6958	4.11%	0.6752	1.03%
3	0.2541	0.2732	7.53%	0.2578	1.44%	0.2563	0.86%
4	0.3142	0.2932	6.67%	0.3064	2.48%	0.3173	0.99%
5	0.6371	0.5817	8.69%	0.6568	3.09%	0.6308	0.99%
6	0.3726	0.3480	6.60%	0.3866	3.76%	0.3700	0.71%
7	0.0848	0.0776	8.51%	0.0879	3.63%	0.0841	0.85%
8	0.8416	0.9068	7.75%	0.8533	1.39%	0.8477	0.73%
9	0.5359	0.5713	6.61%	0.5287	1.34%	0.5422	1.17%
10	0.2490	0.2289	8.06%	0.2566	3.07%	0.2512	0.88%
11	0.1539	0.1441	6.36%	0.1493	2.97%	0.1553	0.94%
12	0.8312	0.7795	6.22%	0.8088	2.70%	0.8402	1.08%
13	0.2198	0.2011	8.50%	0.2134	2.92%	0.2214	0.75%
14	0.3380	0.3113	7.91%	0.3320	1.78%	0.3404	0.72%
15	0.5971	0.5558	6.91%	0.6087	1.94%	0.5914	0.95%
16	0.3849	0.4139	7.54%	0.3686	4.24%	0.3821	0.73%
17	0.6064	0.6580	8.51%	0.5852	3.49%	0.6031	0.55%
18	0.5986	0.5554	7.21%	0.5848	2.30%	0.5955	0.52%
19	0.7540	0.7083	6.06%	0.7876	4.45%	0.7581	0.54%
20	0.1581	0.1697	7.31%	0.1628	2.95%	0.1564	1.05%

The overall error analysis results obtained from the analysis about the three early warning models of natural disaster online public opinion are shown in Table 2.

Table 2: Error comparison of Online Public Opinion Early Warning Models

Early warning model	MAE	ARE	RMSE
BP	0.0733	0.0684	0.0784
GA-BP	0.0286	0.0311	0.0307
Weisbuch-Deffuant	0.0086	0.0104	0.0079

From the test set error comparison results, it can be seen that the warning model based on Weisbuch-Deffuant network has the smallest prediction error for all three kinds of test set samples, with the root mean square error RMSE of 0.0079, and the average relative error MAE is reduced by 6.46% and 1.97% compared with the other two warning models, which indicates that the Weisbuch-Deffuant Network Early Warning Model has good prediction performance for the crisis risk index of natural disaster network public opinion, with the best actual early warning effect and the highest accuracy, which further improves the early warning precision of natural disaster public opinion, reduces the overall prediction error, and can effectively realize the risk early warning of natural disaster network public opinion.

III. B. 4) Experimental results of risk assessment modeling

The test set data is predicted and integrated into a risk assessment model using the Stacking method, which fits and predicts the divided data set, and the classification effect of the risk assessment model is shown in Figure 8.

It can be seen that the risk value of online public opinion prediction about natural disasters designed in this paper is more accurate, and the performance of the model is assessed by the evaluation indexes such as accuracy, macro recall, macro precision, macro F1-score, etc., and the accuracy of the risk assessment model is 99.36%, the recall is 96.22%, the precision is 98.17%, and the F1-score is 97.18%.

Observing for the risk index of the test samples, the risk most of the samples are in the C and D risk levels of 0.31-0.59 and 0.60-0.79, especially concentrated in the medium risk public opinion of C grade, indicating the receipt of a certain degree of public attention.

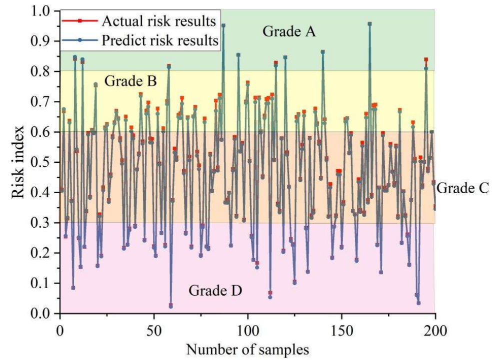

Figure 8: Classification effect of risk assessment model

IV. Conclusion

In this paper, a risk control framework based on deep reinforcement learning is proposed to address the complexity and dynamics of natural disaster public opinion management. By constructing a spatio-temporal decomposition of public opinion event scenario meta-model, combined with knowledge meta-theory and Weisbuch-Deffuant viewpoint aggregation rules, structured modeling and multi-dimensional analysis of the public opinion evolution process are realized. In the empirical study, based on the microblog data of the "2023 Beijing-Tianjin-Hebei Extreme Rainstorm" event, the heterogeneous graph is utilized to mine text-sensitive features and combined with the Weisbuch-Deffuant network model to carry out risk warning. The experimental results show that the classification accuracy of the model on the test set reaches 99.36%, and the root-mean-square error is 6.46% and 1.97% lower than that of the traditional BP and GA-BP models, respectively, which verifies its superiority in predicting the dynamics of public opinion risk. In addition, the risk level analysis shows that most of the public opinion events are concentrated in medium risk (level C), which needs to focus on the real-time changes of public attention and emotional tendency.

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