Modularity-Based Topic Discovery and Analysis of Netizens' Emotional Fluctuations: A Case Study of the "China-US Trade Friction" Topic on Sina Weibo (Postprint)

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Abstract

[Purpose/Significance] Exploring topic communities and emotional fluctuations of netizens in comment networks of hot events, and mastering the development process of public opinion events, is of great significance for comprehensively grasping the development direction of hot events and guiding online public opinion in the new era. [Method/Process] Based on complex network theory, sub-event networks are constructed according to event development based on co-occurrence relationships between words in comments. Topic communities in sub-event comment networks are identified through community detection algorithms. Emotional words are assigned emotional classification attributes based on an emotion lexicon, and netizens' opinions and emotional fluctuations are dynamically tracked based on the event evolution process. [Results/Conclusion] Research results indicate that comment network community detection and coefficient of variation methods can effectively measure the scale and concentration of netizens' topic discussions; the method of assigning emotional classification attributes to emotional word nodes in comment networks can reflect netizens' emotional changes during event evolution; public opinion-derived topics have a sustained impact on the development of public opinion regarding events; and netizens' topic discussion content possesses a certain degree of foresight regarding event evolution.

Full Text

Preamble

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Research on Topic Discovery Based on Modularity and Netizen Sentiment Fluctuation
—Taking Sina Weibo's "China-US Trade Friction" Topic as an Example

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Abstract

[**Purpose/Significance**] Exploring topical communities and netizens' emotional fluctuations in comment networks surrounding hot events, and grasping the development process of public opinion events, is of great significance for comprehensively understanding the development direction of hot events and guiding network public opinion in the new era. [**Method/Process**] Based on complex network theory, this study constructs sub-event networks according to the co-occurrence relationships among comment words, identifies topical communities in sub-event comment networks through community detection algorithms, assigns sentiment classification attributes to sentiment words based on sentiment dictionaries, and dynamically tracks netizen opinions and emotional fluctuations according to event evolution. [**Result/Conclusion**] Research results show that community detection in comment networks and coefficient of variation methods can effectively measure the scale and concentration of netizen topic discussions; the method of assigning sentiment classification attributes to sentiment word nodes in comment networks can reflect netizens' emotional changes during event evolution; derived public opinion topics have a sustained impact on the development of public opinion events; and netizen topic discussion content demonstrates a certain degree of foresight regarding event evolution.

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With the rapid development of various new media platforms such as the Internet, the widespread use of mobile devices, and the arrival of the mediated era characterized by social media, the network has increasingly become the primary carrier and window reflecting social public opinion. Network public opinion refers to the sum total of various emotions, attitudes, and opinions expressed and disseminated through the Internet by the public composed of individuals and various social groups regarding public affairs they care about or are closely related to their own interests. Netizens generate large amounts of emotional text information when expressing their views and opinions on certain events through Weibo. Research on topic discovery and sentiment analysis through opinion information can help understand netizens' emotional trends and overall views on events. Network public opinion events are characterized by fast dissemination speed, strong concealment, and difficulty in control. Therefore, dynamically tracking changes in netizens' discussion content and emotions regarding public opinion events, and using them as an important platform for collecting public opinion, is of great significance for comprehensively grasping the development direction of hot events and making full use of network media characteristics to guide network public opinion in the new era.

2 Research Status

2.1 Weibo Topic Discovery

Research on Weibo topic mining issues has mainly focused on the computer science field, with emphasis on improving classical clustering algorithms to enhance topic discovery effectiveness. Y. Chen et al. [2] developed an incremental clustering framework to detect new topics and employed a series of content and temporal features to timely identify popular topics. G. Stilo et al. [3] proposed a new method for clustering words in Weibo based on similarity of related time series. M. Hu et al. [4] mined user opinions from user reviews. Li Yaxing et al. [5] proposed a real-time co-occurrence network-based topic discovery model using an improved Single-Pass algorithm. Song Lina et al. [6] proposed a SOM clustering method for Weibo topic discovery to improve traditional text clustering deficiencies and effectively discover topics. Additionally, the library and information science field has actively conducted research on such issues. Tang Xiaobo et al. [7-8] mined Weibo themes based on a priori probability latent semantic analysis LDA model and proposed using dependency syntactic analysis to improve traditional text similarity matrices to enhance clustering accuracy. Wang Zhengcheng et al. [9] used the LDA topic model to mine various topics in specific topics, reflected the public opinion trend of specific topics, and identified opinion leaders for topic mining. Xiao Lu et al. [10] calculated text similarity based on sentence components, constructed text similarity matrices, conducted cluster analysis, and identified Weibo hot topics.

2.2 Weibo Sentiment Analysis

Sentiment analysis, also known as opinion mining, is the process of analyzing, processing, summarizing, and reasoning about subjective texts with emotional coloring [11]. Analyzing large amounts of user-posted Weibo is crucial in many fields, and mining user sentiment has broad application value, attracting the attention of many domestic and foreign researchers. Foreign scholars' research on netizen sentiment changes has mainly focused on the Twitter platform. B. Pang et al. [12-13] used manually annotated training corpora and employed Bayesian, maximum entropy, and other methods to analyze movie review tendencies. J. Bollen et al. [14] conducted emotion analysis on tweets posted on the Twitter platform, calculated six-dimensional emotion vectors on the daily timeline, and then speculated on large-scale emotion analysis. X. Zou et al. [15] proposed a new method combining social context and topic context to analyze Weibo sentiment, introducing topic context to simulate semantic relationships between Weibo posts. L. Zhang et al. [16] proposed a new entity-level emotion Twitter analysis method. Due to differences in product design between Chinese and English Weibo and significant differences in language expression habits between Chinese and English, research on Chinese Weibo sentiment analysis is not yet mature compared to English Weibo sentiment analysis. Some scholars have proposed sentiment classification methods for specific research issues. Tang Xiaobo et al. [17] proposed a product review sentiment analysis method based on feature ontology, which used constructed feature ontology to classify feature words, identified implicit features by calculating the collocation weight between sentiment words and features, and constructed domain sentiment dictionaries and Weibo emoticon dictionaries. Yang Liang et al. [18] proposed a sentiment distribution language model to achieve hot event discovery by analyzing differences in sentiment distribution language models between adjacent time periods. Huang Weidong et al. [19] proposed a network public opinion topic sentiment analysis method based on probabilistic latent semantic analysis (PLSA), using the PLSA model to extract sub-topics and construct sentiment word lists for network public opinion topics in different time periods. Some scholars have also used complex network theory for sentiment classification research. Zhang Xiangyang et al. [20] constructed directed networks based on consumer online reviews and established online review sentiment tendency classification models from the topological properties of review networks. Yang Feng et al. [21] proposed an emotion tendency classification method for online reviews based on the shortest coverage path of review sequences using random networks and sentiment word lists.

In summary, scholars have conducted extensive research on constructing sentiment word lists using different sentiment classification methods, using sentiment word lists to predict user-specific behaviors or analyze blog content, and optimizing various clustering algorithms to improve topic discovery. However, research introducing complex network ideas into netizen sentiment fluctuation and topic opinion mining is limited. Therefore, this study selects Sina Weibo's popular topic "China-US Trade Friction" and uses comment data from popular blog posts under sub-events that better reflect netizen attitudes as the data source. Comments are treated as network nodes, and sentiment word nodes are assigned corresponding sentiment classification attributes according to sentiment dictionaries. Edges in the network are determined based on word co-occurrence relationships, thereby constructing comment networks. According to the Louvain algorithm [22], comment network communities are divided to dynamically track netizen opinions and sentiment fluctuation changes in hot events, thereby displaying the complete evolution of public opinion events.

3 Basic Theory and Research Framework

3.1 Basic Theory

3.1.1 Network Community Division Complex networks are an important method for studying and solving complex system problems. The theory and empirical research of complex networks have had a significant impact on the study of infectious disease transmission in biology, protein expression networks, market expansion networks in sociology, widespread phenomena in physics, and virus transmission, control, and defense in computer science [23]. In this study, netizen comment words are treated as nodes, and the relationships between words are treated as edges to construct sub-event evolution networks based on hot events.

Netizen topic discussion content continuously evolves with the unfolding of events, causing comment words to gradually form content representing netizen opinions based on their relationships. Therefore, for comment networks, discovering different opinion communities and their sentiment labels in comment networks will help reveal the evolution of netizen opinions and emotions. The basis for dividing networks into communities can be broadly divided into graph partitioning and community discovery algorithms. The main characteristic of graph partitioning is that it specifies community size and quantity, aiming to divide the network into smaller, more manageable fragments for research. Community discovery mainly determines the number and scale of communities based on the network's own topological structure, that is, naturally identifying different groups within the network.

The purpose of this study is to explore the evolution process of netizen opinions and emotions based on event evolution, without prior knowledge of the specific situation of netizen opinion communities. Therefore, this study adopts the community discovery Louvain algorithm [22] to divide and identify opinion communities in comment networks. M. L. Wallace et al. [24] also pointed out that community discovery algorithms are helpful for analyzing large-scale complex networks and have obvious natural advantages in topic identification.

The Louvain algorithm is a modularity-based community discovery algorithm that does not require prior community information and has good efficiency and effectiveness in studying large networks. The algorithm achieves the decomposition of the entire network into multiple communities by continuously aggregating nodes. The main steps of the Louvain algorithm are as follows:

(1) Treat each node in the network as an independent community, meaning the number of communities equals the number of nodes;

(2) For each node i, sequentially attempt to assign node i to each community where its neighbor nodes are located, calculate the modularity change ΔQ before and after assignment, and record the neighbor node with the maximum ΔQ value. If MaxΔQ $>$ 0, assign node i to that neighbor node's community; otherwise, keep it unchanged;

(3) Compress the network, compress all nodes within the same community into a new node, and repeat step (1) until the modularity of the entire network no longer changes, i.e., reaches its maximum value.

To verify whether communities in the network are appropriately divided, this study uses the modularity index proposed by M. E. J. Newman et al. [25] in 2004 to measure the quality of community division, denoted by Q. The basic idea of modularity is to compare the network after community division with the corresponding null model to measure the quality of community division. The so-called null model refers to a random network model that has certain same properties as the studied network but is completely random in other aspects. Currently, when analyzing network community structures, the studied network is usually compared with a random network having the same degree sequence (first-order null model) [26]. Therefore, the commonly used modularity definition is:

$$Q = \frac{1}{2M} \sum_{ij} \left(a_{ij} - \frac{k_i k_j}{2M} \right) \delta(C_i, C_j)$$

In the formula, M is the number of edges in the network, A = (a_{ij}) is the adjacency matrix of the network, k_i and k_j are the degree values of nodes i and j in the network, and C_i and C_j represent the communities where nodes i and j belong in the network: if two nodes belong to the same community, δ takes the value 1; otherwise, it is 0. In fact, the modularity of a network is the proportion of the difference between the number of edges within communities in the network and the number of edges within communities in the corresponding null model to the total number of edges M in the entire network. Research has found that when the Q value is between 0.3 and 0.7, it indicates that a strong community structure has emerged in the network [27].

In summary, the Louvain algorithm achieves the optimal modularity value by continuously aggregating comment word nodes, thereby determining the division of communities in comment networks. Based on the above theories and ideas, this study identifies opinion communities in comment networks along the development trajectory of events and dynamically tracks and analyzes the evolution process of opinion communities.

3.1.2 Sentiment Dictionary This study selects the Chinese Sentiment Vocabulary Ontology Library from Dalian University of Technology [28]. Its classification system is built upon the influential Ekman's 6-category emotion classification system abroad, with emotions in the final vocabulary ontology divided into 7 major categories. The part-of-speech categories in the sentiment vocabulary ontology are divided into 7 categories, with each word corresponding to a polarity under each emotion category, where 0 represents neutral, 1 represents positive, 2 represents negative, and 3 represents both positive and negative. Among them, one sentiment word may correspond to multiple emotions. Emotion classification is used to describe the main emotion classification of sentiment words, while auxiliary emotions are other emotion classifications contained in the sentiment word while having the main emotion classification. According to the paper "Construction of Sentiment Vocabulary Ontology" [28], emotions are divided into 7 major categories and 21 subcategories. Sentiment intensity is divided into five levels: 1, 3, 5, 7, and 9, with 9 representing the strongest intensity and 1 the weakest. The dictionary contains 27,466 sentiment words, including 11,229 positive words and 10,782 negative words. The format of the sentiment vocabulary ontology is shown in Table 1 .

The comprehensiveness of sentiment words is of great significance to sentiment analysis. The sentiment dictionary used in this paper includes a basic dictionary and a sentiment dictionary based on specific event contexts. This study uses the Dalian University of Technology Sentiment Dictionary as the basic dictionary. However, when studying specific event contexts, using only the sentiment words in the basic dictionary is often insufficient. When studying user opinion mining issues in hot events, high-frequency contextual vocabulary about the hot event is needed. Therefore, combined with manual screening and referring to the scoring situation of sentiment words by Dalian University of Technology, a domain sentiment dictionary for specific event contexts is established [9]. Due to research needs, this study made special treatments for some words. For example, "ZTE" is a positive word with sentiment polarity in the sentiment dictionary, but in this study, it is a representative noun of the issue, and its frequent appearance would affect research results. Therefore, such words are deleted from the sentiment dictionary. Negation words in comment content were also specially treated by observing whether there are negation words adjacent to sentiment words. If negation words exist around sentiment words, the negation words and sentiment words are merged into one word, such as "cannot understand," "not a good person," etc. According to this rule, referring to the sentiment dictionary, the sentiment polarity and classification of such words are inverted, and these words are added to the domain sentiment dictionary. Part of the domain sentiment dictionary is shown in Table 2 .

3.2 Research Framework

Network public opinion events are characterized by fast dissemination speed and difficulty in control, making public opinion guidance and control work a focus of attention for the government and all sectors of society. Dynamically tracking netizens' topic discussion content and emotional changes during the evolution of public opinion events can help grasp the overall macro development direction of hot events. In this study, netizen comments on obtained events are first preprocessed to remove duplicate and spam comments. Comment data are then segmented using the JIEBA segmentation method, removing stop words, punctuation, and other meaningless words. Comment word networks based on event evolution are constructed using the cleaned and segmented comment words. In the network, R language is used to match the 7 sentiment categories in the sentiment dictionary with each sentiment word node to assign sentiment word node attributes. The Louvain algorithm is used to divide netizen comment content communities. Comment data are analyzed from two perspectives: netizen topic comment content and sentiment analysis. Netizen opinions during the overall evolution of public opinion events are mined through netizen topic discussion content, and netizens' attitudes toward the entire event are reflected based on netizen sentiment fluctuations. Finally, from a local perspective, comment content analysis and sentiment analysis are combined to further reveal changes in netizen discussion content and emotions in different periods as the same topic evolves with events, and then explain the reasons for netizen sentiment changes combined with comment content. The research framework is shown in Figure 1 [Figure 1: see original paper].

4 Netizen Comment Network Characteristics Analysis

4.1 Data Selection and Preprocessing

Sina Weibo is a social networking site launched by Sina.com that provides microblogging services. It is an information sharing and exchange platform that provides entertainment and leisure life for the public. According to CCTV Finance statistics, by the fourth quarter of 2017, Weibo had 172 million active users and 392 million monthly active users. Therefore, Sina Weibo is selected as the data source for this study. The topic of "China-US Trade Friction," which is of concern to the government, society, and the public, is selected as the research topic. From March 23, 2018, when the China-US trade war officially began, to April 30, 2018, a total of 3,313 netizen comments on popular blog posts under sub-events of the "China-US Trade Friction" event were obtained. The hot event sub-events, blog posts, and comment numbers are shown in Table 3 .

Regular expressions are used to clean comment content data, such as @, numbers, English letters, usernames, emoticons, etc., extracting only the thematic comment content. The cleaned comment data are then segmented using the JIEBA segmentation method, removing stop words, punctuation, and other meaningless words. Comment word networks based on event evolution are constructed using the cleaned and segmented comment words. In the network, R language is used to match sentiment categories with each sentiment word node using the sentiment dictionary to assign sentiment word node attributes. The comment word network constructed based on event T1 is shown in Figure 2 [Figure 2: see original paper].

The overall number of nodes, edges, and the number of nodes and edges in the largest connected subgraph for each sub-event network are shown in Table 4 . Due to the large disparity in scale between subgraphs, this study extracts the largest connected subgraph in the network for relevant analysis.

4.2 Community Scale Analysis

This study uses the Louvain algorithm in community detection algorithms to identify and classify topic communities based on the topological structure of comment networks, dynamically exploring the evolution process of domain topic communities based on event evolution. Due to different topological structures of comment networks in different sub-events, the number and scale of communities divided in different sub-events vary. The number and scale of knowledge communities in each comment network under the five event windows T1-T5 are shown in Table 5 . The first row represents each event window, and the first column represents community numbers. To clearly display community situations in each event window, topic communities under each event window in Table 5 are sorted by scale from high to low.

To examine whether the divided knowledge communities are reasonable, the modularity of comment networks under each event window is calculated, as shown in Table 6 .

According to Table 6, the modularity values of comment networks under each event window are all between 0.3 and 0.7, indicating that the topic communities divided using the Louvain algorithm in this study are relatively reasonable. The number of communities in sub-event comment networks represents the richness of topic discussions in sub-events. As can be seen from Table 5, as hot events evolve, there are differences in the number of topics triggered by netizens for each sub-event. Among them, the T1 event ("Trump signed a memorandum on tariffs against China, stating this is just the beginning") and the T5 event ("Taiwan authorities announced that ZTE is included in the export control list") triggered a relatively high degree of attention and discussion among netizens.

4.3 Coefficient of Variation Analysis

To compare the concentration degree of topic discussions in each sub-event during the evolution of hot events, this study uses the statistical indicator of coefficient of variation to explore the concentration degree of topic discussions among sub-event communities of different scales based on event evolution. This indicator eliminates the influence of different community scales and connection numbers.

In formula (2), Cv represents the coefficient of variation, σ represents the standard deviation of topic community scale, and is the average community scale. Cv describes the ratio of topic community standard deviation to average number. A higher coefficient of variation level indicates more discrete communities and more concentrated topic discussions. The coefficients of variation for each sub-event are shown in Table 7 .

Analysis of data in Table 7 shows that the coefficients of variation of each sub-event are generally in a fluctuating state. The concentration degree of topic discussions based on event evolution differs, with the coefficient of variation of the T1 event being the lowest. As events develop, the coefficient of variation increases but remains in a fluctuating state. This phenomenon reveals from the perspective of event evolution that in the early stage of public opinion events, netizen topic discussions are relatively dispersed without highly concentrated themes. As public opinion events evolve, key node events gradually emerge, focusing netizen discussion topics in a unified direction.

5 China-US Trade War Topic Discovery and Sentiment Fluctuation Analysis

5.1 China-US Trade Friction Event Topic Discovery Analysis

5.1.1 Netizen Comment Topic Content Analysis To understand the entire development process of events T1-T5 from a macro perspective, the author selects larger-scale communities in the comment network under each sub-event. High-degree nodes in network communities can reflect the main topic content of netizen discussions. Due to space limitations, word nodes with higher degrees in each community of sub-event comment networks are selected, as shown in Figure 3 [Figure 3: see original paper]. Analyzing the topic content of the five sub-events reveals that netizens have conducted relatively sustained discussions on some topics, such as trade and tariffs. As public opinion events ferment, more new topics emerge, such as agriculture, economy, and computer systems in the T2 event; chip, technology, R&D, and nuclear weapons in the T3 event; research talent and science and technology in the T4 event; and Taiwan independence, MediaTek, and development in the T5 event. Notably, the "China-US trade war" topic community ranked 1st or 2nd in the first four sub-events but only ranked 3rd in the T5 event (Taiwan authorities announced that ZTE is included in the export control list). Netizens' main discussion content focused on opposing Taiwan independence and issues concerning mainland China and Taiwan's development, weakening discussions related to the China-US trade war. This phenomenon indicates that derived topics about events gradually emerged during the evolution of hot events.

5.1.2 Netizen Comment Topic Foresight Analysis To more specifically reveal netizen comment topic content, the author focuses on netizen topic discussion content from a micro perspective. By analyzing netizen topic community content during event evolution, as shown in Figure 4 [Figure 4: see original paper], it can be seen that in the T1 sub-event (the beginning of the China-US trade war on March 23, 2018), topic communities about chips and Huawei phones had already appeared in the netizen comment network with relatively high degree centrality. According to Table 3, reviewing the development trajectory of public opinion events, the time point of March 23 was about Trump signing a memorandum on tariffs against China. The T3 event (US sanctions against ZTE) occurred nearly a month later on April 19. The sub-event topic communities are shown in Figure 5 [Figure 5: see original paper]. This phenomenon reflects netizens' foresight regarding the evolution of this public opinion event, with their thinking and prediction reaching a certain depth and level, predicting the development direction of events. During the analysis, the author found that this phenomenon is not an isolated case. For example, in the T3 event (ZTE sanctioned), chip word nodes and Huawei word nodes highly co-occurred. The government and relevant departments should attach great importance to this phenomenon, give full play to Weibo's role as a public opinion collection platform, extract netizen discussion topic content, and make full use of it.

5.2 Netizen Sentiment Tendency Analysis

By analyzing comment tendencies, the emotional fluctuation status of netizens during the entire event evolution process can be grasped from a macro perspective. This study tracks changes in seven major emotion categories in comment content: joy, good, anger, sadness, fear, evil, and surprise. Since each sentiment word node in the comment network is assigned the above seven major category attributes according to the sentiment dictionary, the author uses R language to conduct statistical analysis on sentiment word nodes in sub-event T1-T5 comment networks to obtain netizens' overall sentiment tendency regarding the China-US trade friction topic. Netizen sentiment tendency changes are shown in Figure 6 [Figure 6: see original paper].

From a macro perspective, during event evolution, netizens' emotions of "evil," "anger," and "sadness" toward this event increased, while emotions of "good," "surprise," "joy," and "fear" generally decreased, reflecting that netizens' negative emotions gradually increased and positive emotions gradually decreased as events developed and evolved. Netizens' emotions regarding the China-US trade friction topic concentrated on two extreme emotions, with "evil" and "good" being the main forces expressing netizen emotions, indicating that netizens treated this event relatively objectively, believing it to be both an opportunity and a challenge. Notably, during the development from the T2 event to the T3 event, the emotion of "fear" significantly increased. During the development from the T3 event to the T4 event, the emotion of "surprise" significantly increased while the emotion of "anger" significantly decreased. Reviewing the entire event development process, from the official start of the China-US trade war to China's counterattack, to ZTE being sanctioned, and then to Taiwan's involvement in this event, netizens felt frightened about ZTE being sanctioned and the US curbing China's technological development pace. Against the political background of the long-standing historical issue between mainland China and Taiwan, netizens were not angry about Taiwan's involvement in this event but were more surprised and accusatory.

5.3 Netizen Sentiment Fluctuation Analysis Based on Topic Content

During the continuous evolution of public opinion events, netizens' emotions toward the same topic will produce different sentiment tendencies as events develop, and netizen emotions will show a certain degree of fluctuation. To track subtle changes in netizen emotions, the author selects the same discussion topic communities in different sub-events T1 and T4 from a local perspective, as shown in Figure 7 [Figure 7: see original paper] and Figure 8 [Figure 8: see original paper].

As can be seen from Figures 7 and 8, both communities mainly discuss issues related to China-US trade. The emotional fluctuation changes of netizens in the China-US trade topic under the two sub-events are shown in Figure 9 [Figure 9: see original paper].

According to the emotional change comparison in Figure 9, as events evolved from T1 (official start of the China-US trade war) to T4 (US sanctions against ZTE), netizens' emotions of "evil," "fear," "joy," and "anger" toward this event increased, while emotions of "good" and "sadness" decreased. To deeply explore the reasons for emotional changes, this paper combines community topic content to understand netizen emotional changes. High-degree nodes other than China, US, and trade war nodes in the China-US trade communities of T1 and T4 events are shown in Table 8 .

As shown in Table 8, the China-US trade community topic in the T1 event mainly focused on tariffs, industry, and stock markets, while the T4 event China-US trade community topic mainly focused on ZTE, Huawei, chips, and R&D. Based on community discussion content and emotional fluctuation changes, netizen viewpoints and attitudes can be summarized. The US sanctions against ZTE intensified netizens' panic, anger, hatred, and accusation emotions about the country's future technological development. At the same time, netizens' emotion of "joy" increased while "sadness" decreased, reflecting netizens' confidence and determination in national industries and independent innovation R&D.

Conclusion

This paper introduces complex network analysis ideas, uses the Louvain algorithm to identify and divide topic communities in sub-event comment networks, and determines netizen emotional changes during event evolution based on sentiment word node attributes. However, the research work also has areas for improvement. The selected Sina Weibo data source has insufficient coverage. In subsequent research, more extensive topics and data sources will be selected for more in-depth research on such issues.

References

[1] Liu Yi. Introduction to Network Public Opinion Research [M]. Tianjin: Tianjin People's Publishing House, 2007.
[2] Chen Y, Amiri H, Li Z, et al. Emerging topic detection for organizations from microblogs [C]//Proceedings of the 36th international ACM SIGIR conference on research and development in information retrieval. Dublin: ACM, 2013: 43-52.
[3] Stilo G, Velardi P. Efficient temporal mining of micro-blog texts and its application to event discovery [J]. Data mining and knowledge discovery, 2016, 30(2): 372-402.
[4] Hu M, Liu B. Mining and summarizing customer reviews [C]//Proceedings

of the ACM SIGKDD international conference on knowledge discovery & data mining. Seattle: ACM, 2004: 168-177.
[5] Li Yaxing, Wang Zhaokai, Feng Xupeng, et al. Weibo topic discovery based on real-time co-occurrence network [J]. Computer Applications, 2016, 36(5): 1302-1306.
[6] Song Lina, Feng Xupeng, Liu Lijun. Weibo topic discovery based on SOM clustering [J]. Computer Application Research, 2018, 35(3): 671-679.
[7] Tang Xiaobo, Wang Hongyan. Research on Weibo topic mining model based on latent semantic analysis [J]. Library and Information Service, 2012, 56(24): 114-119.
[8] Tang Xiaobo, Xiao Lu. Research on Weibo topic mining model based on dependency syntactic analysis [J]. Information Science, 2015, 33(9): 61-65.
[9] Wang Zhengcheng, Yuan Zhuxing. Research on Weibo opinion leader mining oriented to topics [J]. Information Science, 2018, 36(3): 112-116.
[10] Xiao Lu, Tang Xiaobo. Research on Weibo hot topic mining model based on sentence components [J]. Information Science, 2015, 32(11): 44-47.
[11] Zhao Yanyan, Qin Bing, Liu Ting. Text sentiment analysis [J]. Journal of Software, 2010, 21(8): 1834-1848.
[12] Pang B, Lee L, Vaithyanathan S. Thumbs up? sentiment classification using machine learning techniques [EB/OL]. [2018-05-08]. https://arxiv.org/pdf/cs/0205070.pdf.
[13] Pang B, Lee L. A sentimental education: sentiment analysis using subjective summarization based on minimum cuts [EB/OL]. [2018-05-08]. https://arxiv.org/pdf/cs/0205070.pdf.
[14] Bollen J, Mao H, Pepe A. Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena [J]. Computer science, 2009, 44(12): 2365-2370.
[15] Zou X, Yang J, Zhang J. Microblog sentiment analysis using social and topic context [J]. PLoS one, 2018, 13(2): e0191163.
[16] Zhang L, Ghosh R, Dekhil M, et al. Combining lexicon-based and learning-based methods for Twitter sentiment analysis [EB/OL]. [2018-05-10]. http://www.hpl.hp.com/techreports/2011/HPL-2011-89.pdf.
[17] Tang Xiaobo, Lan Yuting. Weibo product review sentiment analysis based on feature ontology [J]. Library and Information Service, 2016, 60(16): 121-127.
[18] Yang Liang, Lin Yuan, Lin Hongfei. Weibo hot event discovery based on sentiment distribution [J]. Journal of Chinese Information Processing, 2012, 26(1): 84-90.
[19] Huang Weidong, Chen Lingyun, Wu Meirong. Research on topic sentiment evolution of network public opinion [J]. Journal of Intelligence, 2014, 33(1): 102-107.
[20] Zhang Xiangyang, Nari Sa, Sun Na. Sentiment tendency analysis of online reviews based on directed networks [J]. Information Science, 2016, 34(11): 66-69.
[21] Yang Feng, Peng Qinke, Xu Tao. Sentiment tendency classification of online reviews based on random networks [J]. Acta Automatica Sinica, 2010, 36(6): 837-844.

[22] Blondel V D, Guillaume J L, Lambiotte R, et al. Fast unfolding of communities in large networks [J]. Journal of statistical mechanics, 2008, 2008(10): 155-168.
[23] Lewis T G. Network Science: Principles and Applications [M]. Translated by Chen Xiangyang, Ju Xiulian, et al. Beijing: Mechanical Industry Press, 2011: 1-12.
[24] Wallace M L, Gingras Y, Duhon R. A new approach for detecting scientific specialties from raw cocitation networks [J]. Association for Information Science and Technology, 2009, 60(2): 240-246.
[25] Newman M E J, Girvan M. Finding and evaluating community structure in networks [J]. Physical review E, 2004, 69(2): 1-16.
[26] Wang Xiaofan, Li Xiang, Chen Guanrong. Introduction to Network Science [M]. Beijing: Higher Education Press, 2012: 130-140.
[27] Tang L, Liu H. Social Computing: Community Discovery and Social Media Mining [M]. Translated by Wen Yimin, Bi Yingzhou. Beijing: Mechanical Industry Press, 2013: 20-30.
[28] Xu Linhong, Lin Hongfei, Pan Yu, et al. Construction of sentiment vocabulary ontology [J]. Journal of the China Society for Scientific and Technical Information, 2008, 27(2): 180-185.
[29] Wechsler D. Die messung der intelligenzerwachsener [M]. Bern-Stuttgart: Huber, 1964.

Author Contributions:

Zhang Haitao: Proposed research ideas and methods, conducted data analysis, and revised the paper;
Liu Yashu: Responsible for data collection, analysis, and processing, and wrote the initial draft;
Zhang Xiaohui: Responsible for data collection and organization;
Song Tuo: Responsible for paper revision.

Note: Figure translations are in progress. See original paper for figures.