Evolution of public opinion based on network structure balance

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Abstract: With the development of internet technology, social network has become an important platform for people to get information and communicate with each other. The current researches focus on the identification of opinion leaders in the public opinion network and the analysis of viewpoints between individuals with bounded confidence models. However, few scholars study the evolution of public opinion through theory of network structure balance. Therefore, we propose a novel method based on network structure balance to analyze the evolution of public opinion. First, we establish a diversity evaluation method to calculate node's influence by the comment, forward and praise. Second, we construct the network with positive and negative weights by node's attitude to hot event and the interaction forces among nodes. At last, we merge the balance triangles with the same positive and negative attribute as new nodes, and explain the evolution of public opinion on the network. The analysis of public opinion based on structural balance provides a new way to understand the evolution of public opinion.

1. Introduction

The internet has become the main channels for information transmission, and the exoteric and virtual features make it easier for public opinion to spread. The internet provides a convenient platform where everyone can share their viewpoints by means of texts, pictures, videos, etc. Citizens use the internet to obtain information, convey public opinions, elucidate public opinion and participate in political discussion [1].

There are some differences between the internet public opinion and the traditional public opinion. For example, on the internet, a connection between two users could be established or removed at lower costs, and the effect of opinion leaders is strongly amplified [2]. Therefore, the event related to the public interest can easily develop into internet public opinion. What's more, the impact of online public opinion tends to outweigh the events itself.

In the present study, the researchers pay attention to the factors and mechanisms in the evolution of public opinion. The former uses comments or retweets to study the influence of nodes. The latter describes the evolution of network public opinion and the spread of public opinion among individuals through epidemic propagation model and bounded confidence model, respectively. However, there are two problems in the present research. First, some users tend to set up only friends have the right to review their Microblog post under the background of increased privacy in Microblog, so the performance of opinion leader recognition methods which based comment, has declined sharply. Second, the imbalance of the network is the main reason for the adversarial evolution of public in different directions. However, there are few researches study the evolution of public opinion through structural balance. Therefore, we pro-pose a novel method based on network structure balance to analyze the evolution of public opinion.

The first step, we establish a diversity evaluation method to calculate node's influence through comment, forward and praise. The second step, we construct the network with positive and negative weights by node's attitude to hot event and the inter-action force among nodes. The last step, we merge the balance triangle with the same attribute as a new node and explain the evolution of public opinion on the network.

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2. Related Work

Opinion evolution is a fusion process of individual opinions in which interacting agents within a group continuously update and fuse their opinions on the same issue based on the established fusion rules and reach a consensus, polarization, or frag-mentation in the final stage [3]. At present, the research on the evolution of public opinion is mainly about the information diffusion model.

Information diffusion model originates from the epidemic dynamics model, such as SI [4], SIS [5], SIR [6], SEIR [7] in which S (Susceptible), I (Infected) and R (Removed) correspond respectively to three states of agents. These classic epidemic models are widely used in rumor and public opinion transmission. In 1985, Sudbury [8] first used the sir model of infectious diseases to describe the spread of rumors between different villages, in which people who had not heard of rumors were susceptible to infection and those who heard and wanted to spread were infected. People who have heard but not interested are in a difficult state of infection.

Information diffusion always accompanies with the formation of public opinion [9]. In the bounded confidence model, DW and HK are two typical representatives. The DW [10] model points out that in the process of forming a group of users' opinions, the opinions of other users will not be simply shared and strictly indifferent and to a certain extent, other users' opinions will be taken into consideration to form their own opinions. HK [11] model views update mechanism is different from the asynchronous update of DW model. HK arithmetic average all individual views within the trust threshold as the point of view at the next moment of the individual.

3. Research Framework

In order to illustrate the evolution process of public opinion, we use the posts in Microblog as nodes and the interactive behaviour among nodes as edges.

3.1. Calculate the influence of nodes

The methods of study the influence of nodes in Microblog need to update with the development of Microblog. Most of the previous methods used the review to calculate the influence of nodes. However, with the enhancement of Microblog's privacy protection, individuals tend to set only friends who can review their microblog posts. For instance, actress Yao Chen has 80 million Microblog fans, and she sets only her friends have the right to review her Microblog post. For example, there are only 65 comments on the post "call for china to receive refugees", but the number of retweets reaches 37670 and the number of praises reaches 232675(as shown in Figure (1). Although there are few comments on the post, Yao still plays an important role in the dissemination of public opinion. Ergo, it is meaningful to establish a multivariate method to evaluate the influence of nodes.

In our method, we use Jaccard coefficient (JC) to measures the strength of trust relationships and evaluates the total trust value between nodes to select the opinion leaders. In first step, we adopt comments, retweets and praises to estimate the strength of trust relationships among nodes in social network.

Figure 1 Microblog of Chinese star Chen Yao.

For analysis, we use the number of nodes which both node i and node j comment to estimate the strength of trust relationships between node i and node j. Then, we transform the value of JC metric between 0 and 1 with computing a ratio of the number of nodes who are commented by both node i and node j to the number of nodes that are commented by either node i or node j, but not both. We define this metric as follows:

$$C_{i,j} = \frac{|comment(i) \cap comment(j)|}{|comment(i) \cup comment(j)|} \quad (1)$$

$$R_{i,j} = \frac{|retweet(i) \cap retweet(j)|}{|retweet(i) \cup retweet(j)|} \quad (2)$$

$$P_{i,j} = \frac{|praise(i) \cap praise(j)|}{|praise(i) \cup praise(j)|} \quad (3)$$

Where $comment(i) \cap comment(j)$ represents the comments of node who are commented by other node i and node j, and $comment(i) \cup comment(j)$ represent the number of node who are commented by between node i or node j. $C_{i,j}$ represents the strength of trust relationships between node i and node j. Similarly, $R_{i,j}$ and $P_{i,j}$ represents calculates trust relationships by retweets and praises, respectively.

In the second step, the influence of nodes is calculated by equation (4)

$$\text{Impact}_i = \sum_{j \in M} \omega_1 * C_{i,j} + \omega_2 * R_{i,j} + \omega_3 * P_{i,j} \quad (4)$$

Where M represents a collection of interactions with node i, and $Impact_i$ represents the influence of nodes i. The experimental results show that the best values of ω_1, ω_2, ω_3 are ω_1=0.3 , ω_1=0.5, ω_3=0.2.

Internet public opinion can be implicitly transmitted through the non-directly connected node. A node attracts other nodes in the opinion propagation with an interact force which is directly proportional to the influence of nodes and inversely proportional to the distance between nodes. In other words, the greater the impact of a node, the greater the probability of affecting other nodes. The greater the distance between the two nodes, the less the probability of interaction between them. The interaction force between nodes of public opinion network is similar to the gravity of objects. Therefore, we introduce the universal gravitation into the network public opinion propagation, and calculate the weight among the nodes through the influence of nodes and the distance between nodes.

$$F_{i,j} = K(Impact_i * D_{i,j}^2) \quad (5)$$

Where $impact_i$ represents the influence of node i. $D_{i,j}$ represents the shortest connection path between node i and node j. $F_{i,j}$ represents the interaction force between node i and node j. Relevant research shows that the most suitable number of people for dissemination of public opinion is 3 [1]. Therefore, the maximum length of $D_{i,j}$ is 2.

3.2. Structure balance in the Evolution of Public opinion

In the social network of public opinion dissemination, only the node that agrees or opposes to the hot events will lead to the evolution of public opinion in the corresponding direction. The node which holding neutral attitude about a hot event has less influence on the dissemination of public opinion. In this paper, we assume the attitude of any nodes toward hot event is either agrees or opposes. In particular, any two nodes have the same or inconsistent attitude towards a hot event.

We study the evolution of public opinion by structure balance theory. The core idea of theory is as follows: the edge between any two nodes can be marked as “+” or “-”, which “+” represents two nodes holding same attitude towards the public opinion event, and the “-” represents two nodes holding opposite attitude. We observe the triangle of three nodes, some “+” and “-” combinations appear more reasonable than others in terms in public opinion evolution. Specifically, we noticed 4 different combinations as shown in the Figure 2:

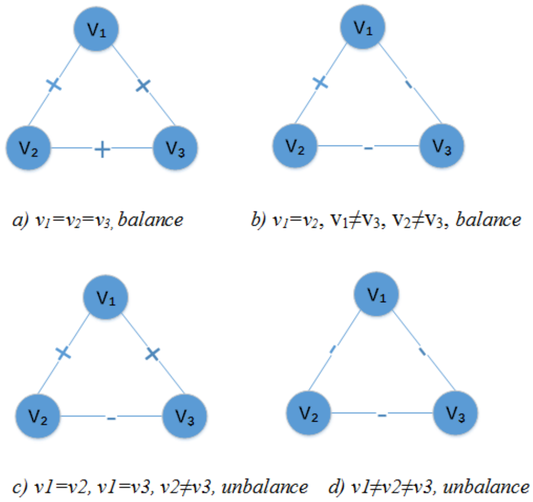

Figure 2 Structural balance.

Network structural balance: For every triangle of three nodes, their associate three edges are either marked with “+”, or exactly one edge is marked with “+”.

Different node haves different influence on the evolution of real public opinion, unbalanced triangles are more than balanced triangles. The unbalanced triangles are the main reason that leads to the antagonistic evolution of public opinion in different direction. Therefore, we use the network structure balance to analyze the evolution of public opinion. In first step, we construct a positive and negative public opinion network through the node’s attitude towards to public events, as shown in Figure 3.

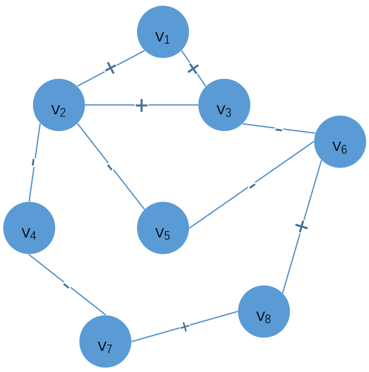

Figure 3 Opinion Network graph with positive and negative Relations.

In the second step, we use university gravity to calculate the interaction force among nodes. In Fig 4, v3=0.3, v5==0.4 , $F_{35} = -3.5 * \frac{0.3*0.4}{r^2} = -0.11$. After updating the weight, we get the weighted public opinion network structure, as shown in the Figure 4.

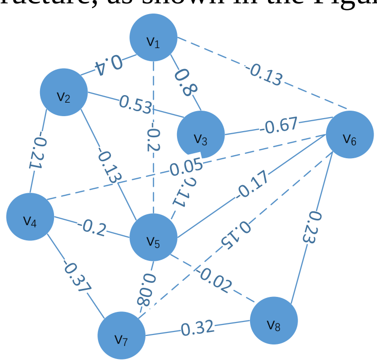

Figure 4 Positive and negative relation Opinion Network Graph with weights.

In the last step, if the sum of the weights of the balance triangles are the same as the positive and negative values, the nodes of these balanced triangles are regarded as a new node. In Figure 5, the new nodes are {v1, v2, v3}, {v4, v5, v6, v7}, {v8}. Then, we construct the public opinion network graph with new nodes, and recalculate the new weight between the nodes, and repeat iterations until the opinion network does not change. We can analyze the positive and negative emotions of the opinion network and the nodes that affect the imbalance of opinion network in different stage through the opinion network formed in the end. The former helps us to understand the evolution of public opinion, and the latter is of great significance for us to establish appropriate strategies for guiding public opinion.

4. Discussion and Comparison

4.1. Data preparation

In the present paper, the typical internet public opinion case, which happened in 2017. The public opinion is case by the judgement of “case of Jiang Ge being killed”. Jiang Ge, a Chinese student study at Hosei University in Tokyo, was murdered with a dagger by Shifeng Chen.

In order to avoid the decrease of the accuracy of the result, the repeated interference information and isolated Microblog content (the sum of the forwarding and comment of the Microblog content is less than 3) should be removed. This paper improves the data cleaning method proposed by Samad, and establishes the following data cleaning rules:

- Remove repeated comments and forward from Microblog.
- Remove self-comment, self-forward and self-praise from Microblog.
- Remove the Microblog content that (the sum of the forwarding, comment and praise of the Microblog content is less than 3.

4.2. Comparison of influential nodes selection methods

After data clean, we compare our method with for methods: Top in- degree, Top out-degree, Hybrid IO-degree (in-degree and out-degree), Top centrality methods.

$$Top \text{ in-degree} = Max\,(in\ comment) \tag{6}$$

$$Top \text{ out-degree} = Max\,(out\ comment) \tag{7}$$

$$\text{Hybrid } IO\text{-degree}=\alpha(\text{in-degree})+(1-\alpha)(\text{out-degree}) \tag{8}$$

$$Top\ centrality = Max\,(\text{in-degree} + \text{out-degree}) \tag{9}$$

Where Top in-degree means that the node haves a maximum in comment. Where Top out-degree means the node have a maximum out comment. Where α increases the value of input comments toward out comment. Where Top centrality means that the node haves high sum of in and out comments.

For compare the method that calculate the influence of nodes, we review five other ways for identifying the influential nodes, which include select nodes with top in-degree, top out-degree, hybrid IO-degree, top centrality and TTV (hybrid IO-degree). Figure 5 represents the percent of return influential nodes use five methods. The result shows that our method with return 32% of all nodes as influential node is the best method among top in-degree with 18%, tops out-degree with 17%, hybrid in-degree with 21%, TTV (hybrid IO-degree) with 23%.

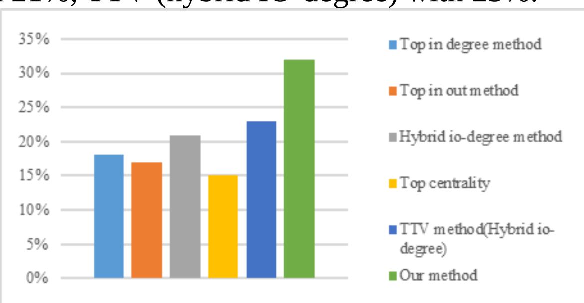

Figure 5 Percent of return influential nodes.

4.3. Analysis the evolution of public opinion

The structural triangles recognition method is affected by the index of comments, forwards, praises. Further research is presented to clarify the relationship between the selection factor w1, w2, w3, G and the influence of balance triangles in Figure 6. We pre-suppose w1=0.5, w2=0.3, w3= 0.2, w1=0.2, w2=0.4, w3=0.4, w1=0.2, w2=0.5, w3=0.2 there schemes to analyse the value of gravitation parameter G. As except, the effect of use comments to calculate influence of node is reduces. The results show that the impact of forward on structural triangles recognition is greater than praise and the optimal value of parameter G is 3.5.

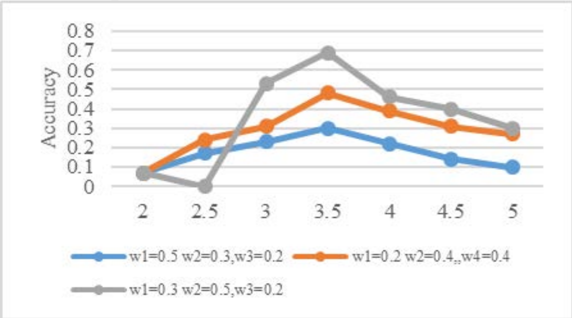

Figure 6 Select the optimization parameter.

In addition, we also analyse the influence of positive and negative emotions on the hot event. Figure 7 show that when public opinion spread more positive emotions than negative ones, public opinion gradually increases negatively. In other words, negative public opinion spreads faster than positive public opinion.

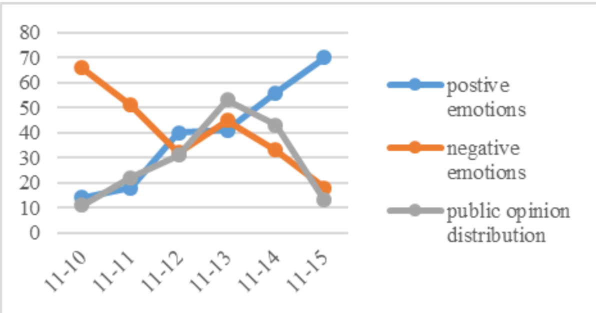

Figure 7 The relationship between positive and negative views and the spread of public opinion.

In Figure 8, it is not difficult to find that the unbalance network structure in public opinion is similar to the distribution of public opinion. In other words, the more un-balance network structure in the evolution of public opinion, the stronger the confrontation of public opinion is, and the easier it is to spread public opinion. Therefore, the analysis of positive and negative emotional network structure balance is helpful to further understand the evolution of public opinion, and formulate the corresponding public opinion guidance strategy.

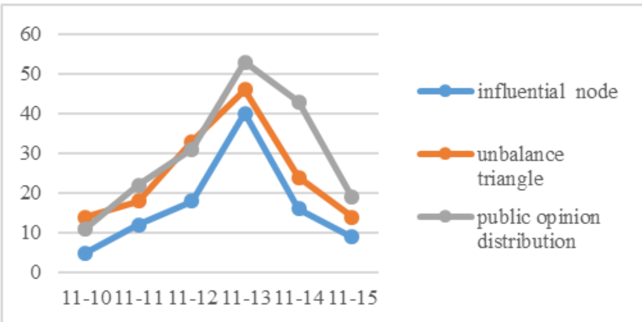

Figure 8: The influence factors of public opinion dissemination.

5. Conclusions

Compare to the previous opinion identification methods, the present paper provides a more accurate and diversity evaluation method for researches to find the influential nodes. We use network structural balance to analyse groups with different emotions, which is helpful to reveal the relationship between the number of positive and negative groups and the spread of public opinion. In additional, it also shows a new beginning for future studies to analyse the evolution mechanism and the guide strategy of the internet public opinion with some theoretical and practical development.

However, there are also some limitations of this research work, shown as followings:

- In the present paper, only the relationships between positive/negative unbalance network and the evolution of public opinion have been taken into consideration. In the upcoming future, we may discuss the mechanism of interaction between different unbalance networks.
- Public opinion messages are time-sensitive, so, in the future we will try to build a structural balance network with time series of Microblog post.
- The number of Influential nodes and unbalance networks in the network, have internal relationships with the evolution of public opinion, we will use opinion leaders and unbalance networks to build a method of public opinion guidance.

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References

[1] Y. Xie, R Qiao, and G Shao (2017), “Research on Chinese social media users’ communication behaviors during public emergency events” Telematics and Informatics, 740-754.

[2] Y. Lian, X Dong and Y Li (2017), “Topological evolution of the internet public opinion” Physica A Statistical Mechanics and Its Applications, 567-578.

[3] S.K Walker (2011), “Connected: The Surprising Power of Our Social Networks and How They Shape Our Lives” Journal of Family Theory and Review, 220-224.

[4] M. Barthélemy, A Barrat (2004), “Velocity and hierarchical spread of epidemic outbreaks in scale-free networks” Physical Review Letters, 178-201.

[5] R. Parshani, S Carmi (2001), “Epidemic Threshold for the Susceptible-Infectious-Susceptible Model on Random Networks” Physical Review Letters, 258-701

[6] Y. Moreno, J.B Gómez (2003), “Epidemic incidence in correlated complex networks” Physical Review E Statistical Nonlinear & Soft Matter Physics, 2.

[7] M. Kamo, A Sasaki (2002), “The effect of cross-immunity and seasonal forcing in a multi-strain epidemic model” Physica D Nonlinear Phenomena, 3-4.

[8] Sudbury (1985), “The Proportion of the Population Never Hearing a Rumour” Physica D Nonlinear Phenomena, 443-446.

[9] H. Zhu, Y Kong (2018), “Effect of users’ opinion evolution on information diffusion in online social networks” Physica a Statistical Mechanics and Its Applications, 2034-2045.

[10] D. Guillaume, N David (2000), “Mixing beliefs among interacting agents” Advances in Complex Systems, 87-98.

[11] R. Hegselmann, R.U Krause (2002), “Opinion Dynamics and Bounded Confidence Models” Analysis and Simulation. Journal of Artificial Societies & Social Simulation, 2.