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Public Opinion Control Based on Sentiment Analysis of Social Network Users

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Abstract

In recent years, social networks have become a vital way for people to receive and disseminate information. While the generation and dissemination of information are more convenient and rapid, it also provides convenience for fake news. Public opinion on social networks is unrestricted by time and space. If a large-scale adverse social network public opinion spreads without timely and effective control of its development, it will become a bad social event. As a result, research on public opinion control on social networks has received widespread attention over the past few years. In this paper, we select a representative social network platform-Weibo as the research object and establish user influence indicators based on the personal attributes and content characteristics of Weibo users. Then we use LDA for topic word extraction and SnowNLP text sentiment analysis based on user interaction content. We evaluate the sentiment tendency of the opinion leader's Weibo text and its comment content, then discover the influence of high-influence users on the follower's sentimentality through the user influence and sentiment orientation of the new type of opinion leader and the emotional theme of the comment. Finally, we achieved the result of controlling the spread of public opinion on social networks.

Keywords

Social Network; Sentiment Analysis; Public opinion control; User influence; LDA.

1. Introduction

In recent years, social media has assimilated into our daily life, due to the rapid development of information technology. Foreign social networks mainly include Facebook, Twitter and Instagram, and domestic social networks mainly include QQ, WeChat, WeChat, Baidu Tieba, Douban and Zhihu, etc. These social network platforms have become important ways for netizens to express their opinions and emotions. Massive network information data flows on social network platforms. Users of these social network platforms can view the real-time dynamics of social network friends without permission. Even more important, the social network platform will recommend information of interest based on basic user information and historical browsing. Users can also share information with any network user on social media. Network users get used to convenient and rapid interaction method penetrates all aspects of the work, study and life. In the meantime, the development of 4G, 5G and other wireless communication technologies and the popularization of mobile devices have also made network information data generated faster. In short, social network platforms have the characteristics of excellent comprehensiveness, broad interactivity, extensive range of information dissemination, and fast speed, which greatly enhance the effectiveness of information dissemination. However, while social networking platforms facilitate information dissemination, they also make rumors and adverse information more difficult to control. In social networks, some connections between users, which are derived from real-world relationships, are strengthened through network communication, while other relations derive

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from common network behaviors of network users, gradually forming a network community structure. Therefore, a social network must be a multi-relationship network, and there must be multiple relationships between users as network nodes[1]. The rise of social networks not only allows people to discover their potential social benefits but also raises people's concerns about the spread of rumors and negative public opinion on social networks.

Since social networks have large numbers of users, high-frequency connections, and faster dissemination and acquisition of information resources, the network behavior and contact range of netizens have fundamentally changed. In the current environment where the Internet and human society are intertwined, online public opinion has been deeply involved in real life, forming a brand-new online public opinion field, which significantly affects public opinion events' tendency. Kim[2] analyzed the dissemination process of news information and user feedback by social network analysis, then how they interact and influence under the same ideology. Valerio [3]used reposting frequency to define user relevance and analyze user relationship intensity and the influence of personal social circles on information dissemination. Yoo[4] used information diffusion theory to analyze the diffusion rate of public opinion information on social media and tested the impact of crucial factors on the information diffusion rate by retrieving data information on Twitter Impact. Mark[5] simulated the process of spreading public opinion on social media networks, which was based on the epidemic SIR model, and analyzed the characteristics of public opinion spread by explaining peak times, inflection points and virus cycles.

Therefore, it is meaningful and significant to predict the development and communication trend of public opinion. Then effectively prevent public opinion crises in social networks and correctly guide public opinion is an urgent issue for social security in public opinion networks.

Contributions. This paper makes the following contributions:

• Combining the influence of opinion leaders and followers' sentimental tendencies in popular Weibo comments, we can obtain the development tendency of online public opinion promptly, which is helpful for relevant regulatory authorities to control the spread of negative online public opinion.

• By combining text sentiment analysis with LDA topic word extraction, we can obtain more accurate user sentiment tendencies and honest thoughts in the comment area.

• Although Weibo has a forceful anti-crawler mechanism, we still crawl the actual data available on Weibo, providing a guarantee for the follow-up empirical research results.

The article is organized as follows. In Section I introduces the characteristics of social networks and the importance of controlling the spread of public opinion on social networks. In Section II introduces the public opinion characteristics of social networks and the importance of new opinion leaders in social networks, then briefly describes the methods of sentiment analysis and keyword extraction In Section III. In Section IV we establish user influence indicators based on user attributes and content characteristics and calculate the influence of crawled users, then perform sentiment analysis and LDA keyword extraction on popular microblogs and comments of opinion leaders in Section V. We give our relevant conclusions and suggestions in Section VI.

2. Research on the Spread of Public Opinion on Social Networks

2.1. Social network public opinion dissemination

2.1.1. Characteristics of public opinion on social networks

Internet public opinion based on traditional media public opinion dissemination. It uses online social media as a carrier to expand public opinion through the Internet and express the opinions, attitudes and feelings of netizens[6]. It is a considerable influence and specific trend of the public with real-time general opinions or remarks on focus or hot issues. Social network public

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opinion is a reflection of public opinion, and it is also a mapping of public opinion on social networks[7]. As an expression of the public's attitudes and feelings towards hot social events, social network public opinion shows the objective social phenomenon developed under the overlapping relationship between society and network society[8].

This article summarizes the following characteristics of the mobile social network public opinion proposed by scholars:

(1) Interactivity and immediacy: In the social media environment, any user can participate in the process of information production and dissemination for active creation, sharing, discussion and communication. Each user may become the leader of information, who create a fairer information exchange environment. In the meantime, as the main participants and promoters of online public opinion dissemination, netizens are the main contributors to the dissemination of online public opinion information[9].

(2) Mobility and Spread widely: With the popularization of smartphones and tablet computers, the mobile Internet has developed rapidly, contributed to the dissemination of information on APP has become commonplace. Whether it is the application of making friends, instant messaging, or online games, knowledge information, and e-commerce in business applications, users can communicate and share information. The participation and discussion of thousands of netizens formed a complex information chain, time chain and development chain, which became part of the event and developed simultaneously[10]. The essential body of public opinion on social networks is quite large and extensive, with a quite fast-spreading speed, a rather wide-spreading scope and an enormous social influence.

(3) Dynamic, diverse and sudden: Public opinion on social networks includes the feelings, thoughts and attitudes of different users. Compared with traditional public opinion, the stand of netizens changes faster and their opinions are more diverse[11]. Internet public opinion involves large numbers of fields, and public opinion hotspots are complex and changeable. Some hot social events, including ' against corruption ', ' gap between the rich and the poor ' and other topics are the crucial concerns of netizens. With the help of openness, interactivity, virtuality, convenience, anonymity and other characteristics of the new media environment, emergencies can spread and alter promptly[12].

In short, online public opinion in the social media environment is more diverse, spontaneous, interactive, and sudden. Therefore, strengthening the supervision and control of public opinion on social media networks has become a new hot spot for academics and industry regulators.

2.1.2. User Behavior of Internet Public Opinion in Social Media Environment

Lee[13] conducted a public opinion survey on online comments on social media to analyze the public's tolerance for information from other Internet users and the willingness of Internet users to express opinions on social media. Gull[14] obtained the attributes and polarity of all feedback information by natural language classification, and use naive Bayes probability and frequency distribution methods to study and check user behavior. Pablo Porten-Cheé[15] believed that compared with the preferences of mass media, public opinion users express their attitudes and preferences with more information, and use the silent spiral theory to investigate and analyze German Internet users' attitudes towards climate change. Meitz[16] assumed that the perception of credibility varies with the types of online media platforms and locales, and utilized quantitative analysis methods to analyze the role of credibility perception in the dissemination of information on social media. Deng[17] proposed an approach to classify user sentiment on social media, which analyzed netizens' emotions in the process of public opinion dissemination through two developed corpora.

2.1.3. Opinion leaders and user influence

Opinion leaders not only provide information in the interpersonal communication network but also influence others. They play a critical intermediary or filtering role in the process of public

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opinion dissemination[18]. They disseminate information to the audience and form two levels of information transmission. The rapid development of social media has shaped new types of opinion leaders. For example, bloggers with massive followers on Weibo, whose influence primarily comes from the love and interaction of followers on social media. The high flow of social media can even make ordinary people become famous overnight and become celebrities[19]. Viral marketing or word-of-mouth marketing in social media is the primary method of influencing multitudes of other users, who may be affected through a small number of influential people in social networks[20]. Social media opinion leaders can use a huge fan base to control the spread of public opinion. Therefore, the research on the influence of social media opinion leaders is of great significance for guiding the development of events to a positive trend, to make a virtuous circle of information dissemination.

2.2. Sentiment analysis

2.2.1. Text sentiment analysis

Text sentiment analysis, also known as opinion mining[21], refers to the process of collecting, processing, analyzing, summarizing and reasoning subjective texts with sentimental colors, involving artificial intelligence, machine learning, data mining, natural language processing, etc. Interdisciplinary research in multiple research fields. From the perspective of the research process, text sentiment analysis includes the entire process of crawling the original text, preprocessing the text, constructing a corpus and sentiment vocabulary, and sentiment analysis results[22].

According to the text level, sentiment analysis tasks can be divided into text level[23], sentence level[24] and word level[25]. The focus of chapter-level analysis is to distinguish the entire document as subjective or objective, positive or negative[26]. The sentence-level analysis is more effective than text-level analysis because a document includes subjective and objective sentences. Studies have found that 44% of the sentences in reports are subjective sentences, and most people’s impression of news is objective[27]. There is an inseparable relationship between the subjectivity of words and sentences or documents. There is a 56% possibility that sentences containing adjectives are subjective; verbs, nouns and adverbs also have a considerable influence[28]. Therefore, words are the key to text sentiment analysis.

2.2.2. Internet public opinion topic recognition

Topic recognition mainly recognizes the objects and domain-related ontology concepts modified by the evaluation words. The following approaches primarily used for topic recognition tasks:

(1) Based on the topic recognition of co-word analysis, co-word analysis can reveal the relationship between the topics represented by the topic words. Ding[29] constructed a post-topic two-mode network model, and selected word frequency, topic weight, and word frequency growth rate characteristics to extract the effective keywords required by the model. Shang[30] used the co-occurrence of lexical items to construct a dynamic co-word network and obtained the feature weight of Weibo text through the degree centrality of the complex network. Wu[31] sorted and clustered Weibo according to the high-frequency words of Weibo, and analyzed the sentiment of hot search on Weibo from both subjective and objective aspects, and used the gray model to obtain the development trend of public opinions.

(2) Sequence labeling, mainly including hidden Markov model and conditional random field. Ren[32] proposed a method based on the LSTM network model, which uses six-lexical tagging and adds pre-trained word embedding vectors to obtain better performance than traditional machine learning models. Wang[33] used GRU to access the semantics of the input data and then gathered the context of the output label through the conditional random field CRF, which result was better than rule-based or general machine learning methods.

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3. Research Design

3.1. Overview of hot events

Since patients with symptoms of novel coronavirus were found at the South China seafood Market in Wuhan at the end of December 2019. As of April 2021, over 100,000 people have been diagnosed with the novel coronavirus in China. In the meantime, 17,000 doses of the new crown virus vaccine have been vaccinated nationwide. A total of nearly 170 million people have been diagnosed with the novel coronavirus epidemic abroad, and hundreds of thousands of people are diagnosed every day. The novel coronavirus epidemic is still spreading around the world, severely hitting the economies of all countries and regions and affecting all aspects of human lives, work, and studies all over the world. There are hot searches related to "new crown" on social media every day.

3.2. Data collection

Weibo is one of the most representative social network platforms. Users can publish text, pictures, videos and other forms on Weibo to realize instant sharing and communication of information. Weibo's convenient interactive method makes it possible to own massive active users in China. People had to stay at home due to the impact of the new crown epidemic, so Weibo has become an effective way for people to obtain information and entertainment when they live at home. In the second quarter of 2020, the monthly active users of Weibo will reach 523 million, increasing 37 million users over the same period last year. Among them, the proportion of active mobile users is as high as 94%. Compared with traditional information media (such as TV, radio), users can participate in the information exchange and sharing of the Weibo social network through multiple access methods such as PC, mobile phone, tablet, etc. This convenient and swift social network service notably shortens the time of Internet public opinion events' occurrence and propagation. Therefore, we choose Weibo to crawl data from many social media platforms, with "new crown" as the core keyword. In the early stage of the new crown epidemic, its hot topics mainly concentrated on 'new crown epidemic', 'new crown virus', 'new crown viral pneumonia', etc. While in the middle and late stages of the epidemic, keywords mainly focused on keywords such as 'new crown vaccine', 'new crown virus mutation', and 'new crown vaccination'. Table 1 shows the new crown epidemic timeline and its related hot searches.

Table 1. Hot searches related to the new crown epidemic

Time	Related hot searches	Reading volume
2019.12.31	Wuhan Health Commission notified the situation of pneumonia	33.58 million
2020.01.01	massive new coronaviruses in the South China seafood market	840 million
2020.01.07	Zhejiang successfully isolated a new coronavirus strain	660 million
2020.01.23	Wuhan city closure	2.44 billion
2020.02.11	WHO names new coronavirus covid-19	1.35 billion
2020.03.21	China's new crown vaccine starts human injection experiment	510 million
2020.09.29	Cumulative deaths from new coronary pneumonia worldwide exceed 1 million	50.67 million
2021.02.17	Variant strains of new coronavirus discovered in many countries	850 million

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In order to make the crawled data more comprehensive and easier to quantify the indicators in the data processing process, the key users are divided into different types. The classification type refers to the eight types of bloggers investigated by Zhou[34] and selects the type of bloggers with significantly preeminent influence. Eventually, we choose to examine four types of bloggers: (1) the government and news organizations; (2) experts and scholars; (3) stars and celebrities; (4) self-media. Randomly select users with a higher number of followers from the bloggers who have published Weibo with the keyword 'new crown', then number them: official Weibo of government and news organizations(A1-A5), personal Weibo of experts and scholars (B1-B5), personal Weibo of stars and celebrities (C1-C5), personal Weibo of self-media (D1-D5), only the microblogs of the past three months are counted in the table. The details are shown in Table 2.

Table 2. Statistics of four types of bloggers' microblogs

No.	Weibo	Fans	Likes	Reposts	Comments
A1	3370	118122154	94951073	35905607	6427928
A2	3133	129528125	82721529	54278743	5706467
A3	5835	102659360	65450862	2127538	3528572
A4	1186	15841154	12031950	971866	822602
A5	4254	78953825	20004877	1275139	1344977
B1	209	1630534	1113622	129684	50855
B2	221	3513166	375721	29413	48601
B3	468	8475198	414667	129955	56131
B4	1282	2099877	210406	55105	41185
B5	1032	1201582	2173660	225121	124117
C1	61	110481518	14964986	10040908	2910420
C2	19	60100354	9079982	9737760	1863949
C3	39	40579083	12520582	7866200	879667
C4	41	57497471	8762253	6014053	2137167
C5	515	23507856	3440003	219890	508466
D1	33	2425172	295507	62375	28738
D2	148	4554612	324324	113080	37128
D3	121	4261310	68728	41387	12056
D4	194	4939826	765017	280026	59476
D5	64	2293190	1121652	164389	81414

3.3. User influence index selection

Combined with the actual situation of the Weibo platform, we can notice that there is a relationship between users and their followers. As we know, user behaviors include posting, reposting, commenting, and likes. From another perspective, users also have authentication marks such as identity authentication and official authentication. So user influence can be judged by these factors. In short, user's influence can be measured from two aspects: users' attributes and behavior. Users' attributes can be accessed according to Weibo: (1) Number of follows; (2) Number of followers; (3) Weibo authentication. Users' behavior can be divided into: (1) Number of posts and reposts; (2) Number of reposted; (3) Number of comments; (4) Number of likes. Therefore, this article will establish user's influence indicators from the following three aspects.

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(1) In terms of user relationship, the number of users' fans can reflect the user's influence to a certain extent. Therefore, there are data frauds in Weibo, for instance, users buy "zombie fans" or hiring "water soldiers" to like. So the number of fans cannot be used to directly evaluate the influence of users. Thereby, we converted the indicator of the number of fans into the proportion of the number of active fans. The standard for active fans is that the number of fans is greater than or equal to 20 and the number of Weibo posts is greater than or equal to 10. Because of the limitation of Weibo crawlers, we crawled only part of the fans to calculate their active percentage of fans.

$$AF_i = af_i * F_i \tag{1}$$

Among them, AF_i is the number of active fans， af_i is the proportion of the i-th user's active fans， and F_i is the total number of fans.

$$Raf_i = \begin{cases} 1, & 0 \leq AF_i \leq 5million \\ 2, & 5million < AF_i \leq 10million \\ 3, & 10million < AF_i \leq 30million \\ 4, & 30million < AF_i \leq 50million \\ 5, & 50million < AF_i \end{cases} \tag{2}$$

Raf_i represents the user's active fan rating score， AF_i is the number of active fans.

(2) In terms of user behavior, the main behaviors of Weibo users include comments, reposts, and likes. Considering that the influence of Weibo posted by users is different in various periods, the post-activity of the user is proposed. In the Tn time, the number of original microblogs sent by the user is On, and the number of reposted microblogs is Rn. This article only calculates the activity of the microblogs posted in the past three months, and assigns them to the three-month weight distribution is 0.5, 0.3, and 0.2. The available post-activity index is

$$a_i = [\sum_i^n \beta_i \,(O_i + R_i)/T] \tag{3}$$

$a_i$is the posting activity of the i-th user in the past three months, $\beta_i$is the weight of each month, and Trepresents the total time length.

Besides, the number of reposts, comments, and likes under each microblog of a user can more intuitively reflect the influence of the user or the popularity of a public opinion event. Considering that the number of fans of each user will also have a direct impact on the number of reposts, comments and likes. This indicator is defined as the influence of the user's Weibo content.

$$Q_i = (TR_i + C_i + L_i)/\, AF_i \tag{4}$$

Q_i is the influence of the i-th user's Weibo content, TR_i is the number of reposts, C_i is the number of comments, L_i is the number of likes, AF_i is the number of active followers of the ith user.

(3) In terms of user authentication, Weibo is currently divided into Weibo authentication and official authentication. Weibo authentication includes identity authentication, interest

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authentication, gold V authentication, etc. Official authentication includes enterprise authentication, government authentication, media authentication, and agency authentication. Because of the mentioned different types of authentication, this article sets the indicator as user credibility.

$$Reliability_i = \begin{cases} 0, & \text{No authentication} \\ 0.5, & \text{Rest authentications} \\ 1, & \text{Identity authentication} \\ 2, & \text{Official authentication} \end{cases} \tag{5}$$

Based on various indicators, this paper draws the formula for calculating user influence as shown in (6)

$$I_i = \alpha_1 Raf_i + \alpha_2 a_i + \alpha_3 Q_i + \alpha_4 Reliability_i \tag{6}$$

Among them, I_i is the influence of the i-th user, Raf_i is the user′s active fan rating score, a_i is the posting activity of the i-th user, $Reliability_i$ is the user credibility of the i-th user, α_i is the weight value of each index, which will be calculated by the entropy weight method.

3.4. Index weight determination-entropy weight method

The entropy weight method is used to judge the disorder of index values in information theory. The entropy weight of the index is calculated from the entropy value, then all the indexes are weighted by the entropy weight of the index. Eventually, an objective evaluation result is obtained, which is the entropy of the index. The smaller the value, the greater its weight and the higher its importance. Compared with subjective weighting methods such as the analytic hierarchy process, the use of the entropy weight method can effectively avoid the doping of subjective factors. In the meantime, it can objectively reflect the differences between data through weights, so it has more stable objectivity and higher accuracy. Therefore, it can interpret the evaluation results better. The formula of the entropy method is shown in (7)

$$x'_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{7}$$

Use the following formula to calculate the entropy value Ej

$$E_j = -\frac{1}{\ln n} \sum_{i=1}^{n} x'_{ij} \ln x_{ij} \tag{8}$$

The calculation formula for the entropy weight vector is shown in (9)

$$w_j = (1 - E_j) / \sum_{j=1}^{m} (1 - E_j) \tag{9}$$

Substituting the scores of the four types of bloggers into the calculation, the weights are shown in Table 3.

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Table 3. User influence index weight

index	active fan rating score	posting activity	Content influence	user credibility
weight	0.17	0.63	0.10	0.10

Then substituting the scores of each user's indicators into its user influence as shown in Figure 1.

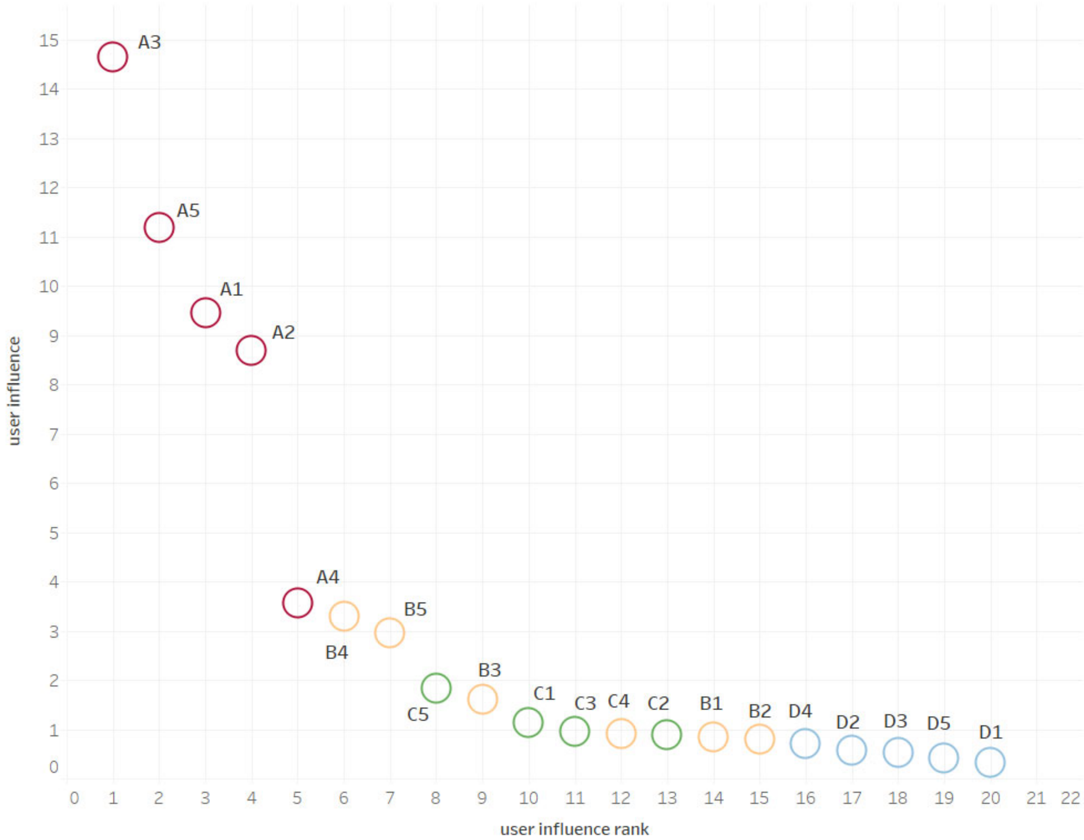

Figure 1. User influence ranking

4. Sentiment Analysis and Sentiment Tendency of Comments Based on LDA

As a new type of opinion leader, the sentimental tendency in the Weibo platform has a more rapid and direct influence on the following users. So the sentimental trend of the comment area (divided into positive emotion, neutral emotion and negative emotion) is used to measure the emotion of the opinion leader towards the following users' influences. Therefore, the negative sentiment information of negative public opinion comments such as rumors can be identified in time through sentiment analysis, so as to reduce the loss caused by negative public opinion.

This article chooses the method based on the sentiment dictionary to analyze the sentiment of the 20 bloggers on one of their Weibo text and its comments, which owned high flow. Basic idea: The sentimental tendency of each blogger is determined by the emotional words contained in Weibo. Assign a weight to the sentiment word and get the weighted sum of the sentimental trend of the Weibo, then use SnowNLP to measure the sentimental tendency of all the comments under this Weibo. If it is larger than 0.7, it is a positive emotion, and it is less than 0.5 is a negative emotion, and the rest is neutral. Ultimately, we use the implicit Dirichlet

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distribution to generate subject words to judge its sentimental trend again. The results of sentiment analysis are shown in Table 4.

Table 4. Sentiment analysis results of different bloggers

NO.	Emotion	Comment sentimental tendency			LDA Subject Words
		Positive	Neutral	Negative	
A1	negative	50%	19%	31%	Surrogacy, Abandoned, law
A2	positive	50%	16%	34%	Tencent, Ali, monopoly
A3	positive	47%	12%	41%	Korea, kimchi, China
A4	positive	78%	78%	22%	Occupation, players, e-sports
A5	positive	53%	17%	30%	Graduates, Former students, Support,
B1	positive	83%	11%	6%	Doctor, beautiful, happy new year
B2	positive	39%	16%	44%	Doctor, prosthesis, operating room
B3	positive	60%	7%	33%	Surrogacy, abandonment, child
B4	negative	57%	8%	34%	Popular science, drug addiction, anesthesia
B5	negative	42%	12%	46%	Fishbone, hospital, scary
C1	positive	58%	14%	28%	Correct, Yang Mi, apology
C2	positive	45%	17%	38%	Congratulations, come on, good morning
C3	positive	40%	40%	20%	William Chan, love you, handsome
C4	positive	63%	14%	23%	cute, high school student, happy
C5	positive	40%	19%	41%	Xiaomi, Mr. Lei, endorsement
D1	positive	67%	14%	19%	Happy, staying up late, life
D2	positive	57%	12%	31%	video, popular science, error
D3	positive	67%	19%	14%	Cute, girl, beautiful
D4	positive	56%	16%	29%	Friends, social, lonely
D5	positive	40%	17%	43%	Baby, business, black heart

The combination of emotional orientation and LDA subject terms can quickly derive the attitude of the commenters below the blog post towards the news and the reasons. For example, in A1, subject terms such as "surrogacy", "abandonment", and "law" reflect that the incident is ngative news, so the emotional tendency of the commenter is negative.

5. Conclusion and Suggestion

This article proposes the role of a new type of social network opinion leader that combines user influence and sentiment analysis in the dissemination of online public opinion and uses 'new crown' as the keyword to elicit the new type of opinion leader user influence. Above all, according to the types of Weibo users, they are divided into four categories of bloggers. The four indicators of user activity level, post-activity, Weibo content influence and authentication are assigned and weighted, and then substitute the user data to calculate the user influence result. The official Weibo users of the government and news organizations have the highest influence, and the self-media Weibo has the lowest influence. Scholars, experts and celebrities have a similar impact on Weibo. Finally, 20 bloggers' microblog texts and their sentimental orientation analysis and LDA keyword extraction. Combined with the sentiment orientation of the comments help to quickly discover the thoughts and emotions of most users in the control of the spread of public opinion on social networks.

Through the results of user influence and the influence of new opinion leaders on the emotional tendency of commenters, the following management suggestions are obtained in the process of public opinion dissemination on social networks: First, give full play to the user influence of the

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government and news organizations. The empirical research here and other related literature show that this type of blogger has the highest impact. If such bloggers make false comments, it will cause a series of adverse public opinions to spread rapidly. Therefore, the official Weibo of the government and news organizations should continue to keep the frequency of updating Weibo with the latest hot news briefs. At the same time, their Weibo must be managed and reviewed by experts with rich media experience. Avoid or reduce the occurrence of fake news. Second, restrict fans from commenting on Weibo's comment area. A celebrity star’s Weibo has a large number of individual fans. When the user has multiple public opinions, a large number of similar texts of fan comments will appear under Weibo to achieve the purpose of controlling the remarks. This behavior will seriously interfere with the acquisition of a large number of netizens’ real emotions. Therefore, the comments should be restricted from appearing in large quantities of the look-alike text or the same user sending multitude of meaningless comments in a short time.

References

[1] Sun Gengxin, Bin Sheng. Network Public Opinion Communication Model Based on Interest Matching in Multi-relational Social Networks[J]. Journal of University of Science and Technology of China, 2018, 048(009):730-738.

[2] Kim K , Baek Y M , Kim N . Online news diffusion dynamics and public opinion formation: A case study of the controversy over judges' personal opinion expression on SNS in Korea[J]. Social ence Journal, 2015, 52(2):205-216.

[3] Arnaboldi V, Conti M, La Gala M, et al. Ego network structure in online social networks and its impact on information diffusion[J]. Computer Communications, 2016, 76: 26-41.

[4] Yoo E , Rand W , Eftekhar M , et al. Evaluating information diffusion speed and its determinants in social media networks during humanitarian crises[J]. Journal of Operations Management, 2016, 45(jul.):123-133.

[5] Mark Freemana, James McVittieb, Iryna Sivakc 1, et al.Viral information propagation in the Digg online social network[J]. Statistical Mechanics and Its Applications,2014,415(1):87-94.

[6] Wang Xiwei, Xing Yunfei, Zhang Liu, et al. Research on the development trends and trends of Internet public opinion in social media environment at home and abroad[J]. Information and Documentation Work, 2017(04):8-16.

[7] Wang Xiwei, Xing Yunfei, Zhao Dan,Li Jiaxing. Research on the dissemination of online public opinion information in a mobile environment based on social network analysis——Taking Sina Weibo's "Smog" topic as an example[J].Library and Information Work,2015,59(07):14-22.

[8] Shenyang, Wu Jingthorn. Research on Network Public Opinion Deduction Based on Complex Factors[J].Journal of Information,2013,32(12):1315-1325.

[9] Guo Chunxia, Liu Hui,Chu Jiewang. Study on the Big Data Capacity Building of Internet Public Opinion Governance in the New Media Environment[J].Information Theory and Practice, 2018, 41(12):46-54.

[10] Huang Wei, Li Rui, Meng Jialin. Research on the Dissemination Elements and Operating Mechanism of Multimedia Network Public Opinion under Big Data Environment[J].Library and Information Service,2015,59(21):38-44+62.

[11] Huang Wei, Zhao Jiangyuan, Xu Yejing. Research on the Interoperability Elements and Mechanism of Multimedia Network Public Opinion Knowledge Base Group[J].Library and Information Work,2019,63(20):43-50.

[12] Jung K , Park H W . Tracing interorganizational information networks during emergency response period: A webometric approach to the 2012 Gumi chemical spill in South Korea[J]. Government Information Quarterly, 2016, 33(1):133-141.

[13] Lee M J, Chun J W. Reading others' comments and public opinion poll results on social media: Social judgment and spiral of empowerment[J]. Computers in Human Behavior, 2016, 65: 479-487.

[14] Gull R, Shoaib U, Rasheed S, et al. Pre processing of twitter's data for opinion mining in political context[J]. Procedia Computer Science, 2016, 96: 1560-1570.

[15] Porten-Cheé P, Eilders C. Spiral of silence online: How online communication affects opinion climate perception and opinion expression regarding the climate change debate[J]. Studies in communication sciences, 2015, 15(1): 143-150.

[16] Meitz T G K, Ort A, Kalch A, et al. Source does matter: Contextual effects on online media-embedded health campaigns against childhood obesity[J]. Computers in Human Behavior, 2016, 60: 565-574.

[17] Deng S, Sinha A P, Zhao H. Adapting sentiment lexicons to domain-specific social media texts[J]. Decision Support Systems, 2017, 94: 65-76.

[18] Ji Dan, Guo Zheng. Study on the Influencing Factors of Internet Opinion Leaders on the Effect of Crisis Information Dissemination[J].Information Magazine,2015,34(02):22-27.

[19] Wang Yaqian. From celebrities to "micro celebrities": Research on the identity change and influence of opinion leaders in the mobile social era[J].News reporter,2021(03):27-39.

[20] Tan Qi, Zhang Fengli, Zhang Zhiyang, Chen Xueqin. Modeling method of social network user influence[J].Computer Science,2021,48(02):76-86.

[21] Das S, Chen M. Yahoo! for Amazon: Extracting market sentiment from stock message boards[C]//Proceedings of the Asia Pacific finance association annual conference (APFA). 2001, 35: 43.

[22] Ma Li, Gong Yulong. Summary of Research on Text Sentiment Analysis[J].Electronic Science and Technology,2014,27(11):180-184.

[23] Balahur A, Steinberger R, Kabadjov M, et al. Sentiment analysis in the news[J]. Infrared Physics and Technology. 2014, 65: 94-102.

[24] Jiang L, Yu M, Zhou M, et al. Target-dependent twitter sentiment classification[C]//Proceedings of the 49th annual meeting of the association for computational linguistics: human language technologies. 2011: 151-160.

[25] Taboada M, Brooke J, Tofiloski M, et al. Lexicon-based methods for sentiment analysis[J]. Computational linguistics, 2011, 37(2): 267-307.

[26] Pang B, Lee L, Vaithyanathan S. Thumbs up? Sentiment classification using machine learning techniques[J]. arXiv preprint cs/0205070, 2002.

[27] Wiebe J, Wilson T, Bruce R, et al. Learning subjective language[J]. Computational linguistics, 2004, 30(3): 277-308.

[28] Voll K, Taboada M. Not all words are created equal: Extracting semantic orientation as a function of adjective relevance[C]//Australasian Joint Conference on Artificial Intelligence. Springer, Berlin, Heidelberg, 2007: 337-346.

[29] Ding Shengchun, Wang Nan, Wu Liangchanyuan.Research on Weibo Hot Topic Recognition Based on Keyword Co-occurrence and Community Discovery[J].Modern Intelligence,2018,38(03):10-18.

[30] Shang Xianli, Wang Xuedong. Text Feature Extraction Method Based on Dynamic Co-word Network in Weibo Topic Recognition[J].Library, Information, and Knowledge,2016(03):80-88.

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202301_6(1).0015

[31] Wu Qinglin, Zhou Tianhong. Analysis of Chinese Weibo Public Opinion Based on Topic Clustering and Emotion Strength[J].Information Theory and Practice, 2016, 39(01):109-112.

[32] Ren Zhihui, Xu Haoyu, Feng Songlin, Zhou Han, Shi Jun. Sequence tagging Chinese word segmentation based on LSTM network[J]. Application Research of Computers,2017,34(05):1321-1324+1341.

[33] Wang Renwu, Meng Xianru, Kong Qi. The GRU+CRF Method of Entity-Attribute Extraction [J]. Modern Information,2018,38(10):57-64.

[34] Zhou Quan,Tang Shukun.Research on the Perceived Credibility of Social Media Information Sources and Its Influencing Factors——An Empirical Analysis Based on the Survey of Weibo User Convenience Samples[J].Journalism and Communication Research,2015,22(04):18- 35+126.