College Students' Service Feedback Based on a Complex Network

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Abstract

The ideas of others always influence people because they are social animals. They will evaluate a movie based on the rating level and change their decision based on someone's advice. It is expected that the comments on the news are reversed suddenly because of a few people, especially in the context of the communication wave set off by the Internet as a new media. It is worth noting that there is a relationship between the deviation of public opinion and the intimacy between people, and confidence and openness also play a role. Recently, there has been renewed interest in dynamic models of research opinions. Our goal is to build a dynamic model of opinion offset based on various influencing factors and then use it to control public opinion more accurately and reduce the loss caused by them. We analyzed existing models and found that few articles considered people's confidence, openness, and intimacy together. Therefore, we designed new models that considered all the influencing factors. We tested the model with actual data and achieved high accuracy. Finally, we found that opinions would eventually converge to a peak value, and the time needed for convergence was affected by intimacy, openness, and confidence.

Keywords: Public opinion influence, Opinion deviation, Complex network, The level of openness, The level of confidence

1 Introduction

1.1 Prior Work

Public opinion is a general opinion or attitude expressed publicly on a particular topic and expresses the public's views. It is widely spread with obvious subjective tendencies and is invisible but plays a vital role in our lives. Taking the judgment of criminal cases as an example, "Do you and I, and our neighbors and friends, collectively decide that lawbreakers should suffer more when crime increases?" Justin T. Pickett asked when he researched the relationship between public opinion and criminal justice policy. He gives evidence for the effects of public opinion on court decision-making, capital punishment policy and use, correctional expenditures, and incarceration rates [1].

Moreover, public opinion is often a proximate cause of policy, affecting policy more than policy influences opinion [2]. The impact of opinion remains strong even when the activities of political organizations and elites are taken into account [3]. Public opinion is powerful because human beings' instinct as social animals drives them subjectively to the opinions of others. When public opinion becomes the sword of malicious people and lies become the gimmick of sensationalists for profit, it is our urgent responsibility to end this phenomenon from the root. In addition to punishing rumormongers, we also need to understand the causes of this phenomenon.

In theoretical research, Auletta et al. showed that the minority could influence the majority's deviation from the optimal decision [4]. Based on their study, Vincenzo Auletta et al. formally defined Discrete Preference Games in 2017. Then researchers found an important factor driving public opinion—the degree of relationship intimacy—and people began to establish an opinion deviation model dominated by relationship intimacy. Bhawalkar et al. proposed a general coevolutionary idea of game formation with dynamic social relations, but the construction of this model had not made progress at that time [5]. Based on this, Auletta et al. studied the coevolution process of opinion formation and the cross-influence of social relations. A polynomial time algorithm calculates the set of all pure Nash equilibria and all optimal social equilibria for a given game. It was published in the Opinion Formation Games with Dynamic Social Influences in 2017 [6]. And Fei Xiong proposes a dynamic opinion model by the evolutionary game theory, which can improve the recommendation [7].

For model building, in 2008, Feng Fu et al. investigated the coevolutionary dynamics of opinions and networks. They found that one system goes from a diverse world where a wide variety of ideas are present to a uniform one where everyone shares the same view [8]. Then A. Sattari et al. constructed a non-consensus opinion model. They found that the nodes holding the same opinion demonstrate a phase transition from small clusters to large spanning sets when the concentration of that opinion increases [9]. In 2011, Daron Acemoglu et al. defined asymptotic learning and compared Bayesian models with non-Bayesian models. Then, they found that both models lead to consensus and are unlikely to lead to asymptotic understanding [10]. Then, Anahita Mirtabatabaei et al. explained the convergence of the model: all trajectories of the bounded confidence and influence models eventually converge to a steady state under fixed topology [11]. Soon, people began to notice the role of stubborn agents who never updated their opinions [12]. In 2014, Javad Ghaderi and R. Srikant studied the equilibrium and convergence rates in social networks with persistent agents [13]. After that, agents are classified into three categories: open-minded, moderate-minded, and closed-minded, while the whole population is

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DOI: 10.53106/160792642022112306012

divided into three subgroups accordingly [14]. Then, P. F. Lazarsfeld et al. defined an opinion leader: opinion leaders are an essential source of information and influence in a team. They can influence the attitude of the majority [15]. Opinion leaders may produce or accelerate people's behavior changes [16]. Based on that, people built some leader-follower opinion dynamics models to simulate well. For example, Yiyi Zhao et al. used their model to demonstrate collective opinion evolution in three cases: no opinion leader, single opinion leader, and multiple opinion leaders [17]. Researchers also pay attention to instances where agents' opinions on two or more interdependent topics are influenced [18].

Weiguo Xia et al. proposed an asynchronous discrete-time opinion dynamics model on a social influence network. At each instant, a single individual updates her expressed and private opinions. Assuming all individuals activate at least once within a finite period and the influence network is rooted, we established convergence to consensus when no individual was attached to her prejudice [19]. Nan Zhao et al. built a novel evolutionary game model to describe the evolution of behavior and perspective more accurately. They improve the traditional dynamic link weight model from this perspective to increase adaptability. In addition, we introduce the information infiltration mechanism and the individual behavior and view the coupling mechanism in the model. Under the effect of these two mechanisms, the proportion of cooperative behavior strategies in social groups increases significantly, and the emergence of collective behavior is extensively promoted [20]. Zhan Bu et al. proposed a novel and powerful graph K-means framework composed of three coupled phases in each discrete-time period. Specifically, the first phase uses a fast heuristic approach to identify those opinion leaders with a relatively high local reputation. The second phase adopts a novel dynamic game model to find the locally Pareto-optimal community structure. The final stage employs a robust opinion dynamics model to simulate the evolution of the opinion matrix [21]. Barrat proposes a recommendation method with indirect interactions that adequately uses the users' relationships on social networks and rating data based on the local influence between users and global power over the whole network [22]. In 2021, Tinggui Chen et al. found that environmental forces have a more significant impact on the number of subtopics, and the amount of information in subtopics determines whether the subtopic can be the critical factor forming the derived public opinion [23].

The dynamic opinion model based on a complex network has application value in many fields. Jorge Castro et al. developed GRS Group Recommender Systems based on opinion dynamics. Compared with other systems, their work would have a flexible aggregation method, member relationships, and agreed-upon recommendations [24]. We can also use it in other fields. For example, Quanbo Zha et al. have submitted a paper that reviews opinion dynamics in finance and business [25].

In 2014, in Modeling Opinion Dynamics in Social Networks, Abhimanyu Das et al. proposed the Modeling problem of how users update their opinions based on the views of their neighbors [26]. This model not only takes into account the stubborn behavior of experimenters but also captures the user's tendency of conformity, inputs the two as parameters into the theoretical model constructed, and verifies that the model is consistent with the facts under reasonable assumptions through analysis and simulation. Opinion formation has a conformity bias; agents give more weight to opinions that conform to their ideas. Combining some aspects of the Flocking and the deGroot Models, they study the subjects' response not only as a function of the size of the neighborhood, and the facts used by them are not easily identifiable types, and the point of view is also not dualistic. In that paper, the researchers presented adjacent opinions in a structured way, but the authors did not prove whether this harms opinion formation.

In the same year, Abir De et al. presented a different Model and estimation algorithm in the paper "Learning a Linear Influence Model from Transient Opinion Dynamics" [27]. It was the first attempt to learn linear opinion propagation dynamics from observed individual subject opinion values without attracting steady-state behavior. Compared with well-known baselines, such as the voter model, biased voter model, forced model, and DeGroot's linear model, the model presented here produces significantly more minor prediction errors by 2-15 times. The model focuses on the estimation error of a single influence edge rather than aggregate behavior such as a bifurcation. It is also the first attempt at learning linear opinion propagation dynamics from observed opinion values of the individual agents without appealing to steady-state behavior. At the same time, Fei Xiong proposes an opinion model with the topic impact in which personal opinions and topic features are characterized by a multidimensional vector. There are many classical models for complex networks. Most real complex networks have small-world effects: smaller average path lengths and more significant agglomeration coefficients. So Watts and Strogatz proposed a small world network model, then Newman and Watts proposed the NW model to improve it [28]. But most real complex network degree distribution obeys power law distribution. Based on this, Barabas and Albert proposed a scale-free network model. There are also LC models suitable for the more general case, and the BBV model considers the influence of topology and weights in the dynamic evolution of the network.

1.2 Our Work

Although many high-precision models have been established for this problem, many models consider a single factor. After a detailed analysis and calculation of the existing model, we proposed an innovative model in which we consider various factors, such as people's confidence, openness, and intimacy. Then, we designed a questionnaire to collect a large amount of actual data from students in school, tested the model, optimized the model constantly, and finally achieved good results. We propose to exploit complex networks to solve the problems. The source of the complex network can be traced back to the "Seven Bridge problem" raised by the mathematician Euler in the 18th century. Later, with the rapid development of complex systems, it was applied to various fields.

2 Problem Formulation

2.1 Subsection

Our model takes into account the influence of people's preexisting opinions. At the same time, in disseminating ideas, people tend to adopt views similar to their own or prefer the opinions of people they trust. Therefore, the model also takes this phenomenon into account during opinion propagation.

Since the spread of opinions in real life does not only depend on influence, we divide honest opinions $\boldsymbol{z}$ into original opinions $\boldsymbol{h}$, which refer to people's judgment based on their situation and understanding, and realistic opinions $\boldsymbol{c}$, which refer to the value of ideas people get after the spread of views. For example, in an event or field that people do not know much about, realistic views tend to take up more weight, and people will be more receptive to listening to the opinions around them; however, for events that they are familiar with, original thoughts tend to take up more weight. Therefore, we assume that each person's "level of confidence" is $\boldsymbol{\mu}$, so the honest opinions are equal to the weighted sum of the two.

$$z = \mu h + (1 - \mu)c. \tag{1}$$

To describe the more significant influence of similar opinions, we use the set of identical opinion holders in the HK model; there is its corresponding threshold of similar opinions $\boldsymbol{\varepsilon}$ for each person, the absolute value of the difference between other people's opinions and their own opinions is less than the threshold, and then the two are said to be similar. People who hold the same opinions have a more significant influence on each other. The set of identical opinion holders is.

$$S_i(\vec{z}) = \{j \mid \ |z_i - z_j| \le \varepsilon\}. \tag{2}$$

We obtain realistic opinions from disseminating honest views in the previous round.

$$c_i^{t+1} = \begin{cases} \frac{w_{ij}}{\Sigma w_{ij}} z_i^t, \ \frac{|S_i|}{n} < \sigma_i \\ \frac{\Sigma z_j^t}{|S_j|}, \ \frac{|S_i|}{n} < \sigma_i, j \in S_i \end{cases}, \tag{3}$$

where $\boldsymbol{\sigma_i}$ represents the level of openness of individual $\boldsymbol{i}$, i.e., the degree of acceptance of various opinions. When there are more similar opinions, realistic ideas are obtained from the average of similar views because there are more opinions identical to one's own. So one is more likely to adopt similar statements rather than easily change one's opinion. When there are fewer similar opinions, they do not still stubbornly adopt similar opinions but vary their views based on the influence matrix.

It can be seen that the greater the degree of openness, the easier it is to accept the public's thoughts. The previous degree of confidence is more similar to the degree of acceptance. Still, the degree of faith is more descriptive of each person's belief in their judgment and, to some extent, includes the degree of approval but also the estimation of opinions based on one's position, so there are still differences between the two.

The original opinions describe the values of the views based on the original judgment. When a round of opinion propagation is over, the honest thoughts of that round will strengthen or weaken its decision, so the fundamental ideas of the previous round will impact the original view of the next round.

$$h_i^{t+1} = \mu h_i^t + (1 - \mu) c_i^{t+1}. \tag{4}$$

The consensus of the group will also have an impact on the person's opinion. In most cases, views will be closer to the plurality of the views of their group. That is,

$$c = qM_z + (1 - q)c, \tag{5}$$

where q represents the acceptance of the consensus and is the plurality of opinions.

By observing the actual situation, we will also find that the opinions of individuals tend to converge on the views of people who are close to them and have significant influence. That is, ideas are more influenced by a few people who are close to them than others, i.e.

$$c = p \sum\nolimits_{i, a_i \ in\ top\ k} a'_i z_i + (1 - p) \sum\nolimits_{i, a_i \ not\ in\ top\ k} a''_i z_i, \tag{6}$$

where $\boldsymbol{a'}$ and $\boldsymbol{a''}$ represent the normalized coefficients of the influence of close and distant relationships, respectively, and $\boldsymbol{p}$ represents the degree of acceptance of the opinions of intimate relationships. A degree of acceptance of 1 indicates that one listens very much to the views of friends and relatives and hardly trusts other people's thoughts.

We divided the respondents into three categories:

(1) Firm: A determined person does not quickly revise his opinion, so his value of $\boldsymbol{\sigma}$ will be lower. For some stubborn people, their value of $\boldsymbol{\sigma}$ equals 0. At this point, they will not accept the public's general opinion but will only modify their views based on similar arguments. Therefore, even if perspectives converge, it is still possible for their ideas to change to an intermediate state, but it will take longer. For highly stubborn people, the value of $\boldsymbol{\sigma}$ is not only the smallest, equal to 0, but for the most confident ones, the value of $\boldsymbol{\mu}$ equals 1. Their original opinions will not be affected by the surrounding thoughts, and the final valid ideas will be the same as the actual opinions.

(2) Intermediate: Intermediate people's levels of openness and confidence are between 0 and 1, allowing them to be influenced by their opinions while also retaining their original thoughts to a certain extent.

(3) Open-minded: These people are very open, approximately 1, meaning they tend to take a public opinion. Or the confidence level is low, and they can promptly correct their original judgments. When the level of openness is 1, it means that they always accept the opinions of the public; when the level of confidence is 0, it means that they will not stick to their original judgments but always depend on the views of the outside world.

Regarding the level of confidence, we believe that the level of trust will differ for different events, depending on whether they understand the matter and whether they have a deep understanding. The story of openness is more inclined to the personality of the person itself, so the degree of transparency of each person can be regarded as a fixed value.

2.2 Data Comparison

2.2.1 Data Source

We interviewed 478 students in a college and distributed four rounds of questionnaires to investigate the students' views on in-depth counseling work. In each game of questionnaires, we asked students to write their opinions on in-depth counseling. The difference is that in the first round, we calculated the intimacy of each student with classmates, roommates, and friends. And the preliminary views of the students on in-depth counseling by counselors were also obtained. In the third and fourth rounds, one can also see the distribution of opinions of students with a high degree of intimacy with themselves.

We have established a questionnaire system and used it to collect data. Figure 1 shows the intimacy network we launched based on the data collected from the questionnaire using the relational database neo4j.

Figure 1. The network of opinions

Ultimately, we collected 1292 valid questionnaires, and Figure 2 shows the proportion of the initial dissenting opinion values of 1st question. The 'null' is unsubmitted opinions. And the 1~4 are combined displays because the share is minor.

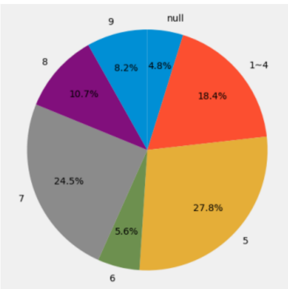

Figure 2. The first round of questionnaires

2.2.2 Real Data Processing

We obtained an opinion influence matrix composed of all participants by the results of the questionnaires, as well as the opinion values for each round of the questionnaire. However, there are some invalid values, which were set to zero.

The number of people who know each respondent and their influences, which somehow measures whether he is more open, can be used as a basis for the value of $\boldsymbol{\sigma}$. The value of $\boldsymbol{\mu}$, on the other hand, is calculated by the number of people who know the respondent and his influence on them.

Since the influence values in the questionnaire were taken from 1 to 10, excluding those who did not fill out the questionnaire in the first round, we normalized the influence by taking the e index and dividing it by the rest of the sum. Finally, we obtained an influence matrix with a sum of 1 in each row.

Finally, our Complex network dynamic model is substituted to predict future opinion change and compared with the objective opinion situation.

3 Problem Solution

3.1 Simulation Results

We simulate the initial value of different opinions and generate the initial idea through a Gaussian distribution. The final situation will converge around that peak when there is only one opinion peak. When there are more opinion peaks, the last case converges to the mean value of the initial opinion. Additionally, the value of converging views is strongly influenced by the views held by the firm. We assume that the level of openness and confidence are both 1:8:1. The final evolution is shown in Figure 3.

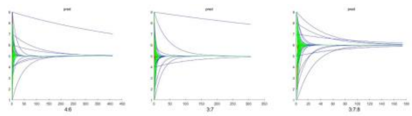

Figure 3. Results of different initial distributions

We also examine the effect of the ratio of assertiveness in the population, assuming here that the level of openness remains 1:8:1. The result is shown in Figure 4 and Figure 5. In all cases, the red line (less assertive) is mainly in the innermost part, the green line (moderately strong) is in the middle, and the blue line (more emphatic) is in the outermost position. The time required for convergence tends to be shorter as the proportion of less confident individuals increases. The larger the percentage of those with higher confidence, the longer it takes for the opinions to converge. At the same time, when the proportion of less faith is 0, the opinion evolution differs from other evolutionary situations, probably because less confident people can change their opinions faster during the opinion evolution process so that the overall opinion trend can be smoother. In contrast, when the percentage of those with a higher confidence level is 0, the general opinion evolution trend is rapidly approaching the middle peak, and the time required is much shorter.

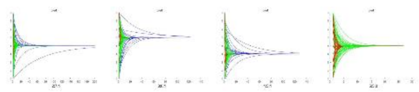

Figure 4. Results when the percent of people with lower confidence is larger

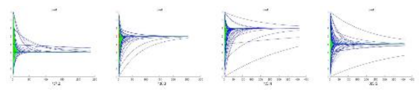

Figure 5. Results when the percent of people with higher confidence is larger

3.2 Trend Comparison

The genuine opinions, most of which vary from 5 to 10, can be seen from the Figure 6 that the trend prediction of opinion evolution is correct, with a prediction accuracy rate of approximately 72.52% and an average opinion prediction deviation of roughly 0.2. However, the predicted values are slightly more concentrated because the number of questionnaire rounds is small. The opinion evolution pattern shown is not very obvious yet but still conforms to the basic design.

The level of openness and confidence selected for the prediction are based on the influence matrix and may not be comprehensive, so we can see that in the actual case, more people keep their opinion at ten than predicted, which indicates a high level of confidence in the question.

3.3 Robustness Discussion

For the other questions, do they also conform to the above pattern? We substituted the other questions in the questionnaire into the model to make predictions and ended up with an accuracy rate of 89.28% (for the second question), with an average prediction error of approximately 0.1 per round; the third question ended up with an accuracy rate of 89.98%, also with an average prediction error of roughly 0.1 per round. Figure 7 shows the change in opinion for the third round of questions. The primary trend is consistent.

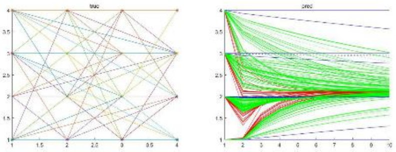

Figure 6. True opinions and pred opinions of 1st question

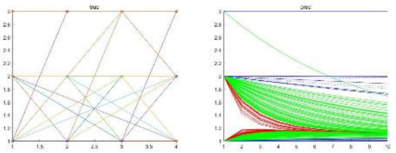

Figure 7. True opinions and pred opinions of 3rd question

In the 2nd question, the actual data is mostly 2 and 3, and the predicted value is the same. A few opinion values are close to 1 and 4, and most of the opinions will be between 2~3. For the 3rd question, similarly, the four rounds of actual data are mostly 1~2, and the model's predicted value will also be concentrated between 1~2. The model was able to predict the evolution of opinions accurately. From the predicted graphs, we can also see how the future opinion evolution will be. Both questions will gradually approach the median value and will be slightly lower than it.

It can be found that the accuracy of the prediction is higher than the first question because the first question's opinion value is from 1~10, but the last two questions' opinion value range is smaller than the first one; it is 1~4 and 1~3, so the opinion value will become more refined, and the error will be minor.

4 Conclusion

In this paper, we first introduce the definition and application background of the opinion dynamic model and then summarizes the development of the dynamic opinion model. Next, we comprehensively considered the influence of people's confidence, openness, and intimacy on opinion shift and constructed a Complex network dynamic model, which achieved good results in simulation. Next, we collected objective data, used the model to make predictions, and obtained a high accuracy rate. We found that opinions would eventually converge to a peak value, and the intimacy, openness, and confidence influence the time for convergence. Our model can be used to control public opinion to reduce the influence of a wrong general idea, such as rumors and slanders, on people. The prediction of accurate data shows that our model still has some biases. And our proposed model may not be applicable to large data samples. So next, we will further improve the prediction accuracy and robustness of our model.

References

[1] J. T. Pickett, Public Opinion and Criminal Justice Policy: Theory and Research, *Annual Review of Criminology*, Vol. 2, No. 1, pp. 405-428, January, 2019.

[2] P. Burstein, The impact of public opinion on public policy: A review and an agenda, *Political Research Quarterly*, Vol. 56, No. 1, pp. 29-40, March, 2003.

[3] F. Xiong, X. Wang, S. Pan, H. Yang, H. Wang, C. Zhang, Social recommendation with evolutionary opinion dynamics, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Vol. 50, No. 10, pp. 3804-3816, October, 2020.

[4] V. Auletta, I. Caragiannis, D. Ferraioli, C. Galdi, G. Persiano, Minority Becomes Majority in Social Networks, *International Conference on Web and Internet Economics*, Amsterdam, The Netherlands, 2015, pp. 74-88.

[5] K. Bhawalkar, S. Gollapudi, K. Munagala, Coevolutionary opinion formation games, *Proceedings of the forty-fifth annual ACM symposium on Theory of computing*, Palo Alto, California, USA, 2013, pp. 41-50.

[6] V. Auletta, I. Caragiannis, D. Ferraioli, C. Galdi, G. Persiano, Robustness in Discrete Preference Games, *International Conference on Autonomous Agents and Multiagent Systems*, Sao Paulo, Brazil, 2017,1314-1322.

[7] F. Xiong, Y. Liu, L. Wang, X. Wang, Analysis and application of opinion model with multiple topic interactions, *Chaos*, Vol. 27, No. 8, Article No. 083113, August, 2017.

[8] F. Fu, L. Wang, Coevolutionary dynamics of opinions and networks: From diversity to uniformity, *PHYSICAL REVIEW E*, Vol. 78, No. 1, July, 2008.

[9] A. Sattari, M. Paczuski, P. Grassberger, Comment on "Dynamic Opinion Model and Invasion Percolation", *Physical Review Letters*, Vol. 109, No. 7, Article No. 079801, August, 2012.

[10] D. Acemoglu, A.E. Ozdaglar, Opinion Dynamics and Learning in Social Networks, *Dynamic Games and Applications*, Vol. 1, No. 1, pp. 3-49, March, 2011.

[11] A. Mirtabatabaei, F. Bullo, Opinion Dynamics in Heterogeneous Networks: Convergence Conjectures and Theorems, *SIAM Journal on Control and Optimization*, Vol. 50, No. 5, pp. 2763-2785, September, 2012.

[12] D. Acemoglu, G. Como, F. Fagnani, A. Ozdaglar, Opinion Fluctuations and Disagreement in Social Networks, *Mathematics of Operations Research*, Vol. 38, No. 1, pp. 1-27, February, 2013.

[13] J. Ghaderi, R. Srikant, Opinion dynamics in social networks with stubborn agents: Equilibrium and

convergence rate, Automatica, Vol. 50, No. 12, pp. 3209-3215, December, 2014.
[14] G. Fu, W. Zhang, Z. Li, Opinion dynamics of modified Hegselmann-Krause model in a group-based population with heterogeneous bounded confidence, *Physica A-Statistical Mechanics and its Applications*, Vol. 419, pp. 558-565, February, 2015.
[15] H. L. Gosnell, Book Reviews. Paul F. Lazarsfeld, B. Berelson, and H. Gaudet, The people's choice: how the voter makes up his mind in a presidential campaign, *American Journal of Sociology*, Vol. 51, No. 6, pp. 574-575, May, 1946.
[16] S. E. Parsegov, A. V. Proskurnikov, R. Tempo, N. E. Friedkin, Novel Multidimensional Models of Opinion Dynamics in Social Networks, *IEEE Transactions on Automatic Control*, Vol. 62, No. 5, pp. 2270-2285, May, 2017.
[17] Y. Zhao, L. Zhang, M. Tang, G. Kou, Bounded confidence opinion dynamics with opinion leaders and environmental noises, *Computers & Operations Research*, Vol. 74, pp. 205-213, October, 2016.
[18] S. Qin, G. Z. Dai, A new local-world evolving network model, *Chinese Physics B*, Vol. 18, No. 2, pp. 383-390, February, 2009.
[19] W. Xia, H. Liang, M. Ye, Expressed and Private Opinion Dynamics on Influence Networks with Asynchronous Updating, *2020 59th IEEE Conference on Decision and Control (CDC)*, Jeju Island, Korea, 2020, pp. 3687-3692.
[20] N. Zhao, S. Miao, Y. Zhang, A Novel Co-Evolution Model Based on Evolutionary Game about Social Network, *Symmetry*, Vol. 14, No. 3, Article No. 581, March, 2022.
[21] Z. Bu, H. J. Li, C. C. Zhang, J. Cao, A. H. Li, Y. Shi, Graph K-means based on Leader Identification, Dynamic Game, and Opinion Dynamics, *IEEE Transactions on Knowledge and Data Engineering*, Vol. 32, No. 7, pp. 1348-1361, July, 2020.
[22] A. Barrat, M. Barthélemy, A. Vespignani, Weighted evolving networks: Coupling topology and weight dynamics, *Physical Review Letters*, Vol. 92, No. 22, Article No. 228701, June, 2004.
[23] T. Chen, X. Yin, J. Yang, G. Cong, G. Li, Modeling Multi-Dimensional Public Opinion Process Based on Complex Network Dynamics Model in the Context of Derived Topics, *Axioms*, Vol. 10, No. 4, Article No. 270, December, 2021.
[24] J. Castro, J. Lu, G. Zhang, Y. Dong, L. Martinez, Opinion Dynamics-Based Group Recommender Systems, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Vol. 48, No. 12, pp. 2394-2406, December, 2018.
[25] Q. Zha, G. Kou, H. Zhang, H. Liang, X. Chen, C. Li, Y. Dong, Opinion dynamics in finance and business: a literature review and research opportunities, *Financial Innovation*, Vol. 6, No. 1, Article No. 44, January, 2021.
[26] A. Das, S. Gollapudi, K. Munagala, Modeling Opinion Dynamics in Social Networks, *WSDM'14: Proceedings of the 7th ACM International Conference on Web Search and Data Mining*, New York, USA, 2014, pp. 403-412.
[27] A. De, S. Bhattacharya, P. Bhattacharya, N. Ganguly, S. Chakrabarti, Learning a Linear Influence Model from Transient Opinion Dynamics, *Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management*, Shanghai, China, 2014, pp. 401-410.
[28] M. E. J. Newman, D. J. Watts, Renormalization group analysis of the small-world network model, *Physics Letters* A, Vol. 263, No. 4-6, pp. 341-346, December, 1999.

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