

Event Evolution Graph

Based on Social Media Comments

Weng Xu 2203589

University of Wales Trinity Saint David,

Assignment of Research Methods and Professional Development

Contents

1. Introduction.....	1
2. Literature Review.....	3
2.1. Public Emergencies.....	3
2.2. The Life Cycle of Online Public Opinion.....	3
2.3. Evolution of Online Public Opinion Based on Machine Learning.....	4
2.4. Event Evolution Graph.....	5
2.4.1 Rule-based Templates.....	6
2.4.2 Machine Learning-Based Relation Identification.....	6
2.4.3 Event Generalization.....	7
2.4.4 Graph.....	8
3. Methods.....	9
3.1. Research Philosophies.....	9
3.2. Data Mining and Collection.....	10
3.3. Knowledge Graph.....	10
3.4. Natural Language Processing.....	12
3.5. Machine Learning.....	13
4. Results.....	15
5. Evaluation.....	15
References.....	16

1. Introduction

With the widespread use of technology, social media such as Twitter and Facebook are more widely used to provide more personal community services through user information sharing, dissemination and acquisition. Public emergencies will trigger public opinion on major social media and generate a large number of relevant user discussions. In a public social network environment, topics can be used to find news of

a specific topic or content, which can greatly facilitate information dissemination, content search, event detection, and topic analysis. Online comment data is the most objective remarks of users on a certain event. Both positive and negative comments exist, which can truly reflect the objective facts of offline events, and at the same time, it is an intuitive mapping of current key issues in society.

In this paper, it proposes a method for graphing online comment data based on latent topic information in Weibo. With users centered on the comment topic distribution, the frequencies of all tags appearing among these users are then calculated. The evolution path of user discussions can be clearly presented through the data of online social media, and the evolution law and evolution characteristics of Internet topics can be summarized more conveniently through graphs.

The evolution of social network discussion topics often involves multiple subjects, and the subjects interact with each other during the evolution process, resulting in uncertainty in the evolution path. The current research mainly focuses on the motivation and law of the evolution of public opinion. Research on the law of public opinion evolution focuses on how to divide the development stages of public opinion based on the order of occurrence and development cycle of public opinion events, and analyze the law of the evolution of public opinion from each stage. These studies can provide a basis for the implementation of public opinion supervision on social network platforms. Focus on key events and control key nodes to provide decision-making basis.

Existing researches on network public opinion prediction mostly focus on the prediction of network public opinion trends, emotions, risk levels, etc. The trend of online public opinion is based on the data of the number of posts and discussions of netizens, and predicts the possible trend of public opinion in the next period of time, which will provide a good help for the early warning of public opinion outbreaks on social media platforms.

Solve the evolution analysis of emergencies from the perspectives of event evolution and risk subject association to further enhance the diversity of analysis perspectives and the effectiveness of analysis results, thereby helping relevant companies or institutions to carry out risk decision-making and emergency management in a more targeted manner Work.

2. Literature Review

2.1. Public Emergencies

Public emergencies refer to events that require urgent measures to prevent major impacts and serious threats to the public and society[1]. Internet public opinion on public emergencies is a combination of "Public emergencies" and "Internet public opinion".

Coady analyzed terrorism and emergencies and believed that such events would have an impact on social values, ethics, and codes of conduct[2]; At the same time, it is difficult to predict and prevent and control[3]; Brennan and others took SARS as an example and believed that emergencies are a form that needs to be handled by unconventional methods and social mechanisms need to be innovated [4]; Shi Rui believes that emergencies include natural disasters to social events, economic events to political activities, and local events to national or even global events, involving disaster management, economics and politics[5].

Worldwide, such as the SARS epidemic, the Indonesian tsunami, the Wenchuan "5.12" earthquake, the Japanese earthquake and the Fukushima nuclear power plant leak, etc. are all emergencies[6].

2.2. The Life Cycle of Online Public Opinion

The evolution of online public opinion is a cyclical process, and identifying the key nodes of online public opinion helps deepen the knowledge of online public opinion and better grasp the evolutionary dynamics of online public opinion[7].

Changes in Internet users' emotions will affect the spread of Internet public opinion, and predicting users' emotions in Internet public opinion can help platforms better understand the development of Internet public opinion.

Liang GH et al. combined the communication characteristics of public crisis events and divided the life cycle of online public opinion development into four stages: latency period, attack period, duration period, and quelling period, and systematically analyzed public crisis event-type online public opinion based on the theory of public opinion evolution life cycle[8].

Fink proposed a life-cycle model of latency, eruption, dissemination, and recovery periods, which was applied to the public opinion communication of emergencies [9]. Robert also proposed the 5R theory of crisis management, which is the stages of

reduction, preparation, response, recovery, and resilience [10]. Yuan XLL et al. studied the dissemination paths of online messages through social network analysis, based on the characteristics of network density, accessibility, centrality, kernel, and structural vulnerability, and suggested that provinces and cities where events occur, national news agencies, and online media play an important role in the dissemination paths[11]. Renbin X et al. combined artificial ant colony algorithm and optimization theory to establish a Kuramoto one-based model for synchronous evolution of Internet public opinion, and finally showed that increasing the input cost to some extent can improve the synchronization performance of the weakly coupled system[12]. li Q et al. calculated the influence of nodes by rating, forwarding and praising public opinion, and then constructed a weighted network to illustrate how online public opinion evolves[13].

2.3. Evolution of Online Public Opinion Based on Machine Learning

Prediction techniques based on intelligent machine learning algorithms mainly use gray system theory, neural network models, and support vector machines.

The prediction of online public opinion based on the theory of gray system. Some scholars have applied the theory of gray system to the prediction of online public opinion. Du Zhitao et al. used the gray prediction method to build a prediction model and showed that the model has good effect on the prediction and early warning work of online public opinion[14]. Zeng Zhendong proposed to first establish a GM(1,1) prediction model for online public opinion and corrected the original prediction results by using SVM method, and the results showed that the method was helpful to improve the accuracy of public opinion prediction[15]. Shi et al. used the particle swarm algorithm to optimize the parameters of the GM(1,1) power model and combined with the GM(1,N) model to build a combined gray model for predicting the spread of online public opinion, and the empirical evidence shows that this method is more accurate than the multi-factor gray model[16].

The template method is limited by the quality and coverage of the template, and then a method based on machine learning is produced, which is still essentially classified according to the characteristics of the text corpus. The more mature classification algorithms for machine learning include the KNN algorithm and the SVM algorithm. Subsequently, methods based on neural networks and kernel functions appeared, which alleviated the problem of sparse features. The kernel function method

directly takes the structure tree as the processing object, and uses the high-dimensional feature space to implicitly calculate the distance between objects, which is flexible. to extract event relations. The causal extraction method based on the sequence annotation model can directly obtain the causal event pairs from the text, which points out a new direction for the research of causal relationship extraction. However, sequence annotation data is relatively scarce.

Neural network-based prediction of online public opinion. Radinsky used machine learning and data mining techniques to achieve event prediction[17]. Zeng Ziming used BP neural network to predict the outbreak disease transmission network public opinion. Jingchao Sun et al. constructed a network opinion prediction model based on recurrent neural network[18].

A study on support vector machine based prediction of online opinion. yang HL et al. used a new multiclass support vector machine approach to predict document-level comments and demonstrated the effectiveness of this approach[19]. Guo Jiangmin et al. used a support vector machine model with improved hybrid frog-jumping algorithm for parameter search of SVM to achieve opinion prediction[20]. Tian Shihai et al. used an improved latent semantic analysis and support vector machine (LSA+SVM) for public opinion warning in the field of unexpected security[21].

2.4. Event Evolution Graph

Ontology is the basic content of public opinion, including all ideologies of users participating in social network public opinion, that is, the interlaced sum of various views, positions, attitudes and emotions expressed by users. The public opinion ontology has different forms of expression, which can be traditional texts, or multimedia forms such as pictures, emoticons, audio, video, and external links.

The carrier is the general term for various information technologies, tools, platforms, and social media terminals that support the occurrence and development of social network public opinion. As a virtual medium for the dissemination of public opinion, carriers include but are not limited to various news websites, social networking sites, blogs, forums, application software and various information generation, dissemination, reception, processing and other technologies provided by them.

Events do not exist in isolation, and there is often a semantic relationship between events. Among them, the causal relationship is an important semantic relationship,

which indicates the sequence of events in time and the relationship between causing and being caused.

It has been well applied in the evolution analysis of network public opinion, but there is a certain difference between "event" and "public opinion". Compared with the "event" text, the "public opinion" text is less normative and has more obvious value sparsity, but its logic is simple and easy to identify and extract; while the "event" text contains elements such as the actor and the victim and role information, the association between events is more complex.

2.4.1 Rule-based Templates

Ittoo et al. proposed a method for causal pair extraction based on part-of-speech, syntactic analysis, and causal templates. Firstly, some sentence templates expressing causal relationship are extracted by using sentences that clearly contain causal relationship, and then this template is used to extract causal relationship in other sentences[22][23]. Kozareva uses causal trigger words to extract noun causal pairs in the text and uses this causal pair to judge whether a sentence is a sentence describing causal logic[24]. Other scholars such as Sorgente[25], Zhao S[26], etc. have used the method of rule templates to identify causality.

Qiu J used the structural characteristics of Chinese texts to summarize causal sentences into two types: explicit and fuzzy, and used the summarized causal sentence rules to extract causal relationship pairs, and used Bayesian classifiers to judge whether fuzzy causal sentences are causal sentences[27].

2.4.2 Machine Learning-Based Relation Identification

When using machine learning to realize relationship recognition, it is generally used in combination with rule template methods or feature-based methods. After forming rule templates or generating features, classifiers are used to identify sentence relationships.

Riaz M et al. proposed an unsupervised learning model to automatically identify the relationship between specific events in online news articles[28]. And Ittoo et al. achieved part-whole relationship recognition through a minimal supervision algorithm [22]. Radinsky et al. divided causal connectives into three classifiers by using rule templates, constructed relationship recognition rules, and extracted causal relationships

from about 150 years of news headlines through supervised training on a large amount of data[17]. Sorgente et al. used artificially constructed dependency syntactic rules to extract possible causal pairs, and used a Bayesian classifier to filter out noise word pairs that are not causal pairs[29]. Some scholars also use machine learning methods such as support vector machine (SVM)[30].

2.4.3 Event Generalization

After generalization, network media public opinion events can represent a class of topical events more representatively, and can show the connection between events from a higher level.

Most scholars extract the subject, predicate, object and indirect object in the sentence[31][32][33]. This method of using the subject-predicate-object to represent events mostly uses well-structured texts such as news texts as data sources[34]. Sentence components can be extracted from these news texts more completely. However, some texts do not have a complete subject-verb-object structure, such as the news title used by Zhao S. Because the title is relatively concise, the extraction method described above cannot represent the event well. So he proposed to use verbs and noun phrases to represent events, Verbs and nouns are the collection of verbs and nouns in the title. Which event representation method to use specifically depends on which method is suitable for the data source used to extract the main components[35].

Radinsky proposed that verbs get the class of verbs through verbnet to represent generalization; nouns use conceptual words in wiki to represent generalization, and calculate the relationship between the body of the news article and the body of the Wikipedia article related to the concept The cosine similarity for disambiguation. Using the method of hierarchical clustering, the events with similar semantics are clustered together. Based on the same idea, Zhao S et al. pointed out that verbs can use verbnet to find the class of verbs, while nouns can use wordnet to find their hypernyms, and events are converted into events represented by verb classes and hypernyms, which can filter out some too specific event[26].

2.4.4 Graph

The event-centered public opinion knowledge map research is mainly for event knowledge map modeling, event extraction and detection for network public opinion.

Based on natural language processing and semantic web technology, a method for automatically constructing an event-centered knowledge graph from news articles is created. Through event-centered browsers and visualization tools, users' understanding of public opinion events is enhanced, and promotion The reconstruction of the event plot[36]. The construction methods of event knowledge graphs are described and summarized, including sentence-level event extraction models, cross-sentence or document-level event extraction methods, and event coreference, causality, and temporal relationship extraction methods. The performance and future research of related methods are tested. Trend[37].

Different from the research on knowledge map construction for a certain component or theme of public opinion, the research on event-centered public opinion knowledge map construction is mainly based on event-centered research, focusing on events and their relationships, and correlating and expanding event elements. It mainly includes two categories, one is the research on the method and technology of event graph construction, and the other is the research on event graph. Through the literature research method, the definition, construction process, identification method and other research results of the domain event graph are sorted out and summarized, and three event extraction methods based on rules, feature learning and neural networks are summarized, and event extraction is compared and analyzed , related methods of event relationship extraction[38]. The event graph construction technology, event knowledge representation, event knowledge extraction, relationship extraction, etc. are systematically described, and according to the typical application of event knowledge graph in the field of public opinion, the current challenges and future of event knowledge graph construction methods and technologies are pointed out Research Outlook[39]. The research related to the affairs map is mainly to analyze the network public opinion through the construction of the affairs map. Taking medical public opinion as an example, the rule template is used to identify and extract event relationships, and the Internet public opinion affairs map and abstract Internet public opinion affairs map are respectively constructed through Word2vec and K-means clustering, and the evolution path of Internet public opinion is analyzed from different levels[40]. The event extraction technology is used to extract public opinion sub-events, combined with various text analysis and text mining technologies to construct an event map, and based on the event map to generate a summary of multi-dimensional feature

network public opinion events, reflecting the characteristics of public opinion events from different perspectives[41].

Relevant results have been carried out in the fields of financial stock forecasting, aviation accidents, special operation risk warning, disaster events, medical and health, etc., and have confirmed that the theoretical method of event map theory has a good performance in the application process of solving real-world problems. This problem-oriented research perspective has great significance for the solution of real social problems. Q.Mao et al.[42]introduced evolutionary event ontology knowledge (EEOK), which constructs the evolutionary models of five different event domains, including explosion, fire, geological disaster, traffic accident, and personal injury, and according to each event domain Different evolution modes of events, an event prediction model is proposed to capture the internal laws of event evolution; H.L.Nguyen et al. [43]proposed a new method to represent social events and their relationships as a knowledge graph, discover and decompose social events, and effectively Improve the comprehensibility and traceability of social events; P.Heyvaert et al. [44]introduced the Semantic Academic Event Dissemination (SAD) generator, which is used to generate RDF and academic event websites, and the generator contains CSV files of academic event data , and use annotations to generate knowledge graphs and websites with event information to query event knowledge graphs; Y. Zhao et al.[45]mainly study event detection tasks, build event-centric knowledge graphs, and perform event extraction and detection. Identify event-triggering words in document sentences and further classify event types.

3. Methods

3.1. Research Philosophies

Based on different research questions, using real related network public opinion events, an empirical study is carried out on the proposed network public opinion prediction method to determine its feasibility and effectiveness. Positivism is a research philosophy that originates from the natural sciences and is based on the belief that knowledge can be acquired through empirical observation and objective measurement. It assumes that reality exists independently of human perception and can be studied systematically to discover universal laws and principles.

The relationship between online reviews, event evolution graph, and objective facts: online reviews are the events that netizens transfer from offline to online, and we can learn more about events in the real world from online reviews; As a data basis, the objective facts reflected by online comments are depicted in the form of graphs; therefore, the evolution direction of Internet public opinion in reality can be observed from the event evolution graph formed by online reviews, as shown in Figure 1.

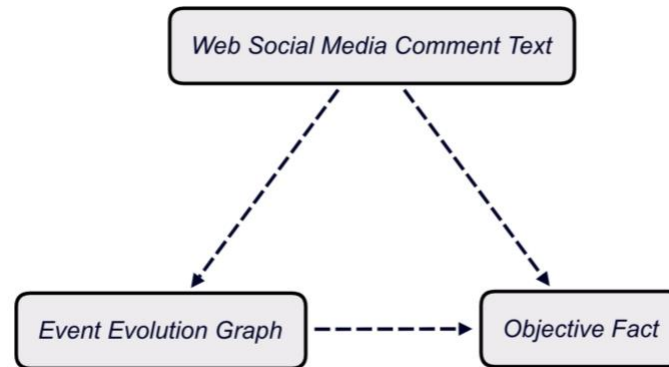


Fig. 1. The relationship between the fact, online reviews and event evolution graph

3.2. Data Mining and Collection

The data source of this article selects social media such as Twitter or Facebook to obtain relevant texts (online comments). Mainly use web crawlers to capture the required corpus. Web crawler technology emerges as the demand for network data increases. This article mainly implements the web crawler function of Internet public opinion based on python language. First determine the keywords of the events to be crawled, and each event may correspond to multiple keywords. According to the keyword, find the corresponding URL, and use this as the initial URL of the crawler. The finally obtained fields include: comment time, text.

3.3. Knowledge Graph

The nodes of the event graph are events, so the basis of abstract event graph construction is event extraction. The method of event extraction adopted in this paper is to use rule templates[40]. The first is to integrate the causal words in the causal sentence in the text. Based on these keywords, a rule template can be constructed; secondly, for a new sentence, the rule template can be used to determine whether the

sentence contains causal words. If so, mark the sentence as a causal sentence; for the marked causal sentence, continue to use the rule template, use keywords to distinguish the cause part and the result part, and then extract the required events from it; finally, take the extracted event as the node. Taking the relationship between event pairs as the edge, and using the gephi tool, a map of network public opinion can be formed.

The event trigger word is an important feature to characterize the event type, so the recognition of the event type must first extract the event trigger word. The format of a rule template is $\langle Pattern, Constraint, Priority \rangle$. Among them, *Pattern* is a regular expression containing causal trigger words, *Constraint* contains some syntactic constraints in some sentences, and *Priority* matches the upper-level templates first when matching[26].

Use the rule template to match the cause and result parts of the sentence, divide the sentence into two parts and each become a small sentence, and extract the cause event and result event to form event pairs according to the results of part-of-speech tagging.

In essence, it is a collection of semantic objects contained in events that occur in the real world, attributes describing the objects, and relationships between objects, such as event participant entities, that is, individuals, groups or organizations that participate in events; event entities, that is, events itself; event-time entities and spatial entities, etc. And, semantic relationships such as forwarding, commenting, and likes between event participant entities; semantic relationships such as initiation, attention, and promotion between event participants and event entities; coreference, causality, timing, and sequence between event entities Inheritance logical semantic relationship.

An event is a combination of things or states that one or more related subjects participate in, and this process occurs or lasts at a specific point in time or period of time and within a specific spatial range. Through the construction and visualization of the map, the content and relationship of the event can be clearly described and represented, and the internal and external relationship between the event and its elements can be analyzed.

3.4. Natural Language Processing

The clustering algorithm requires the sample points to be numerical, which is

convenient and fast to calculate the distance or density between the sample points for effective division. Each sample point in this study is an event, which requires that an event originally represented by text be represented by a numerical value. It is a widely used method to realize this conversion by selecting word vectors. The two word vectors to be used in this study are: TF-IDF method and word2vec method.

In the actual extraction task, because each type of event may involve different subjects, the relationship between entities is also relatively diverse. Event relationship extraction is to extract the logical relationship between events. The extraction of event relations can further describe the evolution of events, which is beneficial to obtain the evolution process of events, and can help prevent them in advance. Sequential relationship refers to the sequence of time and space or logical sequence to express continuous actions or the relationship of successive succession, and the order of appearance cannot be exchanged between previous and subsequent events. The event causality extraction is divided into explicit causality extraction and implicit causality extraction according to whether the cause and result prompt words appear at the same time or contain causal prompt words in the text.

The weighting strategy is formed on the basis of the One-Hot vector form. One-Hot is actually a bag-of-words model, which converts all the words in the text into numerical values, so that the entire document is converted into a dimensionally equivalent word vector matrix. One-Hot uses the number of all words in all texts as the final dimension of each document. In each dimension, if the word exists in the document, it is 1, and if it does not exist, it is 0.

Word2vec is a neural network probabilistic language model introduced by Mikolov[46] in 2013. It trains the existing corpus and converts words into space vectors. The basic assumption of word2vec is: judging whether two words are similar in terms of giving mainly depends on whether the distribution of their adjacent words is the same. It adds semantic elements to word vectors and analyzes the relationship between words accordingly.

To calculate the distance between two events, the similarity of words can be calculated by calculating the combination of two events, and then the similarity of the two events can be obtained by weighted average.

The two events are e_1 and e_2 respectively, $e_1 = \{x_i | x_i \in Verbs \cup Nouns\}$, $e_2 = \{x_j | x_j \in V Verbs \cup Nouns\}$, $i = 1, 2, \dots, n$, $j = 1, 2, \dots, m$, use word2vec built-in word

similarity calculation method to calculate the similarity $sim(x_i, x_j)$ of words in two events, and obtain the similarity of $min(n, m)$ most similar word pairs in total. The similarity of events is calculated comprehensively by the similarity of words.

3.5. Machine Learning

Clarify the construction framework of the event evolution graph, and based on this, construct and visualize the map for different themes of social network public opinion events. Construct social network public opinion event evolution graph and spatio-temporal evolution map in a structured and visualized way, express and describe users, entities, relationships, information, etc. of social network public opinion events, and deepen the multi-angle and all-round disclosure of social network public opinion events with understanding.

The abstract event evolution graph is to generalize events, and then discover the more general and common causal relationship of event evolution in a certain network public opinion field. The basic idea of Kmeans is to divide the sample points close to the centroid of the cluster into the same cluster, and improve the clustering algorithm by using the word2vec word vector and the improved distance calculation method to make the generalization result the best. As showed in Figure 2.

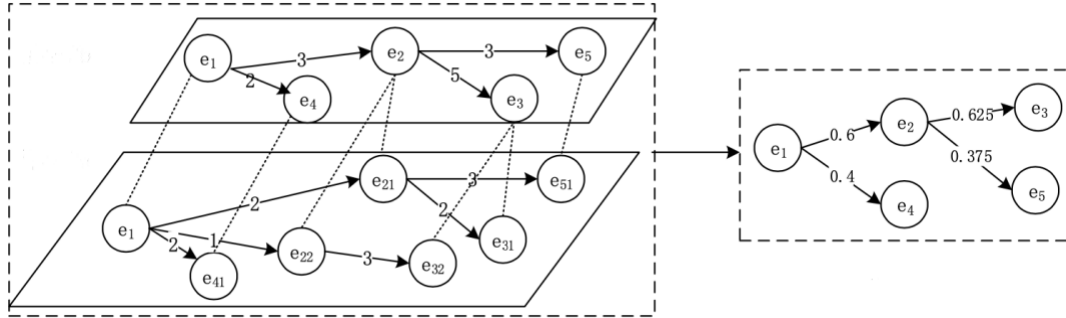


Fig. 2. The schematic diagram of abstract event evolution graph construction

After using the improved clustering algorithm to generalize the events, similar events will be grouped into the same cluster, but the clustering algorithm does not give the representative events of each cluster. The abstract event evolution graph is able to show the relationship between abstract events, so it is necessary to define a label for each cluster. The method used in this study is to select the words with high frequency in each cluster to form events to represent the abstract events of this cluster.

The abstract event evolution graph is a higher level event causal evolution

relationship of the event map, which transforms the original specific causal model into a more general causal relationship, from which we can discover the common event logic evolution relationship in Internet public opinion. After event generalization, the original specific event is transformed into an abstract event, and the relationship between the original specific event is transformed into a general relationship between abstract events.

In traditional relational databases, connection operations between multiple tables lead to low performance, while graph databases are optimized for relational queries across complex data, and thus are more suitable for storing data with large-scale and complex network structures such as knowledge graphs. The study uses graph database for visualization and subsequent correlation query analysis. As the most well-known graph database at present, for example Neo4j also has graph analysis, storage and processing capabilities. In addition, the graph database breaks through the problem that traditional relational databases cannot handle dynamic changes in the relationship between data, and can realize the dynamic storage and effective management of entity and entity relationship information, as shown in Figure 3.

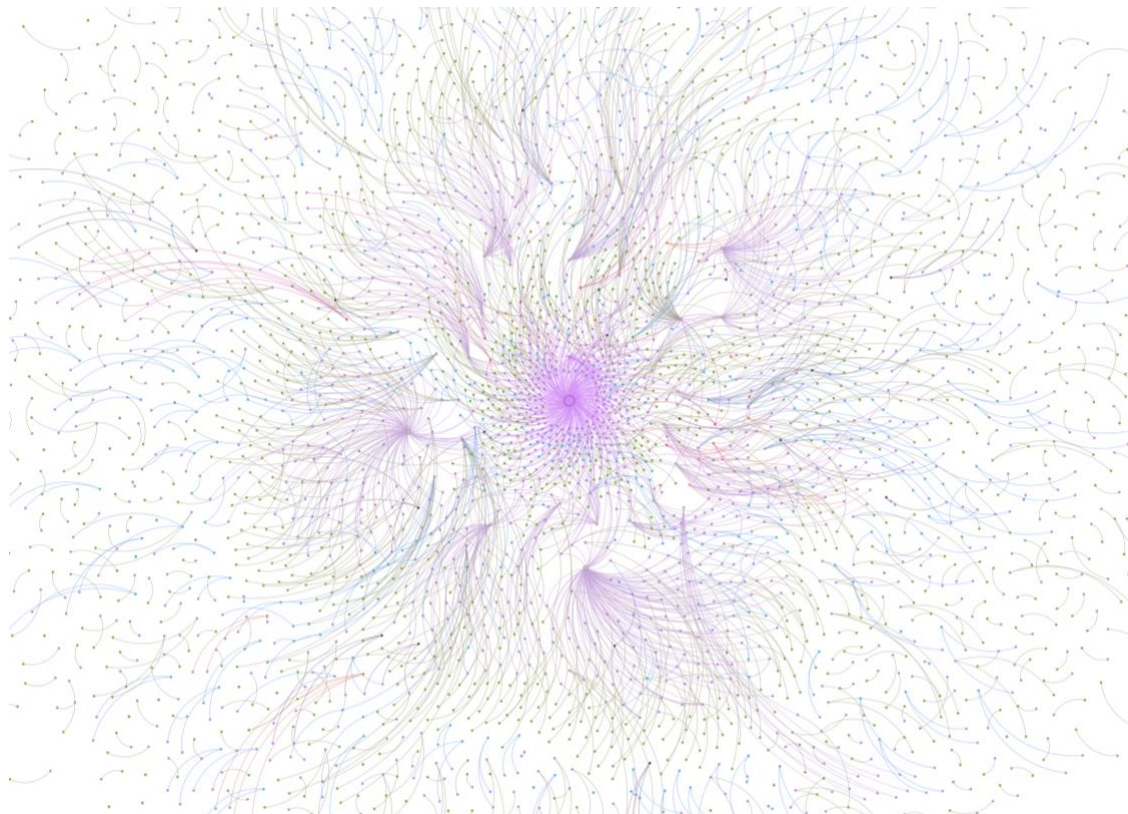


Fig. 3. The Example of Event Evolution Graph

Entities have certain knowledge association characteristics, and the relationship between events can be found according to the association between entities. After generalization, these associated events can express the relationship between events from a higher level and form an abstract logical chain of events, which is convenient for highlighting. Summary and analysis of incident evolution and response rules. The knowledge correlation characteristics of event elements in social media emergencies and the logical characteristics of events show the objective laws and patterns of events in the evolution process. From the perspective of knowledge management, such laws and patterns are tacit knowledge mined from a large amount of data, which is particularly critical and important for revealing the risk transmission mechanism of major emergencies and realizing the whole process management of events. In addition, the semantic transmission path of event evolution is also closely related to the associated risk entities of the knowledge graph, which is conducive to analyzing the risk transmission path with the help of the evolution logic of emergencies.

4. Results

The dataset is obtained from social network media. User comment data is obtained through data mining, and python is used for data preprocessing to remove noise. Use the rule template to match the cause sentence and the result sentence in the text data, and match them to form a causal pair. The Kmeans clustering algorithm (based on TF-IDF and word2vec) was used to cluster the above data, and gephi software was used to visualize the text data to form a event evolution graph, and compare the graph obtained by different clustering methods.

5. Evaluation

Taking network public opinion as the research object, a network public opinion prediction method based on event evolution graph is proposed. Analyze the causal relationship of public opinion events, extract causal event pairs from them, and construct a visual map that can describe the logical evolution relationship of Internet public opinion events, thereby summarizing the evolution characteristics and evolution paths of Internet public opinion. An improved clustering algorithm is used to generalize events and construct an abstract event evolution graph. Due to the method of event representation, distance calculation and update centroid, the kmeans clustering method

has defects such as missing semantic factors, uneven clustering results, and sample points affecting the accuracy of results. The kmeans clustering algorithm is improved based on word2vec event representation, event similarity as the distance between events and update centroid method.

The data sources used in this paper only include users' comments on related public opinion events on a certain social media. The data sources are limited, and the network public opinion event evolution graph constructed is somewhat one-sided. Follow-up studies will further consider the use of multi-source data for research in order to construct a more comprehensive and representative network public opinion event evolution graph; secondly, this study did not consider the real-time nature of public opinion when constructing the network public opinion event evolution graph, and the development of public opinion in the era of big data is changing rapidly. , the new Internet public opinion can update the existing Internet public opinion event evolution graph to ensure that the Internet public opinion event evolution graph is more practical; the amount of data has a certain impact on the construction of the Internet public opinion abstract event evolution graph, and then affects the prediction results. Starting from the perspective of knowledge-driven event correlation and evolution, this paper analyzes the correlation and evolution path of emergencies from the two levels of event and entity by establishing an event graph, and reveals the direction and logical clues of event evolution.

References

- [1] H. Yuan and J. Li, "Research on the collaborative rumor governance mechanism of sudden public events from the perspective of actor network," *Modern Information*, vol. 39, no. 12, pp. 109-120, 2019.
- [2] Coady, "Terrorism, Morality, And Supreme Emergency," *Ethics*, vol. 114, pp. 24-25, Jul. 2004.
- [3] S. Mitchell, S. Shafi, V. Y. Dombrovskiy, et al., "The public health burden of emergency general surgery in the United States: a 10-year analysis of the Nationwide Inpatient Sample—2001 to 2010," *Journal of Trauma and Acute Care Surgery*, vol. 77, no. 2, pp. 202-208, 2013.
- [4] B. Day, R. Burnie M. Kay, M. Ishman, et al., "It Will Happen Again" What SARS Taught Businesses About Crisis Management," *Management Decision*, vol. 7, pp. 822-836, 2004.
- [5] R. Shi, "Research on the Influence of Emotional Motivation on Public Behavior Decision-Making in Group Sudden Public Events," Ph.D. dissertation, Yanshan University, 2018.

- [6] H. Zhang, J. Li, W. Liu, et al., "Research on the construction of major sudden event causality map," *Library and Information Work*, vol. 65, no. 18, pp. 133-140, 2021.
- [7] J. Chen, S. Du, and S. Yang, "Mining and Evolution Analysis of Network Public Opinion Concerns of Stakeholders in Hot Social Events," *Mathematics*, vol. 10, no. 12, pp. 2145-2145, 2022.
- [8] G. Liang and Y. Ju, "Sudden event network public opinion risk assessment analysis based on public opinion evolution life cycle," *Information Science*, no. 10, pp. 48-53, 2018.
- [9] S. Fink, *Crisis Management: Planning for the Inevitable*. New York, NY, USA: American Management Association, 1986, p. 20.
- [10] H. Robert, *Emergency Management*. Beijing, China: China Citric Press, 2004, p. 22.
- [11] X. L. L. Yuan, "Stakeholders identification of internet public opinion in drug safety emergencies based on SNA," *Investigacion Clinica*, vol. 59, no. 4, pp. 302-315, 2018.
- [12] R. X. Renbin, L. Jin, and C. Tinggui, "Modeling and intelligent optimization of social collective behavior with online public opinion synchronization," *International Journal of Machine Learning and Cybernetics*, vol. 10, no. 8, pp. 1979-1996, 2018.
- [13] Q. Li, Y. J. Du, and D. Z. Kong, "Evolution of public opinion based on network structure balance," in *2018 International Conference on Big Data and Artificial Intelligence*, 2018, pp. 5-11.
- [14] Z. Du and X. Xie, "Constructing a network public opinion prediction and early warning model using gray prediction and pattern recognition methods," *Library and Information Work*, vol. 57, no. 15, pp. 27-33, 2013.
- [15] Z. Zeng, "Network public opinion prediction model based on gray support vector machine," *Computer Applications and Software*, vol. 2, pp. 300-302, 2014.
- [16] R. Shi, F. Chen, and J. Zhang, "Research on network public opinion prediction based on combined gray model," *Information Magazine*, vol. 7, pp. 101-106, 2018.
- [17] K. Radinsky, S. Davidovich, and S. Markovitch, "Learning causality for news events prediction," in *International Conference on World Wide Web, ACM*, 2012, pp. 909-918.
- [18] J. Sun, R. Zhou, P. Li, and T. Lu, "Research on network public opinion trend prediction based on recurrent neural network," *Information Science*, vol. 36, no. 08, pp. 118-122+127, 2018.
- [19] H. L. Yang and Q. F. Lin, "Opinion mining for multiple types of emotion-embedded products/services through evolutionary strategy," *Expert Systems with Applications*, vol. 99, pp. 44-55, 2018.
- [20] J. Guo, Y. Wang, B. Zhu, et al., "Network public opinion prediction based on support vector machine," *Network New Media Technology*, vol. 6, no. 5, pp. 29-35, 2017.

- [21] S. Tian and D. Lv, "Improved latent semantic analysis and support vector machine algorithm for sudden safety event public opinion early warning," *Data Analysis and Knowledge Discovery*, vol. 1, no. 2, pp. 11-18, 2017.
- [22] A. Ittoo and G. Bouma, "Extracting explicit and implicit causal relations from sparse, domain-specific texts," in *International Conference on Natural Language Processing and Information Systems*, Springer-Verlag, 2011, pp. 52-63.
- [23] A. Ittoo and G. Bouma, "Minimally-supervised extraction of domain-specific part-whole relations using Wikipedia as knowledge-base," *Data & Knowledge Engineering*, vol. 85, no. 3, pp. 57-79, 2013.
- [24] Z. Kozareva, "Cause-effect relation learning," in *Workshop Proceedings of TextGraphs-7 on Graph-based Methods for Natural Language Processing*, Association for Computational Linguistics, 2012, pp. 39-43.
- [25] A. Sorgente, G. Vettigli, and F. Mele, "Automatic extraction of cause-effect relations in natural language text," vol. 1109, pp. 37-48, 2013.
- [26] S. Zhao, Q. Wang, S. Massung, et al., "Constructing and embedding abstract event causality networks from text snippets," 2017, pp. 335-344.
- [27] J. Qiu, Y. Du, and Y. Wang, "Extraction and representation of feature events based on a knowledge model," in *IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology*, IEEE Computer Society, 2008, pp. 219-222.
- [28] M. Riaz and R. Girju, "Another look at causality: discovering scenario-specific contingency relationships with no supervision," in *IEEE Fourth International Conference on Semantic Computing*, IEEE, 2010, pp. 361-368.
- [29] A. Sorgente, G. Vettigli, and F. Mele, "Automatic extraction of cause-effect relations in natural language text," vol. 1109, pp. 37-48, 2013.
- [30] L. Li, Y. Dang, J. Zhang, et al., "Research on Chinese entity relation extraction based on combined kernel," *Journal of Information Science*, vol. 31, no. 7, pp. 702-708, 2012.
- [31] Z. Li, X. Ding, and T. Liu, "Constructing narrative event evolutionary graph for script event prediction," 2018.
- [32] K. Pichotta and R. J. Mooney, "Using sentence-level LSTM language models for script inference," 2016.
- [33] M. Granroth-Wilding and S. Clark, "What happens next? event prediction using a compositional neural network model," in *Thirtieth AAAI Conference on Artificial Intelligence*, AAAI Press, 2016, pp. 2727-2733.
- [34] A. Semantic, "Script modeling," in *Proceedings of the 20th SIGNLL Conference on*

Computational Natural Language Learning, CoNLL 2016, Berlin, Germany, August 11-12, 2016, pp. 75-83.

- [35] Z. Wang, Y. Zhang, and C. Y. Chang, "Integrating order information and event relation for script event prediction," in Conference on Empirical Methods in Natural Language Processing, 2017, pp. 57-67.
- [36] M. Rospocher, M. van Erp, P. Vossen, et al., "Building event-centric knowledge graphs from news," *Journal of Web Semantics*, vol. 37, pp. 132-151, 2016.
- [37] K. Liu, Y. Chen, J. Liu, et al., "Extracting events and their relations from texts: A survey on recent research progress and challenges," *AI Open*, vol. 1, pp. 22-39, 2020.
- [38] Y. Wang, Z. Shen, Y. Yao, and Y. Cheng, "A review of domain event graph construction methods," *Data Analysis and Knowledge Discovery*, vol. 4, no. 10, pp. 1-13, 2020.
- [39] W. Xiang, "A review of event knowledge graph construction technology and applications," *Computer and Modernization*, no. 01, pp. 10-16, 2020.
- [40] X. Shan, S. Pang, X. Liu, and J. Yang, "Analysis of network public opinion evolution path based on event knowledge graph: a case study of medical public opinion," *Information Theory and Practice*, vol. 42, no. 09, pp. 99-103+85, 2019.
- [41] L. Xia, J. Chen, and H. Yu, "Research on multi-dimensional feature network public opinion event visualization summary generation based on event knowledge graph," *Information Theory and Practice*, vol. 43, no. 10, pp. 157-164, 2020.
- [42] Q. Mao, X. Li, H. Peng, et al., "Event prediction based on evolutionary event ontology knowledge," *Future Generation Computer Systems*, vol. 115, no. 2, pp. 76-89, 2020.
- [43] H. L. Nguyen and J. J. Jung, "Social event decomposition for constructing knowledge graph," *Future Generation Computer Systems*, vol. 100, no. 1, pp. 10-18, 2019.
- [44] P. Heyvaert, D. Chaves Fraga, F. Priyatna, et al., "SAD Generator: Eating our own dog food to generate KGs and websites for academic events," in *European Semantic Web Conference*, Cham: Springer, 2019, vol. 11762, no. 6, pp. 95-9.
- [45] Y. Zhao, X. Jin, Y. Wang, et al., "Semi-supervised auto-encoder based event detection in constructing knowledge graph for social good," in *IEEE/WIC/ACM International Conference on Web Intelligence*, Thessaloniki, Greece, 2019, no. 10, pp. 478-485.
- [46] X. Chen, M. Xia, J. Cheng, et al., "Trend prediction of internet public opinion based on collaborative filtering," in *International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery*, IEEE, 2016, pp. 583-588.