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THE MODEL OF INFORMATION PROPAGATION COMBINED WITH OPINION EVOLUTION ON SCALE-FREE NETWORK

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ABSTRACT

In real life, information dissemination and evolution of opinion are always interpenetrated. People's attitudes affect the formation of their opinions and influence the dynamic process of information dissemination, furthermore, the controversy of topics can be reflected by people's attitude tendencies distribution. In this paper, we present a model that combines information dissemination with opinion evolution and considers the individual attitudes tendencies and investigate how attitude tendencies distribution affects the information dissemination and opinion evolution. We find that the attitude tendencies not only affect the speed and scope of information dissemination, but also affect the convergence direction of public opinion.

KEYWORDS: *Information Diffusion, Opinion Evolution, Scale-Free*

Article History

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1. INTRODUCTION

Most of the real-word systems, such as biological system, World Wide Web, and social system, can be represented by complex networks which nodes represent individuals or organizations and the links between the nodes represent the relationship between them.[1] With the rapid development of the Internet, social networks have covered all network services centered on human society and becoming a hot area for the development of the Internet. The information dissemination and opinion evolution in social networks have drawn wide attention from Statistical Physicist, Social Physicists, and others. [2-11]

Research of information diffusion originates from epidemic dynamics.[6] SI, SIS, and SIR[2, 9] model are the classical models for studying the epidemic dynamics. In the SIR or susceptible-infected-removed model, it divides nodes into three states:S (susceptible), I (infected) and R (recovered), where S indicates that the individual susceptible to disease (or knows nothing about the topic), I indicates that the individual who is infected (or knows something about the topic) and R indicates that the individual who recovered from the disease and was immune to further infection (or knew the topic but lost interest in it and no longer participate in the further dissemination process). The spreading process starts with an initial infected set of nodes which are called seeds. An infected node diffuses the infection(i.e. information, disease) to a susceptible neighbor with a certainly infected rate α. The infected nodes can recover after time $\gamma$from the moment of infection.[12] Many variant models have been proposed, most of these studies concentrateon: How many people will eventually be reached by the news? Namely, the fraction of the population, which ultimately infected (called outbreak size). Is there a propagation threshold for the rate of spreading?[2, 3, 7-9]

Opinion models aim to describe the formation of public opinion and try to reveal the internal mechanism in social systems. Unlike the information dissemination models, opinion models assume that all individuals receive the topic and everyone has a view of it, then the opinion evolve follows the given individual interactions rule. Statistical methods are used to explore how the local rules affect the collective behavior of social agents.[13] According to whether the opinion is continuous or not, the evolution model can be divided into continuous viewpoints model (such as Deffuant model[14]) and discrete viewpoints model (such as Voter model,[15]Sznajd model[16] and Galam models[17]).

Many studies often decouple information diffusion from the evolution of the public opinion. However, in fact, the dissemination of information and the opinion evolution are often accompanied by each other. People focus on hot topics and repost or publish related content (such as microblog, twitter) to express their point of view, then they propagate information and promote the evolution of the public opinion simultaneously once they reposted or published related content. In addition, most of these studies consider the individual interacting rule from the following two aspects: the current opinion of individual $i$and opinions of its neighbors, they do not consider the individual attitude tendency which is influenced by their cultural background, social background, ethnic background, educational background and so on, it ensured an individual to form a stable view of the same kind of incident. Obviously, individual attitude tendency (such as their political stand, the stereotype for some kinds of people) reflects their preferences in the form of their opinion, it is difficult to change within a short time, furthermore, the distribution of attitude tendencies can reflect the controversy about the topic. In [6], Xiong F et al. proposed a three-state opinion modelaccompanied by information diffusion, but did not consider individual opinion exchanges from individual attitude tendencies.

To be more realistic, we propose a model that combines information dissemination with opinion evolution and considers the individual attitudes tendencies to study how the individual attitudes tendencies affect the information diffusion and opinion evolution. The outline of the paper is as follows. In Section 2, a model combine information dissemination with opinion evolution in the scale-free network is proposed. In Section 3, we conduct numerical simulations and show the result analysis. In Section 4 we give our conclusions.

2. METHOD AND MODEL

In our model, considering that some individuals may keep silent on the topic, we divide nodes on the network into four states:S (susceptible), I_1 (unexpressed), I_2 (infected) and R (recovered), where S means the individual knows nothing about the topic, but has a chance to learn it from his friends.I_1 indicates the individual who knows the topic, but it has not yet published its own opinion outside, once it expresses its opinion it becomes infected (I_2) and has the ability to pass the information about the topic to its neighbors(for simplicity, we assume that once someone published its opinion, all of its susceptible neighbors will become unexpressed (I_1)). In reality, most of the time people do not maintain a permanent interest in a topic, after a while, individuals in state unexpressed or infected may be lost interest in this topic and no longer participate in the next information dissemination process and opinion evolution, they become recovered (R) with some certain probability.

The states of the individuals (i.e. susceptible, unexpressed, infected and recovered) are used to describe their epidemic states, in addition, we let τ_i be the enthusiasm of individual i, it is used to characterize their enthusiasm for discussion on this topic. The enthusiasm τ takes the value from $\{-1, 0, 1\}$, where $\tau = 0$represents that the people know nothing about the topic, thus let alone to participate in discussion,$\tau = 1$ represents the people knows the existence of the topic and may participate in the discussion about the topic, $\tau = -1$ represents the people who lost interest in the topic and left the discussion. The person $i$who is in state S corresponding to $\tau_i = 0$, once it becomes unexpressed or infected,$\tau_i = 1$, and changes into $\tau_i = -1$,until it becomes recovered. Last, we let $O_i$be the opinion of individual i. People may support or oppose to the topic, denoted respectively $O = 1$ and $O = -1$. Each individual holds an opinion (either $O = 1$ or $O = -1$) after learningthe topic, then they decide to publish their own opinions or not and become infected or maintain unexpressed as the mentioned above. It was proven that opposite emotions will provoke users to publish their ideas,[18] in our model, individual i will publish its viewpoint while it realizes its neighbors holding the opposite viewpoint. The individual shifts its opinion depend on three points: its neighbors' opinions, its current opinion and its attitude tendencies. Notice that individual's attitude tendencies remain all the time in this model, it reflects the preferences of the form of an individual's opinion. In this work, we assume the attitude tendencies follow the Bernoulli Distribution.

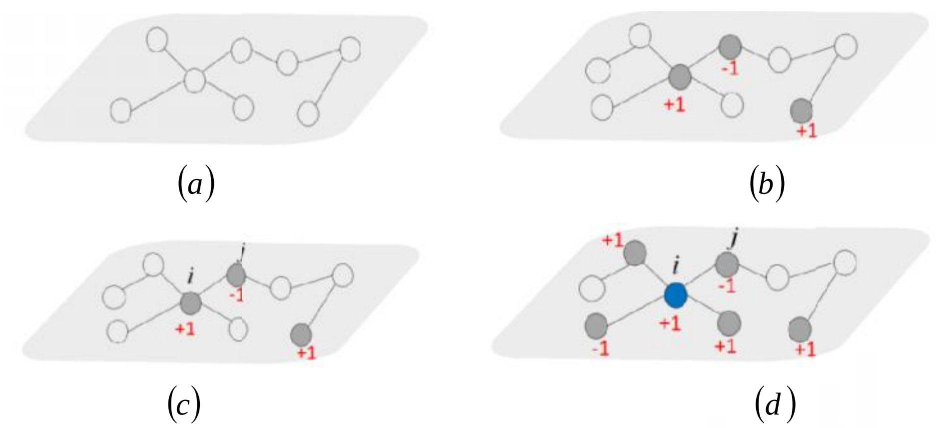

Figure 1: The Process of Information Dissemination. (a) Each Node Begins in State$S$Represented by White Circle, (b) Then a Small Group Nodes Chosen Randomly to be in State I_1(Represented by Circle Filled with Gray, They are the Original Discussion Group), "+1"and "−1" Represent Their Point of View, (c) An Individual i and one of its Neighbor j are Selected Randomly, if $\tau_i = \tau_j = 1$ and $O_i = -O_j$, Then (d) Individual$i$ Publish his Opinion and Become Infected (Represented by Circle Filled with Blue), All of his Susceptible Neighbors Become Unexpressed Simultaneously

First, we give the attitude tendencies distribution, a fraction $p_+$of people prefer to taking $O = 1$, while a fraction $p_- = 1 - p_+$ of people prefer to taking$O = -1$, then the model evolves as follows:

A. The process of information dissemination (see **figure 1**)

- Before the spreading dynamics, each individual is in the susceptible state;
- Small group nodes are chosen to be in state I_1at random, their density denoted by p_0;
- An individual i and one of its neighbor j are selected at random;
- If $\tau_i = \tau_j = 1$ and$O_i = -O_j$, individual i publish its opinion and all its susceptible neighbors become unexpressed, otherwise we re-select a pair of individuals (i, j);

B. The evolution of public opinion (see **figure 2**)

- After i publishes its opinion, its neighbors update their opinions follow the individual interacting rule (it will be introducing later);
- At each time step, both infected individual and the unexpressed individual may become recovered with probabilityδ.

Repeat steps 3 through 6 above until the system reaches a steady state. For a system of size N , after selecting N pairs of individuals(i, j), time step increases by 1.

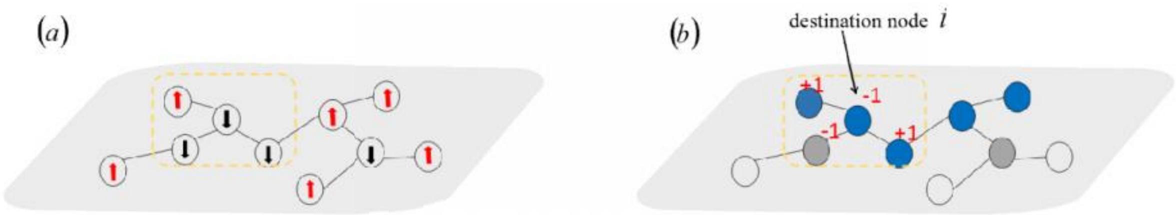

Figure 2: (a) Schematic Illustration of Individual's Attitude Tendencies, Red Arrow Means the Individual Prefer to Taking Opinion$O = 1$, Black Arrow Means it Prefer to Taking Opposite Opinion $O = -1$. (b) Schematic Illustration of the Opinion Update Rules

An individual shifts its opinion is driven by two mechanisms: the first one corresponds to the interpersonal interaction with its neighbors, the second one concerns its attitude tendencies. The probability that an individual$i$changes its opinion is $\beta = \rho^{a \pm b}$ where $\rho$is the fraction that its neighbors who take an opposite opinion, a and b are positive constant, $a > b$. If the opinion of individual$i$ is opposite with his attitude tendencies, then$\beta = \rho^{a-b}$, else$\beta = \rho^{a+b}$. Taking figure 2 as an example,a node i has two of three neighbors taking an opposite opinion and it has the same opinion as for its attitude tendencies, so$\beta = \left(\frac{2}{3}\right)^{a+b}$.

Now let us calculate the probability that an individual publishes his opinion. For a given network, let $p_k$be the probability that a randomly chosen node has degree$k$, and let $S(t), I_1(t), I_2(t), R(t)$ be the fractions of the nodes in each of four states at time$t$, then$I(t) = I_1(t) + I_2(t)$ is the fractions of people who can participate in the discussion.

At time t, the probability that randomly chosen node i which is in a state I_1 or I_2 with degree k is $p_k I(t)$, the probability of i having$m$ of k neighbors in the stateI_1or$I_2$is given by the binomial distribution $\binom{k}{m} I(t)^m [1 - I(t)]^{k-m}$, then the probability that randomly chosen a pair of individuals(i, j) in which node i with degree$k$, meanwhile i and j can both participate in the discussion (i.e.$\tau_i = \tau_j = 1$) is given by $p_k I(t) \sum_{m=0}^{k} \frac{m}{k} \binom{k}{m} I(t)^m [1 - I(t)]^{k-m}$, so we have

$$p_1 = \sum_{k=0}^{\infty} p_k I(t) \sum_{m=0}^{k} \frac{m}{k} \binom{k}{m} I(t)^m [1 - I(t)]^{k-m} \tag{1}$$

Where$p_1$is the probability that node$i$and one of its neighbor j are chosen at random and both of them participate in the discussion.

Now, we can calculate the probability that individual i will publish his opinion,

$$p = p_1 \left[f_+(t)\left(1 - f_+(t)\right) + f_-(t)\left(1 - f_-(t)\right) \right]$$

$$= 2p_1 \left[f_+(t)\left(1 - f_+(t)\right) \right]$$

$$= 2I(t)^2 f_+(t) f_-(t) \quad (2)$$

Where $f_+(t)$ and $f_-(t)$ are the fractions of $O = 1$ and $O = -1$ respectively. From Eq. (2) we can obtain that the process of information dissemination and the opinion evolution will cease until (i) there are neither infected state nor the unexpressed state in the network, or (ii) all individuals have a consistent view.

3.SIMULATIONS AND RESULTS

We research how attitude tendencies influence the information diffusion and opinion evolution. For most real networks having scale-free features (that is, their degree distributions$p(k)$ or the probability that an arbitrary node to be connected to exactly$k$other nodes follows a power-law distribution: $P(k) \sim k^{-\gamma}$, with degree exponent$\gamma \in (2,3]$,[19, 20] [14,15]). We take the Barabasi - Albert (BA) scale-free network[21] as the underlying network, the network generated parameters are set as follows: $N = 10^4, m_0 = m = 10$and $\langle k \rangle = 20$, and set$a = 1$ and $b = 0.2$. All the Monte Carlo simulations are averaged by 2×10^4 realizations in our study.

3.1. Information Diffusion Affected by Attitude Tendencies Distribution

It is realized that, except individuals in state susceptible, the proportion of individuals in the other three states can be used to describe the outbreak size denoted by "R".

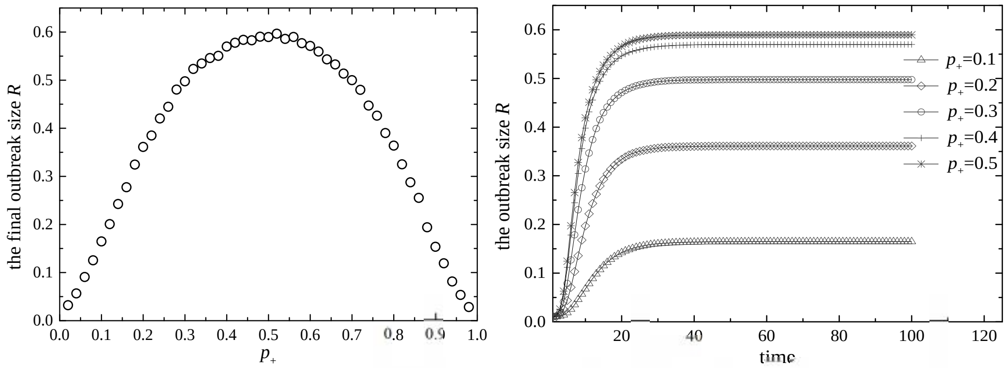

Figure 3: (a) The Final Out Break Size$R$ as a Function ofp_+. (b) The Outbreak Size$R$versus Time for Different Values ofp_+. Simulations are Implemented in BA Scale-Free Network with $\langle k \rangle = 20$, and $p_0 = 0.01, \delta = 0.1$

In figure 3 (a) we plot the final outbreak size R as a function of p_+. As we can see that$R$ first increases, then decreases with the increases of p_+.When the value of $|p_+ - p_-|$ near zero, the ratio of positive and negative attitudes tendencies near 1: 1, and the outbreak size$R$ will reach the maximum, about 0.6. In figure 3(b), the outbreak size R has increased over time, then reach stable,it means information diffuses rapidly at the early step and achieves a stable state. No matter the values of the p_+ is, the outbreak size all stable after the first 30-time steps in this simulation. Moreover, when $p_+ = 0.5$ the outbreak size increases more quickly and greater than others in figure 3(b).

In real life, the smaller the $|p_+ - p_-|$ is, means the more controversial the topic is, it will stimulate the debate between two groups that holddifferentviewpoints, both resulting in accelerating the speed of information dissemination and expand the scope of information dissemination.

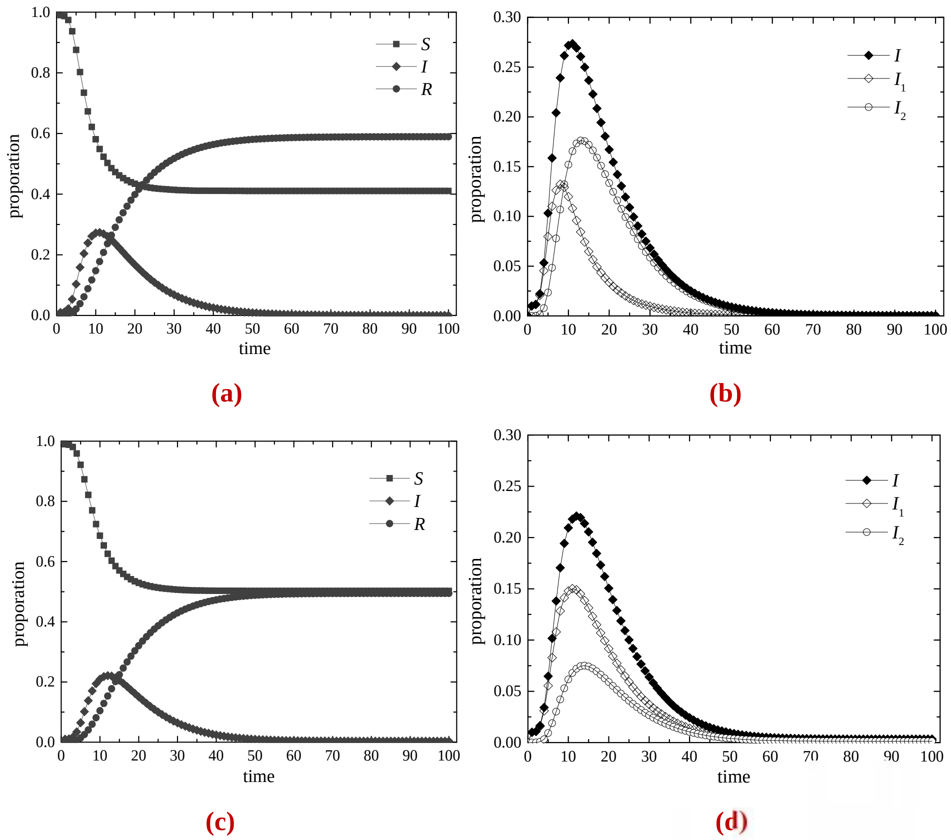

Figure 4: The Probability of Individuals in Different State versus time for (a) and (b)$p_+ = 0.5$, (c) and (d)$p_+ = 0.3$.Simulations are Implemented in BA Scale-Free Network with $\langle k\rangle = 20$, and $p_0 = 0.01$,$\delta = 0.1$

From figure 4, it is clear thatthe evolution of individuals in different epidemic states differs considerably with different p_+. The proportion of susceptible individuals decreases with time until it levels off, while the number of infected and unexpressed individuals increase at the early stage but drops to close to 0 very quickly. As we can see in daily life, the discussion about the news is short-lived in nature, the comment frequency vanishes rapidly with time and the news is covered by another news.

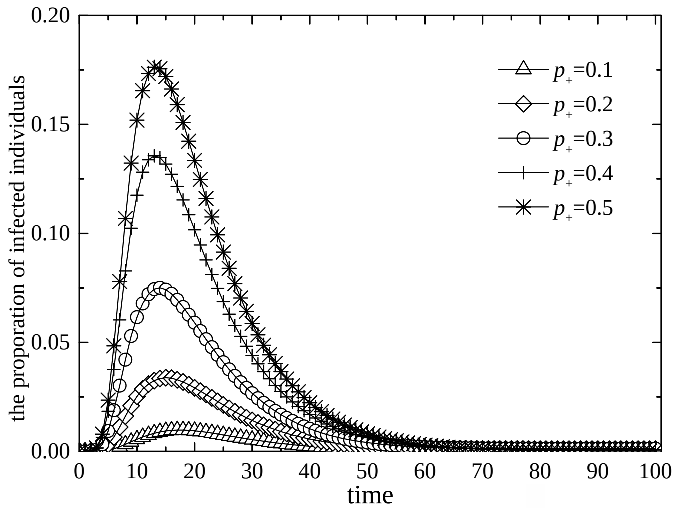

Figure 5: The Probability of Individuals who Publish their Opinion versus Time for Different Values of p_+. Simulations are Implemented in BA Scale-Free NETWORK with$\langle k\rangle = 20$, and $p_0 = 0.01$,$\delta = 0.1$

In figure 5, we investigate how attitude tendencies distribution influences the number of individuals who publish their opinions. Observing the time evolution of the proportion ofindividuals in state I_2 for different p_+, there is a peak in each curve. The proportion of individuals in state I_2increase at the early step, then drop to close to zero after reaching the maximum value, but the peak rise and the proportion of individuals in the state I_2 rising faster and falling more slowly with the increase of p_+.This is corresponding to the reality, when a topic appears, people are excited to participate to thediscussion, however, less and less people discuss it and the topic gradually will fade out of public viewafter a piece of time. If the topic has more dispute, the discussion will more intense and more lasting, which can explainthe controversial of the topic can expand the topic's spread as shown in Figure 3. This is in accordance with the statistical analysis of forum data by Sobkowicz P et al. that "the growth of the discussion depends on the degree of controversy on the subject and the intensity of personal conflict between the participants."[18]

3.2. Opinion Evolution Affected by Attitude Tendencies Distribution

Now, we areinvestigate how attitude tendencies influence the evolution of public opinion. Here, we can use the proportion of $O = 1$ or $O = -1$ to infer the public opinion. For example, we calculated the total proportion of published opinion that$O = 1$ denote by u_+, then plot time evolution of $u_+$for different values of p_+in figure 6. Observing the curves in figure 6, u_+ stabilizes quickly and evolves toward the direction of convergence, no matter what the u_+ is. Which we can infer from figure 6 is that the public opinion is eventually driven towards in a certain direction, regardless of the value of p_+, but p_+can effectively affect the direction of the opinion evolution, the more disputes, the more difficult it is to reach consensus.

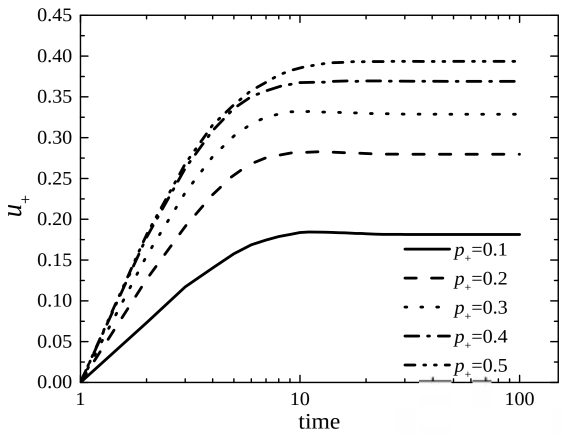

Figure 6: The Evolution of Total Proportion of Published Opinion $O = 1$ for Different values of p_+. Simulations are Implemented in BA Scale-Free Network with $\langle k \rangle = 20$, and $p_0 = 0.01$, $\delta = 0.1$

4. CONCLUSIONS AND PERSPECTIVES

The controversy of the topic is reflected by people's attitude tendencies distribution and the small $|p_+ - p_-|$ means, the more controversy the topic is.In this work, we have investigated how attitude tendencies distribution influences the information diffusion and opinion evolution, and obtain some conclusions as follows: (i) The controversy of topic adds to the "discussion temperature", thus accelerate the diffusion of the topic and expand the outbreak size$R$. The more controversy the topic is, the faster and wider the topic spread, because the discussion will be more intense and more lasting. (ii) Public opinion levels off quickly and evolves toward the direction of convergence. The published positive viewpoint increases at the beginning imply the topic diffusion swiftly when this topic just came out, this is in accordance with the result from figure 3(b). The decrease of the value of $|p_+ - p_-|$ will hinder the formation of consensus public opinion, namely, the controversy of the topic will difficult for the people to reach a consensus opinion.

Underlying network topology plays an important role in the dynamics of social systems. In real life, sometimes people may choose to change the circle of personal relationships rather than change their opinions, which will lead to the evolution of the network topology, therefore the dynamics of an underlying network will be considered in our future work.

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