Phase Transition in Group Emotion

Xuelong Yu, Fuzhong Nian, Yabing Yao, and Li Luo

***Abstract*— This article explores the formation and change of group emotion. The phase of group emotion is defined, and the phase transition of group emotion is studied from the following two aspects: the group with and without network structure (the group with coevolution between emotion and network structure). For the group without network structure, the threshold of group emotional phase transition is obtained, and the phenomenon of group emotional polarization is verified. For the group with co-evolution of emotion and network structure, node attractiveness is defined from three aspects: node emotional propensity, node aggregation degree, and node importance. The new network evolution model based on "node attractiveness" is constructed, and the degree distribution of the network is analyzed. The processes and conditions of phase transition in group emotion are obtained based on this evolutionary network analysis. The results show that there are three phases of group emotion: disorder phase, neutral phase, and extreme phase.**

***Index Terms*— Coevolution, group emotion, node attraction, phase transition.**

I. Introduction

A. Background and Research Status

INFORMATION dissemination promotes not only changes in social network structure, social cognition, and individual behavior but also the occurrence of group phenomenon (the phenomenon that individuals in a group show similar characteristics), such as demonstrations and crowdsourcing [1]. These group phenomena have become research hotspots in the fields of social science and complex science. In the group, since the individual is vulnerable to the influence of group trust and other factors [2]–[6], the individuals' emotions and thoughts tend to be consistent, and the individual's conscious personality gradually disappears; thus, the group emotion and psychology will be formed. In this case, group emotion is prone to emotional polarization, and unexpected group phenomenon often emerges. Group emotion has become an essential factor in describing the cause of group phenomenon. Many phenomena indicate that groups tend to accomplish an incredible thing [7], [8]. Nowadays, the group phenomenon has become the research focus of sociology, psychology, network science, and other sciences. The group behavior, the group emotion, and the group consciousness (the common psychological characteristic of group members) are increasingly and widely discovered and studied [9]–[13]. What cause these phenomena are many reasons, such as cultural factors, political factors, and economic factors. Smolla *et al.* [14] studied the structure that culture can shape social networks. Krtner *et al.* [15] have shown that culture influences individual behavior. Moreover, culture promotes the formation of social beliefs and social consensus [16]. Jurgens and Kirchhoff [17] discussed the constituent basis of group cognition. Shareef *et al.* [4] discussed the main factors of forming group trust in social media. Chen *et al.* [18] studied the comparison of different group's perceptions of social value. In [19] and [20], the evolution of social group behavior established the mathematical model. The emotional transmission significantly promotes not only individual behavior changes but also group phenomenon and group behavior changes [21]–[24]. Furthermore, it is demonstrated that individual emotion is influenced by group emotion [25], [26]. Due to emotional varieties, there are differences among the formed groups. For example, there are obvious differences between male and female groups from the perspective of emotional and cognitive ability [27]. The above literature shows that group consciousness and group emotion have a profound impact on group behavior, group phenomenon, and the development of social network structure. For group emotion, emotional resonance and emotional dissemination between individuals are important factors in group emotion, i.e., there is an attraction based on emotional resonance among individuals, and some emotional information is spread among groups. As for the emotional dissemination, people have studied the emotional dissemination based on the infectious disease model. Hill *et al.* [28] proved that extreme emotions have a long-term propagation phenomenon in social networks and gave the propagation threshold of specific emotions or behaviors based on the improved susceptible, infectious, and susceptible (SIS) model [29]–[31]. Moreover, a more accurate social opinion formation model can be obtained by combining emotional behavior with opinion interaction rules [32], [33]. Concerning gravity, people have studied the gravity phenomenon [34]–[39] based on the distance scale in scenarios, such as information flow, social communication, and scientific research cooperation, which reveals the universal law of gravity in society.

B. Motivations

In the above literature, the phenomenon of gravitation based on an individual scale and emotional resonance among individuals, as well as the phase change of group emotion under this phenomenon, has not been studied. The phase transition refers to the transition between different macroscopic states of a system. The phenomenon of phase transition exists not

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only in various physical systems [40]–[44] but also in the process of information transmission [45]. In society, information and emotion spread in the network altogether [46]–[48]. However, most of the emotion dissemination models are either precise susceptible and infectious (SI) models or improved SI models [29]–[33]. In the study of Hill *et al.* [28], the macro change of group emotion was not considered. Although the SIS model is used to reflect the multiple transmission of emotion, it does not only take account of the direct transmission but also indirect transmission between people who know the information. Sooknan and Comissiong [49] summarized the commonly used social communication models. The susceptible, infectious, and recovered (SIR) model is mentioned more in this study [29]–[31]. This article focuses more on the changes of group emotions with the spread of events. Therefore, the SI model is improved, and the research is conducted on this basis. As the group's emotion will be affected by information dissemination and emotional resonance, this article combines individual emotional resonance with the process of information dissemination to study the phenomenon of the group emotional transformation.

C. Our Work and Contributions

The main contributions of this article are as follows: 1) the model of emotional propagation and the model of the individual emotional transformation are established; 2) the phase of group emotion is defined; and 3) two kinds of groups are constructed: the group without the network structure and the group with coevolution between emotion and network structure. For the group without network structure, the group emotion transition threshold is obtained, and the phenomenon of group emotion polarization is verified. For the group with coevolution between emotion and network structure, the node attractiveness is defined, and a new network evolution model based on node attractiveness is constructed. The phase transition process and condition of group emotion are obtained based on the evolution of network analysis.

II. Model Building

In real society, the individual will produce different emotional tendencies to the acquired information according to the accumulated experience [46]–[48]. When people act together for a specific purpose, they will form a "psychological group" with attraction, such as parades, multi-person parties, and individual speech conferences. As the group is growing, they will exhibit new psychological characteristics, and the behavior of individuals will be different from when they are alone. That is, the group makes individuals to lose the ability of self-determination [2]–[6]. When the group has an apparent emotional tendency to a certain event, the individual is gradually affected by the group to take the group's judgment as their own.

A. Emotional Communication Model

To study the phenomenon of group extreme emotion (an obvious positive or negative emotion) and group emotional transition, we improve the classical SI model [29]–[31] to get a new communication model. The model diagram is shown in Fig. 1.

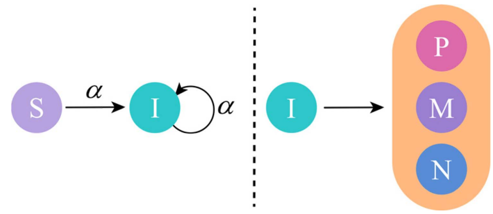


Fig. 1. Schematic of node state transition.

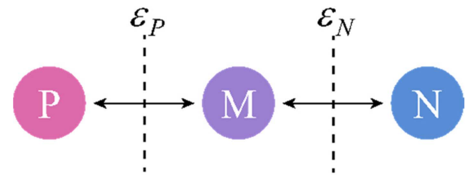


Fig. 2. Schematic of individual emotional state transition.

State S means that the node does not know any events, and state I means that the node knows events and propagates them. State I contains three different emotional states. State P, M, and N indicate the positive emotions, neutral emotions, and negative emotions, respectively.

Fig. 1 shows that individuals who know information propagate information to those who do not know information; that is, nodes in state I propagate information and emotional tendency to nodes in state S with probability α. People who know the information will discuss the formation of information, i.e., the node in state I spreads the information and its emotional tendency to the node in state I with probability α.

The equation for the dynamics of event propagation is shown in the following:

$$\begin{aligned}\frac{ds(t)}{dt} &= -\alpha s(t)i(t)\\ \frac{di(t)}{dt} &= \alpha s(t)i(t).\end{aligned} \tag{1}$$

In (1), the first equation indicates that the node density with state S decreases at rate α (the probability of information dissemination). The second equation indicates that the node density with state I increases at rate α.

Due to the process of information dissemination, people are always influenced by others' feelings or ideas [2]–[6]. Therefore, when an individual's emotional value meets condition $O_i(t) > \varepsilon_P$, the individual's state is P; when an individual's emotional value meets condition $O_i(t) < \varepsilon_N$, the state is N; and when an individual's emotional value meets condition $\varepsilon_N \le O_i(t) \le \varepsilon_P$, the state is M.

B. Model of Individual Emotional State Transition

The model is shown in Fig. 2. Fig.2 shows that the emotional tendency changes since people who discuss with each other are influenced by others.

We assume that individuals with extreme emotions are not susceptible to others. In Fig. 2, the dynamic equation of the individual emotional state transition model is obtained as follows:

$$\begin{cases} \dfrac{dP(t)}{dt} = -(\alpha\phi)^{\frac{1}{P(t)}\sum_{j=0}^{P(t)}\frac{O_j^P(t)-\varepsilon_P}{\varepsilon}}(M(t)+N(t)) \\ \quad + \alpha^{\frac{1}{M(t)}\sum_{j=0}^{M(t)}\frac{O_j^M(t)-\varepsilon_P}{\varepsilon}}M(t) \\ \dfrac{dM(t)}{dt} = (\alpha\phi)^{\frac{1}{P(t)}\sum_{j=0}^{P(t)}\frac{O_j^P(t)-\varepsilon_P}{\varepsilon}}(M(t)+N(t)) \\ \quad - \alpha^{\frac{1}{M(t)}\sum_{j=0}^{M(t)}\frac{O_j^M(t)-\varepsilon_P}{\varepsilon}}M(t) \\ \quad + (\alpha\phi)^{\frac{1}{N(t)}\sum_{j=0}^{N(t)}\frac{O_j^N(t)-\varepsilon_N}{\varepsilon}}(M(t)+P(t)) \\ \quad - \alpha^{\frac{1}{M(t)}\sum_{j=0}^{M(t)}\frac{O_j^M(t)-\varepsilon_N}{\varepsilon}}M(t) \\ \dfrac{dN(t)}{dt} = -(\alpha\phi)^{\frac{1}{N(t)}\sum_{j=0}^{N(t)}\frac{O_j^N(t)-\varepsilon_N}{\varepsilon}}(M(t)+P(t)) \\ \quad + \alpha^{\frac{1}{M(t)}\sum_{j=0}^{M(t)}\frac{O_j^M(t)-\varepsilon_N}{\varepsilon}}M(t) \end{cases} \tag{2}$$

where $O_i^{\psi}(t)(O_i^{\psi}(t) = O_i^{\psi}(t) + \varepsilon$, ε represents the increment of positive or negative emotional value when node i receives the information transmitted by other nodes) represents the emotional value of node i together with state $\psi(\psi \in \{P, M, N\})$; α represents the basic probability of information dissemination. In (2), equations represent the change of the number of nodes in P, M, and N groups, respectively.

In order to describe the state of group emotion more clearly, the definition of group emotional phase is given according to (2).

Definition 1: The phase of group emotion.

The disordered phase (P_1) indicates that the state of individuals in growing numbers of the group is S, which satisfies the condition $|N_G - M(t) - P(t) - N(t)| > \varepsilon_0$. The neutral phase ($P_2$) indicates that individuals in growing numbers of the group know the information and have an emotional state M, which satisfies condition $|N_G - M(t) - P(t) - N(t)| < \varepsilon_0$ but does not satisfy condition $|P(t) + N(t) - M(t)| > \varepsilon_1$. The extreme phase ($P_3$) indicates that the emotional state of most individuals in the group is P or N, which satisfies condition$|N_G - M(t) - P(t) - N(t)| < \varepsilon_0$ and $|P(t) + N(t) - M(t)| > \varepsilon_1$.

N_G represents the number of nodes.

According to Definition 1, the following propositions are given.

Proposition 1: Condition $|N_G - M(t) - P(t) - N(t)| < \varepsilon_0$ is called first-order phase transition of group emotion. Condition $|P(t) + N(t) - M(t)| > \varepsilon_1$ is called second-order phase transition of group emotion.

III. Analysis on the Phase Transition of Emotion in Groups

A. Group Emotional Phase Transition Without Network Structure

In real life, there are many groups in close contact with individuals who eliminate the influence of social relationships due to emotional resonance, obviously such as demonstrators and marchers. The number of people in the group is varied from tens to thousands. The emotion of groups will highlight the phenomenon of group emotional polarization. In this article, such a group is defined as a group without network structure.

In this experiment, we complete all the experimental codes on the "NetLogo" software [50]–[52]. A certain proportion of nodes is required to set as propagation nodes in advance. These nodes represent people who first know the information. About 5% of nodes are randomly selected from all nodes to be used as the initial propagation nodes for spreading information and emotion. Nearly 5% is a commonly used empirical value. This value does not affect the experimental results but is only reflected in the initial propagation speed. Since it is not clear which kind of emotional tendency contains a higher proportion of people who first know the information, the proportion of nodes with positive emotional tendency and the proportion of nodes with negative emotional tendency are, respectively, set to be 50%. Such a proportion can better reflect the change of the group emotion. Thus, there are four types of nodes in the network at the initial moment: the susceptible nodes that do not know the event and the nodes with positive, neutral, and negative emotions toward the event.

All nodes are set to migrate randomly in the simulated world and propagate in contact with each node. When a susceptible node accepts an idea, it becomes a node with state M. Positive emotional threshold $\varepsilon_P = 0.8$ and negative emotional threshold $\varepsilon_N = -0.8$ are set. The emotional values of the three emotional states range from $[-1, -0.8]$, $(-0.8, 0.8)$, and $[0.8, 1]$, respectively. Individuals with extreme emotions are not susceptible to the influence of other emotional individuals. When other emotional individuals transmit information and emotion to the extreme emotional individuals, the communication ability is attenuated with an attenuation coefficient of $\phi = 0.1$.

According to (1), $s(t) + i(t) = 1$, so

$$\frac{di(t)}{dt} = \alpha i(t)(1 - i(t)) \tag{3}$$

where $s(t)$, $i(t)$ represents the density of S state nodes and emotional node, respectively. After (3) is solved, the solution is found in the following equation:

$$i(t) = \frac{i_0 e^{\alpha t}}{1 - i_0 + i_0 e^{\alpha t}}, i_0 = i(0). \tag{4}$$

From (4), the number of nodes that know the information and have basic emotion for it increases exponentially with time. When $t = 0$, $M(t) = 0$, $s(t) \gg i(t)$, group emotional phase is in P_1. When $t \to \infty$, $\exists\tau$ lead to $i(\tau) \approx 1$ by (4).

Let $(dP(t)/dt) \geq 0$ and $(dN(t)/dt) \geq 0$, group growth rate with extreme emotional P is shown in the following equation:

$$\frac{\alpha^{\frac{1}{M(t)}\sum_{j=0}^{M(t)}\frac{O_j^M(t)-\varepsilon_P}{\varepsilon}}}{(\alpha\phi)^{\frac{1}{P(t)}\sum_{j=0}^{P(t)}\frac{O_j^P(t)-\varepsilon_P}{\varepsilon}}} \geq 1 + \frac{N(t)}{M(t)}. \tag{5}$$

As $\alpha^{(1/M(t))\sum_{j=0}^{M(t)}(O_j^M(t)-\varepsilon_P/\varepsilon)} \gg (\alpha\phi)^{(1/P(t))\sum_{j=0}^{P(t)}(O_j^P(t)-\varepsilon_P/\varepsilon)}$, we get (6) from (5)

$$\alpha^{\frac{1}{M(t)}\sum_{j=0}^{M(t)}\frac{O_j^M(t)-\varepsilon_P}{\varepsilon}} \geq 1 + \frac{N(t)}{M(t)}. \tag{6}$$

Furthermore, group growth rate with extreme emotional N is shown in the following equation:

$$\alpha^{\frac{1}{M(t)}\sum_{j=0}^{M(t)}\frac{O_j^M(t)-\varepsilon_N}{\varepsilon}} \geq 1 + \frac{P(t)}{M(t)}. \tag{7}$$

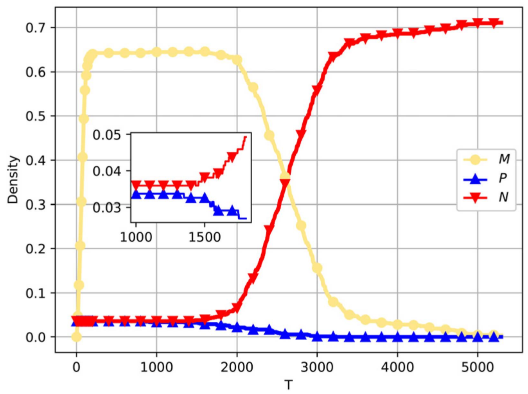


Fig. 3. Schematic of emotional state density.

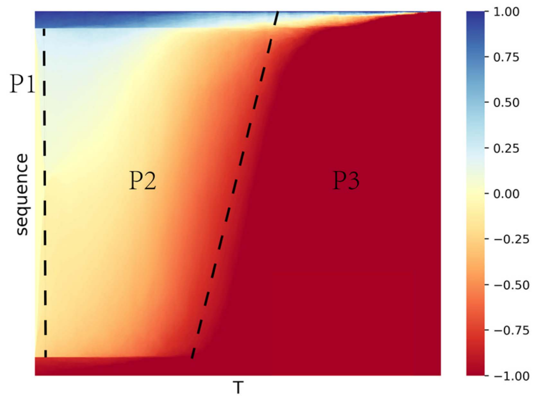


Fig. 4. Schematic of group emotion evolution.

As t increases, the probability of transition from state S to state M for node i is shown in the following equation:

$$\Pr(i|S \to M) = \alpha. \tag{8}$$

The probability of transition from S to state P is shown in the following equation:

$$\Pr(i|S \to P) = \alpha^{\frac{1}{M(t)}\sum_{j=0}^{M(t)} \frac{O_j^M(t) - \varepsilon_P}{\varepsilon}}. \tag{9}$$

While that from S to state N is shown in the following equation:

$$\Pr(i|S \to N) = \alpha^{\frac{1}{M(t)}\sum_{j=0}^{M(t)} \frac{O_j^M(t) - \varepsilon_N}{\varepsilon}}. \tag{10}$$

Obviously, $\Pr(i|S \to M) \gg \Pr(i|S \to P)$ and $\Pr(i|S \to M) \gg \Pr(i|S \to N)$ are obtained from (8), (9), and (10). Thus, $\exists \tau > 0$ and $M(\tau) \gg P(\tau) + N(\tau)$ are satisfied by the number of nodes in P, M, and N groups. At this time, $M(\tau)$ reaches a steady state, and group emotion is in phase P_2.

As t increases, $P(t)$ and $N(t)$ grow exponentially over time is shown in the following equation:

$$\begin{aligned} P(t+1) &= \Pr(i|S \to P)P(t)(1 - P(t) - N(t) + \sigma_1 M(t)) \\ N(t+1) &= \Pr(i|S \to N)N(t)(1 - N(t) - P(t) + \sigma_2 M(t)). \end{aligned} \tag{11}$$

$\sigma_1 (\sigma_1 = (P(t) + M_+(t)/I(t)))$ is the multiple of resources provided by group with emotion N to group with emotion P, and σ_2 $(\sigma_2 = (N(t) + M_-(t)/I(t)))$ is P to N.

When (11) is equal to zero, and when $\sigma_1 = \sigma_2$, $P(t)$, and $N(t)$ have a stable point. As t increases, the following equation holds:

$$\sigma_1 = 1 - \sigma_2. \tag{12}$$

Let the value of random variable X be $\sigma_1 > \sigma_2$ and $\sigma_2 > \sigma_1$, and then, random variable X is subject to 0–1 distribution. $\exists \tau$ leads to $\sigma_1 \neq \sigma_2$. Moreover, $\exists t_0 > \tau$ leads to $P(t_0) = M(t_0) + N(t_0)$ or $N(t_0) = M(t_0) + P(t_0)$. At this time, the group emotion has a second-order phase change, and the group emotional phase is in phase P_3. The experimental results are shown in Fig. 3.

In Fig. 3, orange curve, blue curve, and red curve show the density of node with emotion M, N, and P, respectively.

In Fig. 3, the density of node with emotion M increases exponentially and reaches steady state at time $t = 212$, and the phase of group emotion changes from phase P_1 to phase P_2. At time $t \in [212, +\infty)$, P-state nodes and N-state nodes begin to compete for nodes with state M. When $t = 1250$, the phase transition occurs in the number of extreme emotional nodes, i.e., $\Pr(X = \sigma_2 > \sigma_1)$ has occurred, and $N(t)$ increases exponentially. In the case of group pressure, $P(t)$ does not increase but continues to decline until zero.

At home and abroad, some group incidents frequently occur, such as group-sourcing, demonstrations, and strikes by dissatisfied workers. In the early stages of emotional communication, people do not directly produce extreme emotions but maintain a neutral attitude. The development of random events the constant spread of emotions over time, and group emotion about the event naturally develop within the group. At this time, group thinking and group emotion judgment instead of individual thinking play a role. The process of group emotional change is shown in Fig. 4.

Fig. 4 shows the evolution of group emotion, the phase of group emotion (P_1, P_2, P_3), and the phase transition of group emotion. The red indicates negative emotional tendency, and the blue indicates positive emotional tendency. T represents time, and *sequence* represents the sequence of nodes. At the initial moment, most of the nodes do not know the information, and group emotion is in phase P_1. Over time, most of the nodes get information and produce certain emotional tendencies, and group emotion is in phase P_2. Nodes continue to spread information and emotion between each other, constantly implying each other, and their emotion begin to develop in the extreme direction. From Fig. 4, it is evident that negative emotion prevails in two emotions, and group emotion is in phase P_3. In phase P_2 of Fig. 4, it is evident that when two extreme emotions are competing for neutral nodes, a phase transition occurs, and the number of nodes tending to negative emotions is more than that tending to positive emotions. In the end, there was almost one emotion in the group. Fig. 5 shows a real emotional map. The final result is shown in Fig. 5.

The real data in Fig. 5 are provided by the Institute of WRD Big Data, and the event name is "a certain university

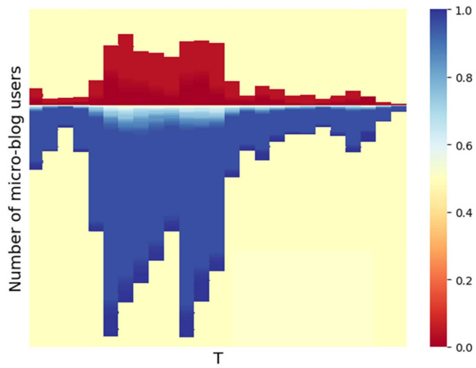


Fig. 5. Real emotional data.

student killed his mother." 50 000 microblog data are randomly selected. The time interval is from 2:00 to 23:59 on April 26, 2019. The function of "sentiment tendency analysis" provided by Baidu artificial intelligence platform is used. Each microblog text is analyzed, and the data with a confidence of more than 70% are retained. The blue indicates positive emotions, and the red indicates negative emotions. The abscissa represents the time, the upper half of the ordinate represents the number of users with negative emotions at time t, and the lower half represents the number of users with positive emotions at time t. The time unit in the graph is the statistical period of hours.

In society, a lot of social beliefs have been formed. However, when social beliefs are challenged, it will lead to a series of group behaviors. In China, for the sake of children's better lives in the future, mothers are expected to give everything to their children, and children should be grateful to their mothers. Such social beliefs can be seen everywhere. This event typically shows the change of group mood after the challenge of social consensus.

As shown in Fig. 5, one kind of emotion is overwhelming to another in the group. Over time, there is almost only one emotional state in the group.

Comparing experimental Fig. 4 with real data Fig. 5, the experimental result shows that when a group without network structure knows an event, explicit extreme emotions for the event are gradually produced, and there is only one extreme emotion in such a group. Real data show that the experimental results are realistic.

B. Phase Transition of Group Emotion in Coevolution of Emotion and Network Structure

On the internet, groups that form a network structure will also experience group emotional phase transition. With the outbreak and spread of an event, nodes of different identities in the network will be gathered by the emotional resonance for the event to form a group with an evolutionary network structure.

To study the transition of group emotion on the network, this article defines node attractiveness from three aspects: node emotion tendency, node clustering degree, and node importance.

Definition 2: Let $A_i(t)$ represents the attractiveness of node i

$$A_i(t) = \omega_2(\omega_1|O_i(t)| + (1-\omega_1)C_i(t)) + (1-\omega_2)\frac{k_i(t)}{k_{\max}(t)}. \tag{13}$$

$\omega_1|O_i(t)| + (1-\omega_1)C_i(t)$ represents the emotional attractiveness of node i. $k_i(t)/k_{\max}(t)$ represents the importance of node i in the network. $\omega_1 (0 \le \omega_1 \le 1)$ represents the weight of node emotion tendency in the emotional attractiveness of node i. $\omega_2 (0 \le \omega_2 \le 1)$ represents the weight of the emotional attractiveness of node i in node attractiveness of node i. $C_i(t)$ represents the clustering degree of node i at time t. $C_i(t) = (E_i(t)/k_i(t)(k_i(t)-1)/2)$, $E_i(t)$ and $k_i(t)(k_i(t)-1)/2$, respectively, represent the actual number of edges and the possible maximum number of edges between k_i neighbor nodes of node i at time t. $k_{\max}(t)$ represents the maximum degree in the network at time t.

Due to mutual attraction, the nodes establish relationships and strengthen communication. Therefore, based on the attraction degree of nodes, the propagation probability of nodes is redefined, and a new network model is defined.

Definition 3: Let $\alpha_{i\to j}(t)$ represents the propagation probability of node i

$$\alpha_{i\to j}(t) = \begin{cases} \alpha + (1-\alpha)A_i(t)A_j(t)\big|_{j\ne i}, \\ \quad j \in \left\{ j|\Omega_j(t) = Mor\Omega_j(t) = \Omega_i(t)\right\} \\ \phi\big[\alpha + (1-\alpha)A_i(t)A_j(t)\big]\big|_{j\ne i}, \\ \quad j \in \left\{ j|\Omega_j(t) \ne Mor\Omega_j(t) \ne \Omega_i(t)\right\} \end{cases} \tag{14}$$

$\Omega_i(t)$ represents the emotional state of node i at time t.

Based on the node's attractiveness, given that the communication between nodes will be reduced if they are no longer attracted to each other, the probability of establishing a connection between nodes is redefined.

Definition 4: Let G represents the evolutionary network of attractiveness

$$G = \left(V, E, p_{ij}(t)\right) \tag{15}$$

V represents the node set of network G; E represents the edge set of network G.

Definition 5: Let $p_{ij}(t)$ represents the probability of establishing connection between node i and node j

$$p_{ij}(t) = \begin{cases} \alpha_{i\to j}(t), & (i,j) \notin E \\ A_i(t)A_j(t), & (i,j) \in E. \end{cases} \tag{16}$$

According to Definition 5, the construction algorithm of attraction evolution network is as follows.

An empty graph with N_G nodes is generated. N_G nodes walk randomly in the simulation world. Each node communicates information and emotion with other nodes and calculates the connection probability $p_{ij}(t)$. The probability $p_{ij}(t)$ of occurrence establishes the connection, and vice versa. $p_{ij}(t)$ and $p_{ji}(t)$ have the same meaning.

For the established connection (i, j), the probability $p_{ij}(t)$ is calculated. If the connected edge event is generated according to the probability $p_{ij}(t)$, the connected edge will be maintained, otherwise the connected edge will be disconnected.

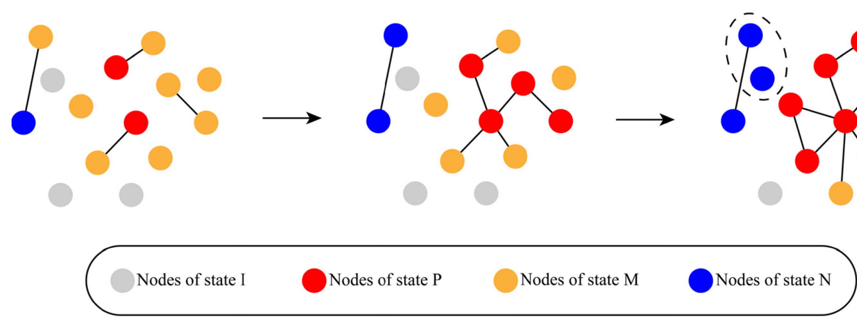


Fig. 6. Schematic of network evolution.

If the node has no neighbors, the direction of node movement is random. If the node has neighbors, the node follows the neighbor with the largest attractiveness. Network evolution diagram is shown in Fig. 6.

In Fig. 6, the dotted ellipse marks two nodes in the figure, indicating that the connection between the two nodes is broken.

According to Definition 5, the degree distribution of network G is given as follows.

Degree k_i of node i consists of the newly established number of links k_i^1 and the number of links k_i^2 retained by calculating the probability of reconnection, i.e., $k_i = k_i^1 + k_i^2$. When condition $(1-\alpha) - \alpha < \delta_1$ is satisfied, the following equation can be obtained:

$$\Pr(k) = \sum_i \frac{(\alpha k_i(t))^{s_i^1}}{s_i^1!} e^{-\alpha k_i(t)} \Pr_2(k) \tag{17}$$

$\Pr_2(k) = \sum_i C_{s_i^2}^{k_i(t)} (A_i(t)(1/\tilde{m}) \sum_{j=1}^{\tilde{m}} A_i(t))^{s_i^2}$ $(1 -_i (t)$ $(1/\tilde{m}) \sum_{j=1}^{\tilde{m}} A_i(t))^{k_i(t)-s_i^2}$ is the degree distribution of the edge preserved by the probability of reconnection. $\tilde{m}$ represents the average number of nodes contacted by the node during the walk in the simulation world. According to (17), when the network shows homogeneity, it will form the network structure of small world network.

When condition $(1-\alpha)-\alpha > \delta_1$ and condition $(1-\omega_2) - \omega_2 < \delta_2$ are satisfied, the following equation can be obtained

$$\Pr(k) = \left((1-\omega_2)k^{-\mu} + \omega_2 \sum_i \frac{(\alpha k_i(t))^{s_i^1}}{s_i^1!} e^{-\alpha k_i(t)} \right) \Pr_2(k). \tag{18}$$

According to (18), in the early stage of network formation, the network is more affected by equal probability and undifferentiated propagation to form a network structure closer to the small-world network.

When condition $(1-\alpha)-\alpha > \delta_1$ and condition $(1-\omega_2) - \omega_2 > \delta_2$ are satisfied, the following equation can be obtained:

$$\Pr(k) = (1-\omega_2)k^{-\mu} + \omega_2 \Pr_2(k). \tag{19}$$

According to (19), when the network is formed to a certain stage and the heterogeneity is highlighted in the network, a more scale-free network structure will be formed.

In the initial stage of information dissemination, most of the nodes do not know the message, and group emotion is in phase P_1. Over time, $\Pr(i|S \to M) \gg \Pr(i|S \to N)$ and $\Pr(i|S \to M) \gg \Pr(i|S \to P)$ are obtained from (8), (9), (10), $M(\tau) \gg P(\tau) + N(\tau)$ will be satisfied, and $M(\tau)$ will reach a steady state. At this time, the first-order phase transition of group emotion occurs, and the group emotional phase transits from phase P_1 to phase P_2. The infected nodes are evenly distributed in the simulated world at the initial moment. With $t \to \infty$, the range of activity of each node is affected by its neighbors, then two extreme groups grow independently, and the number of nodes with two types of emotion undergoes a phase change. Equation (11) changes into the following equation:

$$P(t+1) = \Pr(i|S \to P)P(t)(1-P(t)) \tag{20}$$

$$N(t+1) = \Pr(i|S \to N)N(t)(1-N(t)). \tag{21}$$

According to (20), groups with emotional state P and N grow simultaneously. At time t_1, the condition $|P(t_1) + N(t_1) - M(t_1)| > \varepsilon_1$ is satisfied, which makes that the second-order transition of group emotion and the change of group emotional phase transmit from phase P_2 to phase P_3. Over time, $P(t)$ and $N(t)$ grow exponentially. Due to mutual attraction, nodes gather together to form a number of group networks with different sizes. Let N_G represents the number of group networks, and the probability that node u is not in any group network is as follows:

$$1 - S_i(t) = \frac{1}{N_G} \left[1 - \frac{1}{N_{G_i}} \sum_{i=1}^{N_{G_i}} p_{ij} + \frac{1}{N_{G_i}} \sum_{i=1}^{N_{G_i}} p_{ij}(1 - S_i(t)) \right]^{N_G - 1}. \tag{22}$$

Hence, the probability of nodes in group network i is as follows

$$S_i(t) = 1 - \exp\left\{ -(N_{G_i} - 1) \frac{1}{N_{G_i}} \sum_{i=1}^{N_{G_i}} p_{ij} S_i(t) \right\} - \exp\{(N_{G_i} - 1) \ln N_G\}. \tag{23}$$

According to (22), the following equation can be obtained

$$\frac{1}{N_{G_i}} \sum_{i=1}^{N_{G_i}} p_{ij} \geq \frac{1}{(N_i - 1)\frac{1}{N_{G_i}} \sum_{i=1}^{N_{G_i}} p_{ij}}. \tag{24}$$

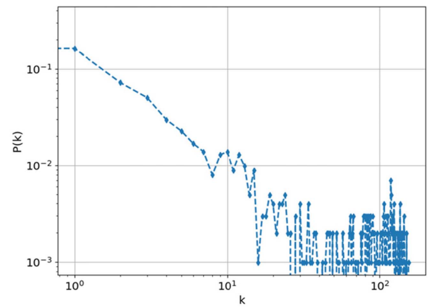
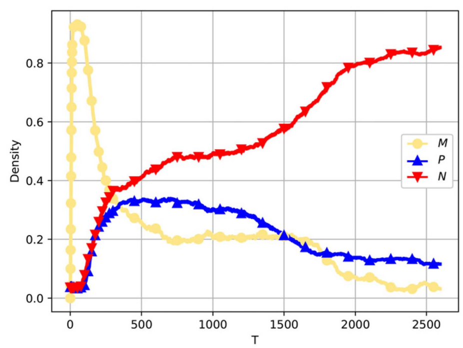
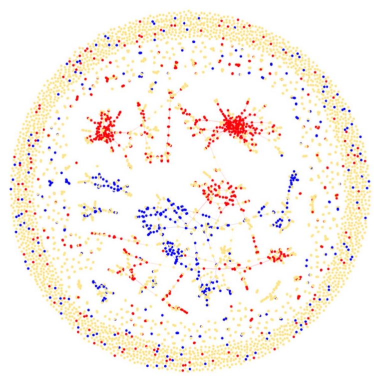


Fig. 7. Network degree distribution.



(a)



(b)

Fig. 8. Node density and the initial stage of evolutionary network. (a) Node density of three emotional tendency states. (b) Evolutionary network at time $t = 50$.

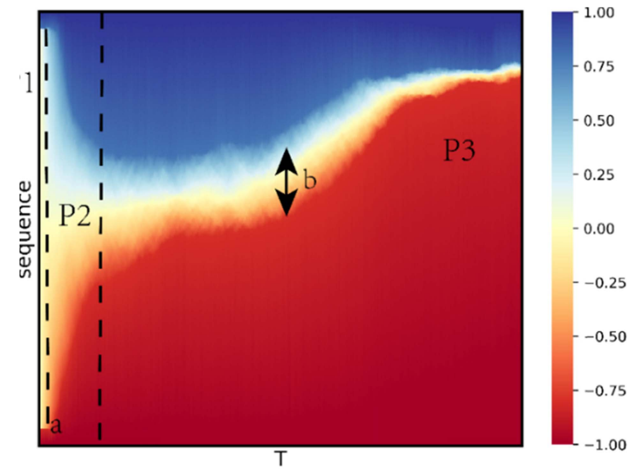


Fig. 9. Group emotion evolution.

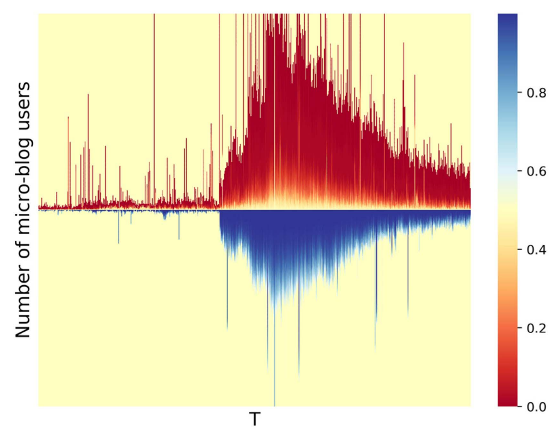


Fig. 10. Real emotional data.

That is to say, the formation of each group network will meet (23). The definition of group network attractiveness is given as follows.

Definition 6: Let $A_{G_i}(t)$ represents the attractiveness of group network i

$$A_{G_i}(t) = \frac{1}{N_{G_i}} \sum_{i=1}^{N_{G_i}} A_i(t). \tag{25}$$

If the nodes of multiple groups meet with the same emotional state, these groups will attract each other and gather together to form a larger group. If the nodes in groups meet with different emotional states, these groups will not attract each other, but they will be connected through the neutral nodes at the edge of the network. At the edge, the growth of the number of nodes with extreme emotion satisfies the (11), i.e., there will be competition for neutral nodes at the edge. Even though the extreme nodes are not to be affected, some nodes will change into another emotional state. The emotional changes of nodes at the edge are consistent with the analysis results in (12). In other words, when two kinds of extreme emotional nodes compete for neutral nodes, their number will undergo a second phase transition. According to (24), there are still $N_G \prod_{i \neq j} (1 - \phi A_{G_i} A_{G_j})$ group networks independent of other group networks.

In this experiment, $N_G = 5000$, $\alpha = 0.3$, $\omega_1 = 0.5$, and $\omega_2 = 0.3$. The experimental results are as follows.

From Fig. 7, the final degree distribution of the network is a power-law distribution. The abscissa represents the node degree, and the ordinate represents the probability of the node degree k. The change of node density of three emotional states is shown in Fig. 8.

In Fig. 8(a), abscissa represents time, and ordinate represents node density of each emotional state (M, P, N). Fig. 8(b) shows that evolutionary network at time $t = 50$. It can be seen from the figure that in a very short period of time, the group emotion has a first-order phase transition, from phase P_1 to phase P_2, and most of individuals hold a neutral attitude toward the event. In the time interval [50, 100], as shown in Fig. 8(b), nodes with similar emotional tendencies will attract each other and evolve into a group network which can attract the surrounding neutral nodes, which makes two

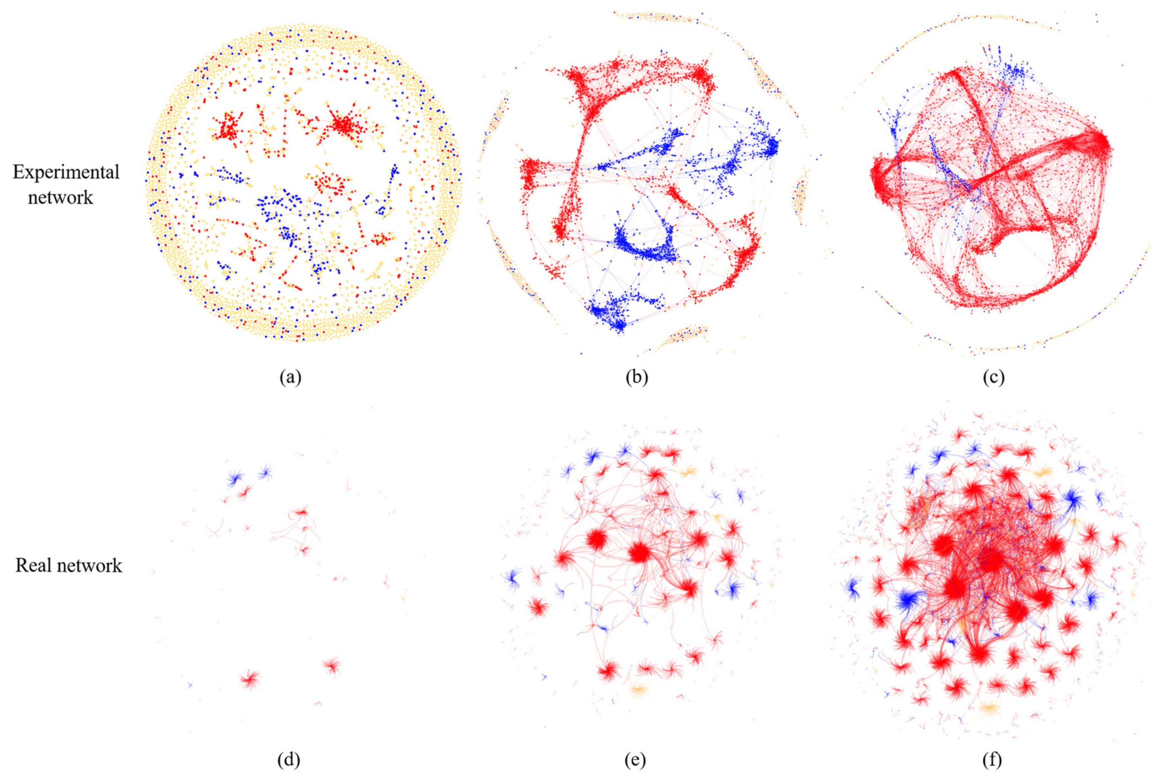


Fig. 11. Network evolution diagram. (a) Initial stage of the experimental network. (b) Middle stage of the experimental network. (c) Final stage of the experimental network. (d) Initial stage of the real network. (e) Middle stage of the real network. (f) Final stage of the real network.

extreme emotional nodes compete for these neutral nodes to undergo a phase change. The neutral nodes are affected by these group networks which have a clearer emotional tendency to the event. The nodes with neutral attitude begin to change into extreme emotional state, the node density of extreme emotion begins to grow exponentially, and the scale of the group network also begins to grow. In the time interval [500, 1400], the node density of the two extreme emotional states reaches a steady state, and the network scale of the nodes also reaches a steady state. There are more nodes with extreme emotion in the group than neutral nodes. The group emotion changes from phase P_2 to phase P_3. In the time interval [1400, 1500], two kinds of group networks with opposite emotions are connected together through the neutral nodes in the network. The internal emotional changes are consistent with the analysis results in (12), and the group emotions have a second phase transition.

Fig. 9 shows the changing process of group emotion, in which the blue indicates positive emotion tendency and the red indicates negative emotion tendency. Abscissa represents time, and ordinate represents node sequence. In the figure, the phase (P_1, P_2, P_3) of group emotions at different time intervals are marked, and the position a and position $b$mark the phase transition point of the number of two kinds of emotional nodes.

The real data in Fig. 10 are provided by the Institute of WRD Big Data, and the event name is "copyright incident of a certain company." 100 000 microblogs are randomly selected. The time interval is from April 1, 2019 to April 11, 2019. The function of "sentiment tendency analysis" provided by Baidu artificial intelligence platform is used. Each microblog text is analyzed, and the data with a confidence of more than 70% are retained. The blue indicates positive emotions, and the red indicates negative emotions. The abscissa represents the time, the upper half of the ordinate represents the number of users with negative emotions at time t, and the lower half represents the number of users with positive emotions at time t. The time unit in the graph is the statistical period of minutes.

The first image of a black hole in the world comes from the European Southern Observatory. However, the image spread widely on the Internet is marked with the name of a certain company, indicating that the copyright of the image belongs to the company. In contemporary society, copyright is a self-evident social consensus and cannot be infringed. Copyright infringement can cause public anger. People who hold different emotions to the event spread the information constantly, which attracts other people's attention, and then spontaneously forms a coevolution network.

In Fig. 10, it can be seen from the figure that two kinds of emotional groups compete for the people, and it is obvious that the growth rate of one extreme emotional group is higher than the other extreme emotional group.

Fig. 11 shows the three stages of the evolution of the experimental network and the real network over time. Fig.11(a)–(c) shows the evolution diagrams of the experimental network at three different time points, whereas Fig.11(d)–(f) shows the evolution diagrams of the real network at three different time points. This real network constructed from 100 000 microblogs in Fig.10. This real network constructed from 100000 microblogs in Fig.10. Rules constructing network edges are based on the real data published microblog author and related root microblog author. The time when the microblog is published is regarded as the time when the edge appears. Using "Gephi" software, the evolution of real network is visualized. The blue node indicates positive emotion, the red node indicates negative emotion, and the orange node indicates neutral emotion.

Fig. 11(a) shows the network structure initially formed by the group. Nodes with similar emotions gather together to gradually form the network, the group emotion phase changes from phase P_1 to phase P_2, and some nodes are still isolated nodes. Fig. 11(b) shows that the network structure is formed during the growth of two extreme emotional groups. The intensive colored part of the figure shows the aggregation phenomenon of extreme emotional nodes, and it shows that when two groups compete for neutral nodes, group emotion in the network begins to tend to one of them. Fig. 11(c) shows the final evolution of the network. The group emotion phase changes from phase P_2 to phase P_3. Most of the nodes in the network are contested by one extreme emotion, but there are still a few group networks with other extreme emotions.

Fig.11(d)–(f) shows the phenomenon of coevolution between group emotion and group network structure, as well as the phase transition of group emotion. Moreover, it verifies the phenomenon of group emotion polarization of "birds of a feather flock together"—the group formed by the individual mutual attraction of emotional resonance—from the perspective of emotion. The real data show that the experimental results are in accordance with the reality.

IV. Conclusion

In this article, we studied the phase transition of group emotion in the group network with and without structure. In the group without network structure, the phase transition condition of group emotional polarization is defined, the process of group emotional polarization is studied, and the phenomenon of group emotional polarization in reality is verified. In the group emotion and network structure coevolution, it is found that the growth of individual emotion and group size are affected by node distance and node attraction. Multiple groups with different extreme emotions will be generated. Experiments show that group emotion based on individual attraction and network structure of the group has a coevolution phenomenon. From the perspective of group emotion, the social phenomenon—"birds of a feather flock together" is verified. At the beginning of propagation, group emotion is in phase P_1. With the spread of network, group emotion phase changes from phase P_1 to phase P_2 and finally to phase P_3. When information propagates in the network, the number of extreme emotional nodes will undergo a phase change, and the number of nodes will increase rapidly. With the further spread of the network, the number of extreme emotional nodes will undergo a phase change, and some nodes in the network will become another extreme emotion. Finally, through the contrast experiment with the real data, the authenticity of the proposed theory is verified.

In the second part of this article, the phase transition of group emotion is studied based on the gravity phenomenon of individual scale and the emotional resonance between individuals. However, the behavior of individuals and groups is affected by many factors, so the work of this article has some limitations. In the future work, we will continue to study the phase transition phenomenon of population dynamics and explore its more general formation mechanism.

V. Simulation Platform and Data Source

The data used for Figs. 5 and 10 are from the Institute of WRD Big Data (https://research.wrd.cn/). We have signed a confidentiality agreement with the institute, and we are unable to offer the source data. The simulation software used throughout this article is the "NetLogo" (http://ccl.northwestern.edu/netlogo/index.shtml). We complete all the experimental codes on the software. Using "Gephi" software (https://gephi.org/), the evolution of real network is visualized.

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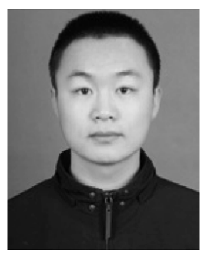

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