A Contral Framework of Polar Opinion Dynamicis Based on Influence Maximization

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Abstract—**The rapid development of social networks has brought a huge amount of information to people's daily lives, which leads people's positions or implicitly assimilates the thoughts of their audiences. We want to speed up the spread of beneficial information and maximize its influence, while for harmful information such as rumors, we want to curb its spread and reduce its influence. By studying the topology of social networks, combining it with the structural control of control engineering, this paper adds the control matrix to the simulation of the polar process of public opinion in order to achieve better guiding purposes.**

***Keywords*—Complex networks ; influence maximization ; Polar Opinion；Degroot model**

I. INTRODUCTION

In this era of information explosion, people can easily obtain a large amount of information, corresponding to the public opinion platform, people's comments have also been fully confided, unknowingly, we and many online neighbors together into a huge "network", everyone's opinions implicitly affect the thinking of those around them, one topic to the end of polar.

Just like a machine system from design to operation, people hope to control it by effective means, the article is also exploring a state equation in the form of observation and control of the public opinion guidance system. In the development of many events not only as expected, we do not change its overall trend of development, through external input to control its polar speed, the pursuit of the event's influence to maximize.

In order to clearly display and intuitively guide the direction of the point of opinion, the article draws on the characteristics of complex networks and topology, which in itself is also very social, public opinion network nature. Through the experiment of generating the network and the simulation of the real data, the article adds external input to the network as a whole on the basis of fitting the polar process, so that the opinion develops more quickly and gathers on the target distribution.

Based on complex networks and graph theory, combined with observation and control methods of state equations, this paper fits the development of public opinion opinions and enhances the influence of events.

II. RELATED WORK

There $G < V, E >$are node sets $V$and edge sets in the network , which represents the connection relationships of the nodes E in ,$W$is the adjacency matrix. Specifically, the study of social opinion issues, node set mainly refers to the user group, and then according to its social platform "like, forward, comment, recommend, participate in the same label topic" and other behaviors to define the connection between them, forming an edge set.

$$x(k+1) = Ax(k)$$

In DeGroot's model, it is assumed that there are N users in A social network and their opinion values at the moment k are expressed by $x(k)$. There is a non-negative matrix A, which represents the interaction between users.

In the Friedkin-Johnsen models, the concept of "stubborn" individuals is added, i.e., users maintain a certain degree of resilience to their existing views.

III. NETWORK STRUCTURE AND DYNAMICIS MODEL

A. The Network Structure

There $G < V, E >$are node sets $V$and edge sets in the network , which represents the connection relationships of the nodes E in ,$W$is the adjacency matrix. Specifically, the study of social opinion issues, node set mainly refers to the user group, and then according to its social platform "like, forward, comment, recommend, participate in the same label topic" and other behaviors to define the connection between them, forming an edge set.

The evolution of the concept of social media is studied on the basis of the Degroot model[1][2], assuming that in a cluster with individual n members, each node retains its initial own opinion, setting a vector $x(t)$ to represent an individual opinion value, and interacting between different individuals can get the relationship between the edges in the corresponding network, setting the dimension n array W to represent the connection relationship between individuals. Further, there will be differences in opinion values between each $(x_i - x_j)$individual[3][4], and different opinion values will have an opinion effect on neighboring nodes, using this connection as the driving force for the evolution of opinion, thus making the matrix a W weighted matrix with coefficients. For stability reasons[4], the matrix W specification is the row random matrix here.

Which $x(t)$ represents the individual point of opinion, specifically set it to the $[-1,1]$value of the range, then according to the previous description of polar, we can set the three attitudes of 1, -1 and 0 to the three directions of polar[7]In this study, the evolution of the 0 end of the neutral attitude was mainly aimed at.

B. Mathematical Model

The study generalizes the evolution process of public opinion of groups into the following

$$x(t+1) = Ax(t) + Bu(t) \tag{1}$$

where, A matrix is a square matrix of n dimension, which represents its own evolution within the target group, and the B matrix is also the square matrix of n dimension, which represents the input of public opinion outside the target group, that is, the way of controlling the target group $u(t)$.

1) The state classification of the nodes

From the relevant social psychology opinion[11][12], according to people's inherent attitude towards their own tenacity to divide the individual into three groups of people, combined with the above-mentioned evolutionary equation, Matrix A is further defined as $A = HL$ where the matrix Hdescribes the tenacity of the individual's attitude, while the matrix is $L$the Laplace transformation of the Wadjacent $L = (I - W)$matrix.

2) Extremists Model

$$\dot{x} = -(I - diag(x)^2)(I - W)x \tag{2}$$

where the extreme $H = -(I - diag(x)^2)$ is a determined attitude, in the face of the influence of neighbors have a strong resistance, in the social environment is suitable to represents the loyal fan's opinions.

3) Positives Model

$$\dot{x} = -\frac{1}{2}(I - diag(x))(I - W)x \tag{3}$$

where the $H = -\frac{1}{2}(I - diag(x))$ represents positives, is more than the extreme stubbornness of the neutrals group, its positive point of opinion difference is smaller, so the power is also smaller, the change process will be slower, and the negative opinion is the opposite, its opinion difference is larger, the power is greater, will accelerate the rate of change of its point of opinion value.

4) Neutrals Model

$$\dot{x} = -(diag(x)^2)(I - W)x \tag{4}$$

where neutrals kind represent groups that do not have a clear opinion and is prone to large-than-drastic changes in attitudes, which are suitable for describing a class of emotional groups.

IV. EXPERIMENTS AND SIMULATIONS

A. The evolution of the group itself

We report simulation over 2 real-world networks.

The first data set belongs to kenneth Read (1954), a tribal social network of the Gahuku-Gama Union in the eastern highlands of New Guinea, consisting of 16 nodes and 58 edges, with an average clustering coefficient of 0.53, which is generally a small sample and a relatively tight network structure.

The second data set is the browsing statistics for a food page on Facebook, which is a open source form Network Repository. Networks contains 620 nodes and 2100 edges based on appreciation for establishing a connection, with an average clustering coefficient of 0.33, which is generally a medium sample and a relatively sparse network structure.

Since an individual's opinion is very subjective, we cannot quantify it accurately, so the $x(t)$initial value is $[-1,1]$ evenly distributed. Bring three independent evolutionary models into the experiment.

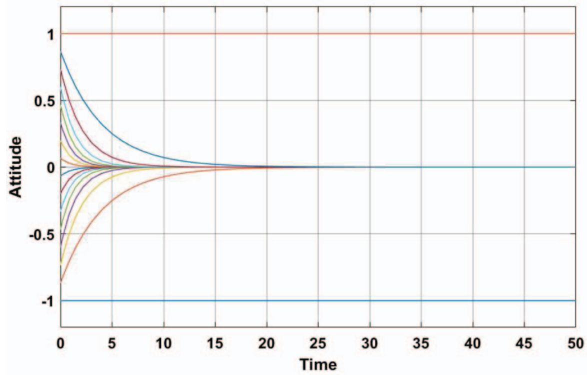

Fig. 1 Tribal evolution of extremists.

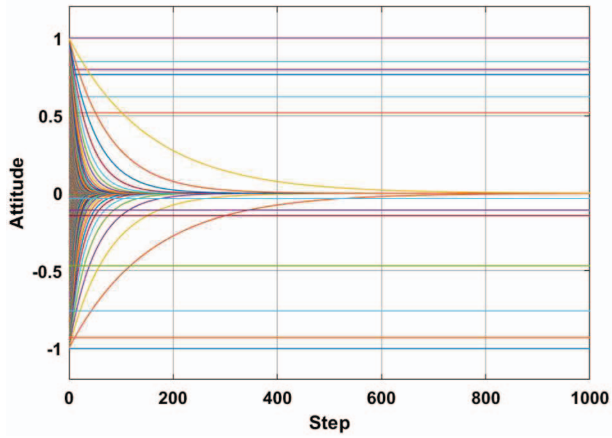

Fig. 2 Facebook evolution of extremists.

The evolution of extremists in both situations is shown in Fig.1and Fig.2.The first is the case of a small sample, from the simulation results of extreme stubbornness, its convergence process is fairly fast, in both positive and negative attitudes are very symmetrical. In particular, the two nodes with initial values set to 1 and -1 at both ends are not affected. and the reason why the opinion values of these two nodes have not changed, is that the model has a strong attitude towards its inherent attitude, and the other nodes have no effective influence on it. The situation of large samples is highly consistent with the trend of convergence with that of small samples, but the disadvantages of a small number of nodes not being affected by other nodes are more exposed.

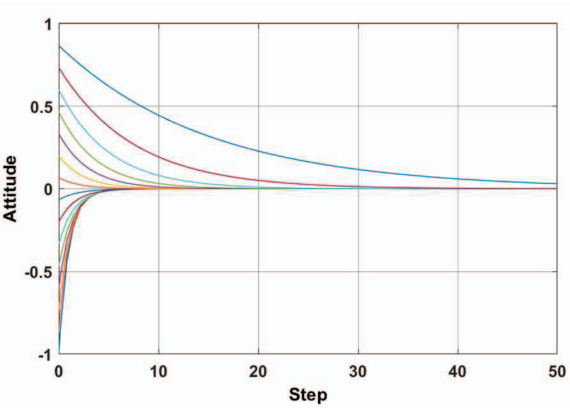

Fig. 3 Tribal evolution of positives.

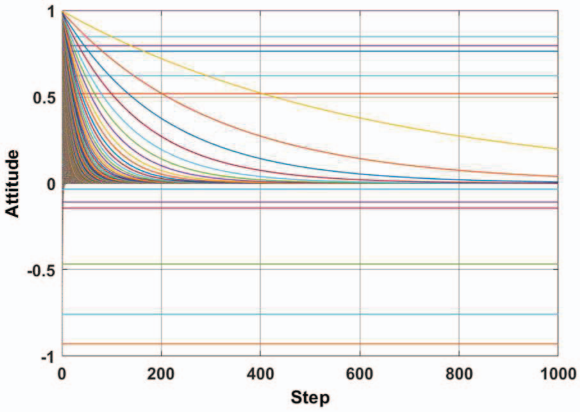

Fig. 4 Facebook evolution of positives.

The evolution of positives in both situations is shown in Fig.3and Fig.4. first is case of a small sample, from the simulation results of the positives model its convergence process is slower, and in both positive and negative attitudes are not symmetrical, positive opinion changes more slowly, while the negative opinion changes quickly, in line with expectations. The situation of large samples is highly consistent with the trend of convergence with that of small samples, but in the case of large samples, some nodes are not affected. These points balance in uncertain way.

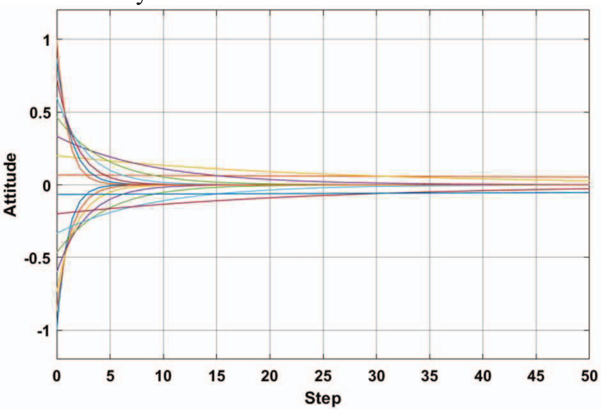

Fig. 5 Tribal evolution of neutrals.

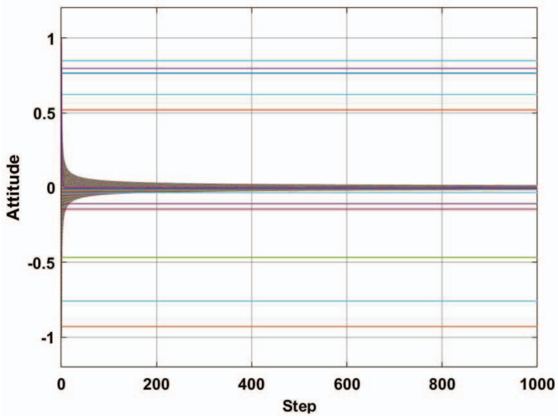

Fig. 6 Facebook evolution of neutrals.

The evolution of neutrals in both situations is shown in Fig.5and Fig.6. The first is the small sample case, from the simulation results of the neutrals, its convergence process is much faster $\dot{x} = -(diag(x)^2)(I - W)x$ than the extreme stubborn attention, and still retains the symmetry in positive and negative, there are no unaffected nodes. In large sample cases, the convergence trend is consistent with that of small samples, but there are still a small number of nodes that are not affected. These points balance in a uncertain way.

B. Add in the study of the evolutionary process after the control input

Inheriting the previous section of the study, we continue to add $Bu(t)$input matrices to observe the evolution of the group's perspective

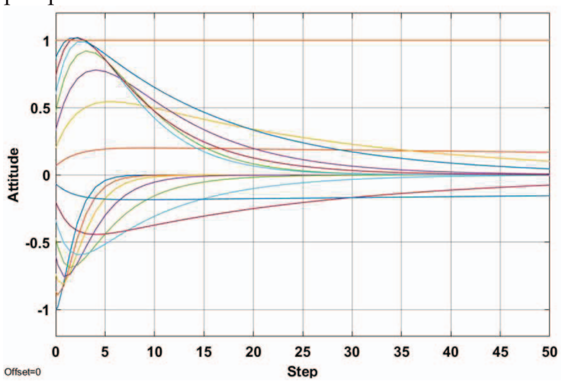

Fig. 7 Tribal evolution of neutrals with positives influnce.

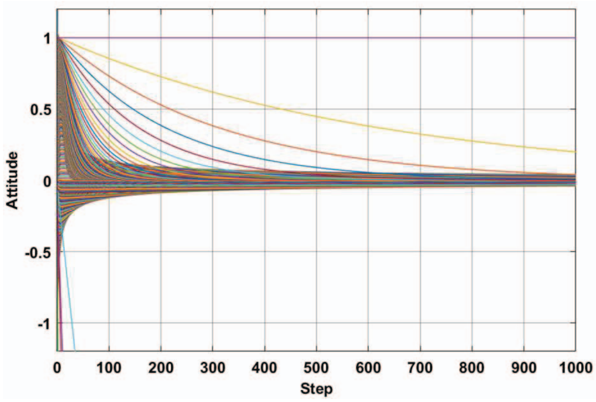

Fig. 8 Facebook evolution of neutrals with positives influnce.

The evolution of neutrals under the influence of positives in both situations is shown in Fig. 4. On the basis of positives, the external input of positives is added, and we can see that compared with the original positives, the new evolution process loses symmetry, the positive opinion changes more slowly and the negative attitude changes faster, while the negative opinion changes faster, and on the whole, slows down the progress of the group consensus. The evolution of large sample is not ideal, there are few curves falling without control, so such way of control doesn't suit large sample when pursue completely control.

For a more intuitive look at the polar of the group, set the error of the polar opinion to ±0.20 and ±0.05 respectively to count the individuals who have completed the polar, setting 100 steps.

The progress with convergence in shown in Fig. 5 and Fig. 6. In the case of a small sample, the first is a relatively loose error of ±0.20 of the case. It can be seen that the three self-convergence of extremism, positives and neutrals all show a relatively fast convergence trend at the beginning, but only the neutrals retain this trend from beginning to end until 16 points converge, while extremism and positives begin to slow down at 15 steps, and ultimately there are still a few individuals who fail to achieve polar. In the influence of neutrals plus centrism, it is clear that convergence has slowed down, and that 10 steps ago there were very few people who had completed polar, indicating that there was also an impact on the individuals who had reached the plan themselves, which was not likely to affect the situation and increased the uncertainty of the network structure.

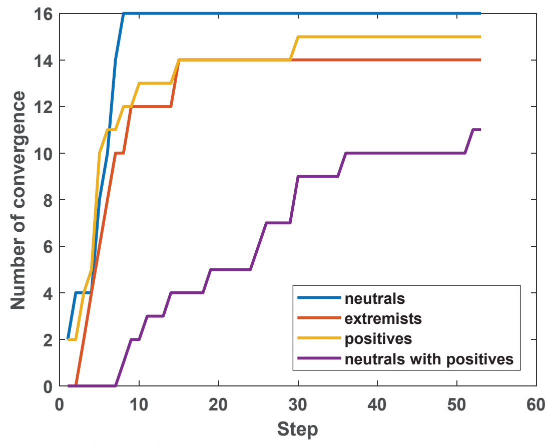

Fig. 9 Tribal convergence summary in 2% error.

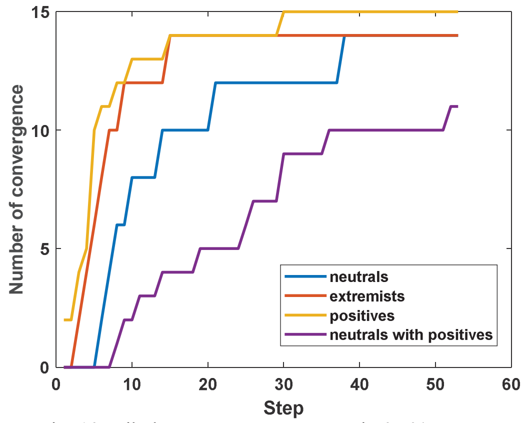

Fig. 10 Tribal convergence summary in 0.5% error.

In contrast to the previous experiment, when the experimental error was strictly reduced to between ±0.05, the evolution of extremism and positives, as well as neutrals under the influence of positives was not greatly affected, while the convergence of neutrals slowed significantly, with the first polar delayed by about 10 steps, and most of the group polar was almost completed by 40steps, about 30 steps later than under loose conditions.

In the case of large sample, convergence trend is consistent with that of small samples, and when the experimental error is strictly reduced to between ±0.05, it still has a great influence on neutrals.

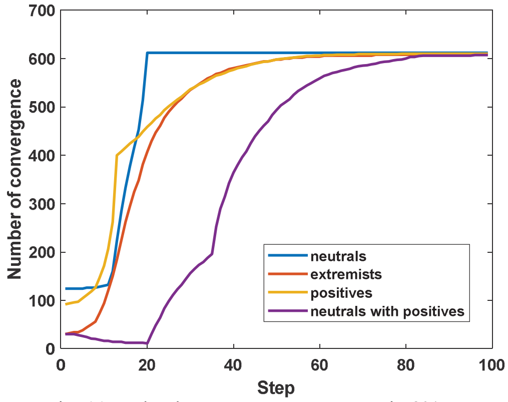

Fig. 11 Fcebook convergence summary in 2% error.

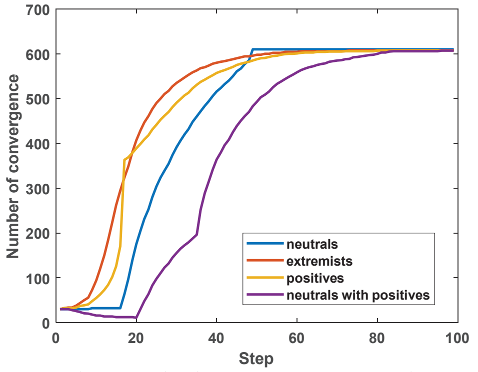

Fig. 12 Fcebook convergence summary in 0.5% error.

By contrast, it can be seen that the neutrals model can converge the fastest under loose conditions, but the requirements can also converge more quickly under strict conditions, and extremism and positives can be preferred. If you need to keep the topic controversial, you can extend the polar process in a way that affects neutrals plus centrism.

V. Conclusion

By classifying the toughness of the user's point of opinion, the experiment simulated the evolution of the general public itself without intervention and the effect of the plus intervention on the polar process. The extreme model is stable, the convergence speed is moderate, the neutral model has a bias towards the positive attitude, the convergence is slightly slower, and the neutrals is not stable, its convergence speed is faster, but not close enough to the planning polar of opinion, in the strict error range convergence situation is not ideal. When neutrals under the influence of positives, its overall convergence speed slows down, but it increases the bias towards positive opinions in the process, and in actual public opinion, similar control methods can be adopted if the topic needs to be fermented for a long time without losing the correct point of opinion guidance.

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