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IMPLEMENTATION OF A SOCIAL NETWORK INFORMATION DISSEMINATION MODEL INCORPORATING NEGATIVE RELATIONSHIPS

Meizi Li, Xue Li, Ya Zhang, Jianguo Pan*

College of Information, Mechanical and Electrical Engineering
Shanghai Normal University
Shanghai 201 418, China
e-mail: panjg@shnu.edu.cn

Ru Yang*

College of Information, Mechanical and Electrical Engineering
Shanghai Normal University, Shanghai 201 418, China
&
Shanghai Engineering Research Center of Intelligent Education and Bigdata
Shanghai Normal University, Shanghai 200 234, China
e-mail: yangru@shnu.edu.cn

Abstract. For the study of information dissemination in online social networks, most existing information dissemination models include only positive relationships, ignoring the existence and importance of negative relationships, and do not consider the influence of inter-individual relationship polarity on dissemination. To solve these problems, we propose a social network information dissemination model incorporating negative relationships in this paper. Drawing on the state concept of the SIR (Susceptible Infected Recovered) model, the three types of SIR states are subdivided into five sub-states. Combining the advantages of the viewpoint evolution model, the influence of relational polarity on node attitudes is added to the modeling of the propagation process. The experiment proves that the method proposed in this paper can show more specifically the changing trend in the number of propagation nodes with different attitudes and portray the process of information propagation in online social networks.

* Corresponding authors

Keywords: Relationship classification, negative relationship, information dissemination model

1 INTRODUCTION

With the rapid development of Internet technology, online social networks are emerging and have become an important platform for information exchange in current society. Information dissemination is the core function of online social network. Thus, the research on information dissemination in online social networks has been one of the most popular research hotspots at present.

Most of the existing social network information dissemination models consider two levels, one is the user's level and the other is the relationship's level. From user-level researches on information dissemination, the current researches have considered the influence of individual differences among network users, individual attitudes, and other factors on information dissemination [1, 2]. Zheng et al. [3] considered the influence of the set of neighbors of a node on the propagation of a single node and classified the states of information propagation into four specific categories. Wang et al. [4] considered the existence of mutual influence between nodes in the dissemination process in the modeling of information dissemination. Xu et al. [5] developed a new propagation model based on the "field" principle using the equilibrium field equation, and also considered the transfer probability between nodes as a variable in the equation. Zhang et al. [6] considered the decay of interest of disseminators. Although these studies consider the interactions between node states to varying degrees, few studies consider the individualized differences in how nodes treat other nodes. In addition, most of the current researches consider attitudes (positive or negative) toward information from an individual perspective, and do not consider the influence of inter-individual relational polarity on communication. From the overall research on information dissemination at the relational level, most of the existing information dissemination models include only positive relationships and ignore the existence and significance of negative relationships. However, the formation of social networks depends on the interconnection and influence of the members in the network. Therefore in the actual social network information dissemination, the relationship between people and the polarity of the relationship are very important factors affecting information dissemination [7].

Considering the above problems, we propose a new model of social network information dissemination that incorporates negative relationships. The model is constructed from three main parts. First, the effect of inter-node relationships on node attitudes is modeled. Second, the node attitude update process is modeled. Third, the three states of the SIR model are refined into five sub-states, and the node state transition process is modeled according to the propagation rules.

The main contributions of this study are summarized as follows.

1. Considering the existence of negative relationships, we propose a model of social network information dissemination incorporating negative relationships, focusing on the influence of the existence of negative relationships among individuals on information dissemination.
2. We combine the infectious disease model and the viewpoint evolution model. The proposed model is able to predict the information dissemination process and important communication features in the network.

2 RELATED WORK

2.1 Online Social Network Information Dissemination

In the field of online social network information dissemination, related scholars have carried out a lot of research work, such as rumor propagation problems in social networks [8, 9], propagation model research [10], information forwarding prediction problems [11], and user influence problems [12, 13]. In research for propagation models, many valuable results have been accumulated based on network structure and group states.

A. Network structure-based propagation model

Independent cascade model (ICM) [14] and linear threshold model (LTM) [15] are typical propagation models based on network structure. They are the two main models that have been frequently used in previous research work on information dissemination. Both take the perspective of the nodes and assume that the nodes in the network are in two states: active and inactive. In the traditional independent cascade model and linear threshold model, the information propagation probability (user influence weight) between nodes and the threshold for nodes to change from inactive to active states are fixed. But in real social networks, the influence of users on other users changes from moment to moment. The traditional independent cascade model and the linear threshold model do not approximate real social networks.

Therefore, researchers have proposed many improved independent cascade models and improved linear threshold models to better model social network information diffusion. Feng et al. [16] modeled the influence probability based on a linear threshold model considering user interaction intensity, structural similarity and social entity similarity. Bozorgi et al. [17] proposed a competitive linear threshold model in order to solve the problem of maximizing influence in a competitive environment. Bao et al. [18] proposed an independent cascade model based on component extensions. Qin et al. [19] proposed a three-step cascade diffusion model to model the information diffusion process by considering the propagation probability and time recession factors among users.

However, both the independent cascade model and the linear threshold model are essentially simulation models, not analytical models. They can find the possibility of being in a certain state by averaging over multiple runs in the simulation, but cannot account for the initial set of parameters that will produce this result. In addition, both models assume that people are limited to two states of believing positive or negative information. This is not sufficient to represent the differences in social behavior in real social networks. Therefore, the results obtained using these two models or some variants based on them may be quite different from the actual propagation dynamics of online social networks.

B. Group state-based propagation model

The group state-based propagation model mainly assumes that nodes are in different states and uses propagation rules to predict the information propagation process. Propagation research (e.g., modeling and process analysis) is the foundation of research in the field of information dissemination. Before examining methods of controlling information dissemination, it is important to provide accurate analytical models. Therefore, in the early stage of information dissemination dynamics research, researchers began to try to construct a real sense of the analytical model of communication. Since the way information spreads on the Internet is similar to the way infectious diseases spread in medicine, many researchers have started to try to model the dynamics of information spread based on the principles of infectious disease transmission [20]. In this process, the classical model of communicable disease information dissemination gradually took shape.

The SIR (Susceptible Infected Recovered) model is currently the most comprehensive and widely used model for the dissemination of information about infectious diseases [21]. Other dissemination models based on infectious disease principles include the SI model [22], the SIS model [23], the SIER model [24], the SHIR model [25], and the SIRS model [26]. The overall idea of these models is similar to that of classical infectious disease models. They have worked on the problem of delineating propagation status, and less work has been done to explore and study the specific factors that lead to changes in propagation rates or immunization rates. Thus, such models have major limitations.

In addition, most of the existing models default all existing relational links to positive relationships and ignore negative relationships. In fact, negative relationships are no less important than positive ones in social networks [27, 28]. The relationship between people in actual social network information dissemination is an important influencing factor for the occurrence of social behavior, and the type of relationship also affects the dissemination status. Therefore, it is very necessary to take negative relationships into account and propose a more realistic model of information dissemination.

2.2 Non-Bayesian Social Learning

Users of social networks have their own attitudes towards all types of messages, they may hold positive or negative attitudes towards information dissemination. In the process of information dissemination, users' attitudes largely influence individual behaviors and decisions. From social learning theory research, it is found that individuals, when faced with newly released information, will subjectively evaluate this new news based on their preferences such as a priori knowledge, interests, and values [29]. The individual subconsciously generates an initial attitude towards the message, but does not always keep this initial attitude value constant. Individuals regulate their initial attitudes by obtaining other individuals' perspectives based on their interactions with other individuals at each moment.

Inter-individual relationships are the main factor influencing individual attitudes. Most of an individual's behaviors can be learned by observing other individuals around them. Bayesian social learning and non-Bayesian social learning are the two mainstream social learning approaches at present [30]. In contrast to Bayesian social learning, non-Bayesian learning uses a local updating mechanism for individual perspectives. It is speculative through principles such as imitation, replication, and similarity of experience. The advantage is that the update of individual attitudes or opinions can be done with a small amount of individual information. Therefore, the non-Bayesian social learning approach is more suitable for complex communication methods such as social networks. The application of non-Bayesian learning methods in social networks is mainly based on empirical derivation of the update approach. It is inferred through principles such as imitation, replication, and similarity of experience. It uses a smaller amount of individual information to accomplish the update of individual attitudes or opinions. In this paper, after considering negative relationships, we use non-Bayesian social learning principles to further explore the interactions between individual viewpoint attitudes on the network and the evolutionary patterns.

3 THE PROPOSED MODEL

The propagation model proposed in this paper is described as follows. To understand the time-series nature of the propagation model, we give a formal representation of the model: $M_{diffusion} = < I, D, t, \Omega, U_t, A_t, U_{t+1}, A_{t+1} >$. I denotes the set of user nodes in the network. D denotes the initial attitude of the current study node towards the propagation event. t denotes any moment in the information propagation process. Ω denotes the set of neighbor relations of the current study node. U_t denotes the attitude of the current study node at time t. A_t denotes the specific propagation state of the current study node at time t. U_{t+1} denotes the updated value of the attitude of the current study node at time t, which is the attitude value at the next moment. A_{t+1} denotes the specific propagation state of the current study node after the update at time t, which is the propagation state at the next moment.

The whole process of propagation is described as follows. The schematic diagram is shown in Figure 1. Any node in the current set of network user nodes I has its own initial attitude D towards the event in the initial phase of the specific event propagation. With the continuous propagation of information, at any time t, the node will consider whether to further update its propagation attitude based on its current attitude U_t and current state A_t as well as its relationship and relationship polarity with its neighbors in the set of neighboring nodes Ω, so as to obtain a new attitude value U_{t+1} at time $t+1$. Then the node further determines the state A_{t+1} at time $t+1$ based on the attitude value U_{t+1}. The above steps are repeated over and over again as the time step is updated.

$$M_{diffusion} = < I, D, t, \Omega, U_t, A_t, U_{t+1}, A_{t+1} >$$

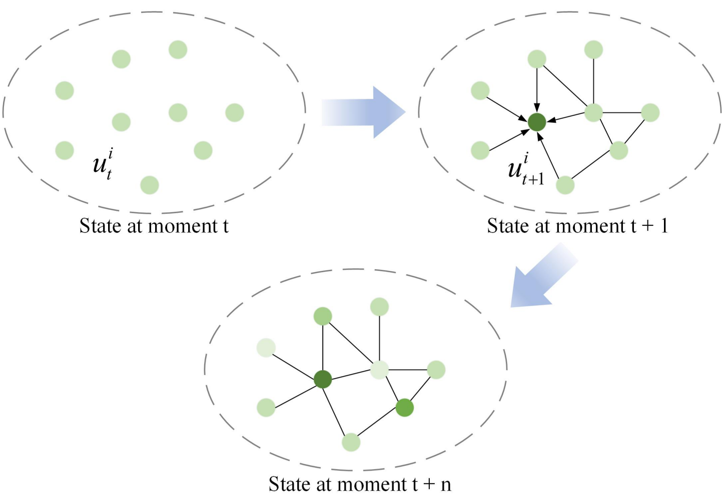


Figure 1. Propagation process diagram

3.1 Model Framework

The model contains two main parts: modeling the influence of inter-node relationships on node attitudes and modeling the information dissemination process that incorporates negative relationships. The general modeling framework of the model is shown in Figure 2.

First, we give eight combinations of interactions and four major types of interaction process analysis based on common sense theory and the results of questionnaires on the influence of interpersonal relationships on information dissemination. Based on the fact that node states are influenced by inter-node relationships, we analytically derive the mathematical expression: the influence of a node j on node i

at a moment t is $a \times u_t^j$. The modeling process of node state update starts from modeling the influence of a single node, and then models the process of combined influence by multiple nodes. The specific update formula and the derivation process are described in the following section.

Second, we first model the node attitude update process, and then carry out modeling of the node state transition process according to the dissemination rules. Based on the SIR model, we divided the model into a base model and an optimization model. The base model extends the three states of the SIR. The optimization model subdivides the three states of the SIR into five sub-states. The conversion probability is also refined. The specific derivations and calculations are described in the later sections.

3.2 Modeling the Influence of Inter-Node Relationships on Node Attitudes

To take into account the influence of interpersonal polarity on information dissemination more reasonably, we conducted a relevant questionnaire survey and analyzed the collected data for reasonableness. The questionnaire mainly investigates the propensity of information dissemination targets to disseminate information sources with different relationship types and the specific propensity of communication targets to disseminate information sources with different relationship polarity. Thus it can provide a basis for the next parameter setting of the relationship polarity to information dissemination modeling and the parameter setting of non-autonomous factors in the dissemination process.

The survey on the influence of interpersonal relationships on information dissemination behavior was sent through the questionnaire platform, and 426 valid questionnaires were returned. The main questions in the questionnaire survey and the specific survey data statistics of the questionnaire results are as Tables 1, 2 and 3.

Options	Amount	Proportion
People who are in positive relationships with themselves	345	80.99 %
People who are in negative relationships with themselves	5	1.17 %
Indifferent attitude	76	17.84 %

Table 1. Source statistics of transmission tendency

Based on the statistical results of the above questionnaire data, we can make the following preliminary analysis:

First, we found that more than 80 % of the respondents said they usually prefer to retweet messages from contacts with positive relationships, while less than 2 % said they usually prefer to retweet messages from contacts with negative relationships. This can indicate that relationships have a strong influence on information dissemination behavior, and more than half of people say they are not willing to

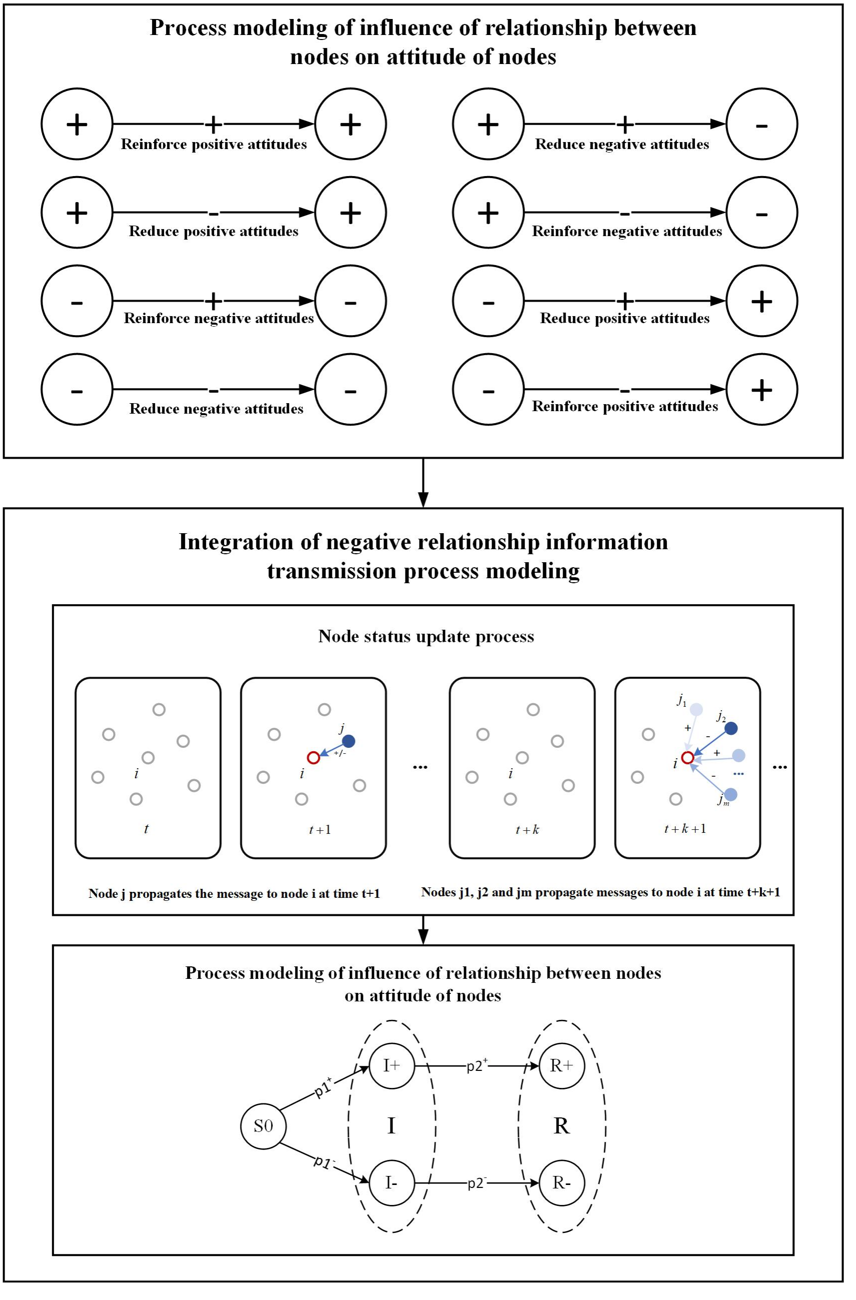


Figure 2. Frame diagram of information transmission model modeling process integrating negative relations

Options	Amount	Proportion
Will not	34	7.98 %
Will do (0 to 30 % chance)	98	23 %
Will do (30 % to 50 % chance)	75	17.61 %
Will do (50 % to 80 % chance)	124	29.11 %
Will do (80 % to 100 % chance)	72	16.9 %
Be certain to do	23	5.4 %

Table 2. Contact probability statistics for positive relationships

Options	Amount	Proportion
Will not	278	65.26 %
Will do (0 to 30 % chance)	106	24.88 %
Will do (30 % to 50 % chance)	27	6.34 %
Will do (50 % to 80 % chance)	9	2.1 %
Will do (80 % to 100 % chance)	5	1.17 %
Be certain to do	1	0.23 %

Table 3. Contact probability statistics for negative relationships

disseminate information shared by contacts from negative relationships, while less than one in ten say they are not willing to disseminate information shared by contacts from positive relationships. Therefore, it can be further shown that negative relationships may have some hindering influence on the dissemination behavior of information itself.

Second, we found that Table 2 and 3 did not show opposite data distributions. Among them, the survey data statistics on the dissemination of positive relationship news are normally distributed, and the survey data statistics on the dissemination of negative relationship news show a power-law distribution. The reasons are as follows: There is no complete trust between people, and most friends still keep a certain distance between them, which is also in line with the laws of social interaction in the real world; The influence of negative relationships is relatively absolute, and people often show very obvious resistance to negative relationships, which is also in line with the laws of social interaction in reality. The above data suggest that the influence of negative relationships on human behavioral performance is relatively easy to assess, which makes our grasp of the assessment of the influence of negative relationships in the modeling of information dissemination more accurate and convincing.

There are two prominent problems with the current research work on social networks: One is that most of them focus on traditional non-symbolic social networks, and relatively little research has been done on symbolic social networks with relationship type labels; another is the relatively little analytical work on the influence of nodal relationships on information dissemination. First, the relational polarity between nodes in traditional studies usually defaults to positive, and while ignoring the existence of negative relationships, it also ignores the influence of negative relationships, especially the influence of the relational polarity of node pairs on node attitudes. The node attitude here refers to an individual's viewpoint on a specific matter. For a specific information dissemination problem, the node attitude is essentially a comprehensive assessment of the node's intention and willingness to disseminate. Second, most of the existing studies based on inter-node relationships are based on two common sense-based assumptions proposed by Li et al. [31]:

1. Trusting relationships spread the same views;
2. Distrustful relationships can spread contrary views.

This assumption assumes that the influence of positive and negative relationships in symbolic social networks are opposed to each other, which simply means that positive relationships drive communication and negative relationships can hinder communication. However, such an assumption is too absolute to model the subtle influence of interpersonal relationships on changes in personal perspectives.

Therefore, to more specifically portray the influence of inter-node interactions and relational polarity on attitudes, this paper analyzes and models the different nodes holding positive or negative attitudes and the inter-node relationships based on existing common sense assumptions and the findings of the questionnaire analysis. It derived 8 combinations of interactions, as Figure 3 shows. This interaction can be expressed as the influence of node j on node i at some t moment is the product of the attitude of node j and the polarity of the relationship between the two nodes, that is, $a \times u_t^j$, where a denotes the polarity of the relationship between nodes i and j. The analysis of the eight specific interactions leads to four types of interaction combinations, as follows.

1. For two nodes a and b holding positive attitudes, if the relationship between a and b is positive, the presence of a will deepen the positive attitude of b. Conversely, if the relationship between a and b is negative, the presence of a will weaken the positive attitude of b;
2. For two nodes a and b holding negative attitudes, if the relationship between a and b is positive, the presence of a deepens the negative attitude of b. Conversely, if the relationship between a and b is negative, the presence of a weakens the negative attitude of b;
3. For node a, which holds a positive attitude, and node b, which holds a negative view, the presence of a diminishes the negative attitude of b if the relationship between a and b is positive, and conversely, the presence of a deepens the negative attitude of b if the relationship between a and b is negative;
4. For node a, which holds a negative attitude, and node b, which holds a positive view, if the relationship between a and b is positive, the presence of a will weaken the positive attitude of b. Conversely, if the relationship between a and b is negative, the presence of a will deepen the positive attitude of b.

To better understand the above interaction process, the above modeling process is explained here with a typical example diagram analysis, as shown in Figure 4.

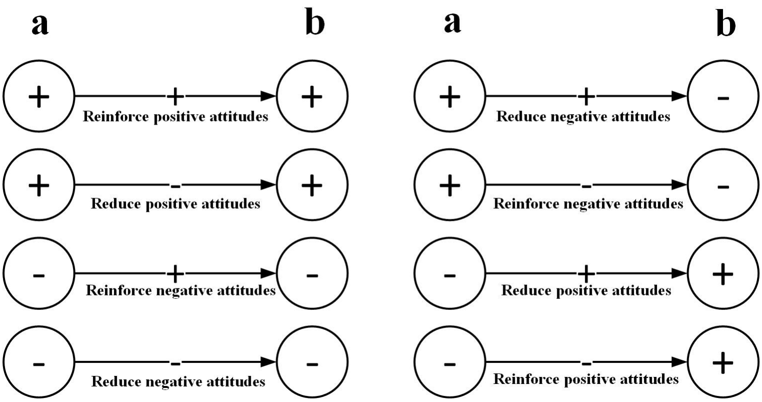


Figure 3. Analysis of the influence of node status between users on the relationship between nodes

Suppose that node u has two neighboring nodes v and w, where the relationship between node u and v is positive and the relationship between node u and w is negative. For a specific event, if the initial state of node u has a negative attitude, nodes v and w both have positive initial attitudes. From the perspective of node u, both neighboring nodes v and w may have an influence on the attitude of node u. Due to the different polarity of the relationship, the influence produced will be different. For node u, because it is friends with node v, the positive attitude of node v may have an influence on it, thus attenuating the negative attitude of it. Conversely, since node u and node w are in an adversarial relationship, for node u, the positive attitude of node w may instead have a strengthening influence on the negative attitude leading to it.

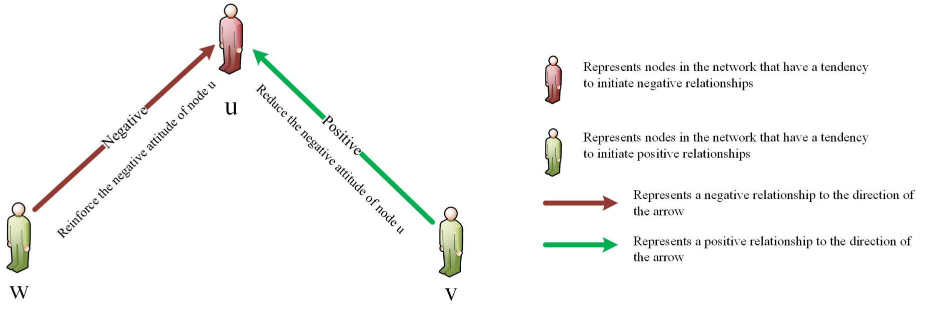


Figure 4. Example diagram of node state change process

3.3 A Model of Information Dissemination Process Incorporating Negative Relations

A. Node Attitude

The node attitude updating process in this paper is mainly based on non-Bayesian social learning principles. For the attitude updating process, given a symbolic social network $G = (V, E, S)$, this paper constructs a specific analytical model of the interactions between nodes and the influence of relational polarity on attitudes, as shown in Figure 3. On this basis, the existing non-Bayesian social learning update method is further optimized to give the specific definition of the single node attitude update method proposed in this paper.

Definition 1. Single node attitude update method: Suppose that node i and node j in the network hold attitudes u_t^i and u_t^j at moment t, respectively, and node j propagates a message to node i at the moment $t+1$, next moment, the attitude of node i will complete the update, and the specific update process is shown in Equation (1):

$$u_{t+1}^i = u_t^i + a\delta(i,j)u_t^i \tag{1}$$

where a denotes the polarity of the relationship, with $a = +1$ if the relationship type is positive and $a = -1$ if the relationship type is negative, $\delta(i,j)$ denotes the convergence parameter of the attitude of node i to node j, which is the rate of change of the attitude of node i under the influence of the attitude of j.

This paper defines the rate of attitude change of node i more intuitively as the inter-node influence function (convergence parameter), which is denoted by the node influence weight $\delta(i,j)$. The specific definitions are as follows:

Definition 2. Inter-node influence function $\delta(i,j)$: Assuming that $k(j)$ is the number of neighbors of node i, $\tau(j)$ denotes the set of neighbors of node i, and node $j \in \tau(i)$ is a neighbor of node i, the influence of j on i is calculated as follows:

$$\delta(i,j) = \frac{k(j)}{\sum_{t\in\tau(j)} k(t)}. \tag{2}$$

$\sum_{t\in\tau(j)} k(t)$ is the sum of the degrees of all neighbors of node i. Obviously, the greater the degree $k(j)$ of node j, the greater its influence $\delta(i,j)$ on node j.

If, at the moment $t+1$, i has multiple neighbor nodes and m of them all propagate to it the same information, then the update of the attitude of node i has to consider the influence of these m neighbor nodes at the same time. And the update of the attitude value of node i is calculated at this time as:

$$u_{t+1}^i = u_t^i + \frac{1}{m}\sum_m a\frac{k(j)}{\sum_{t\in\tau(j)} k(t)}\, u_t^{jm}. \tag{3}$$

To represent the update process more specifically, a schematic diagram of the attitude update of a single node in the network is given in this paper, as shown in Figure 5. From the update process, the value of $\delta(i, j)$ determines the rate of change of the attitude of the node. The larger the value calculated by $\frac{k(j)}{\sum_{t \in \tau(j)} k(t)}$, the closer the attitude of node i is to the propagating node.

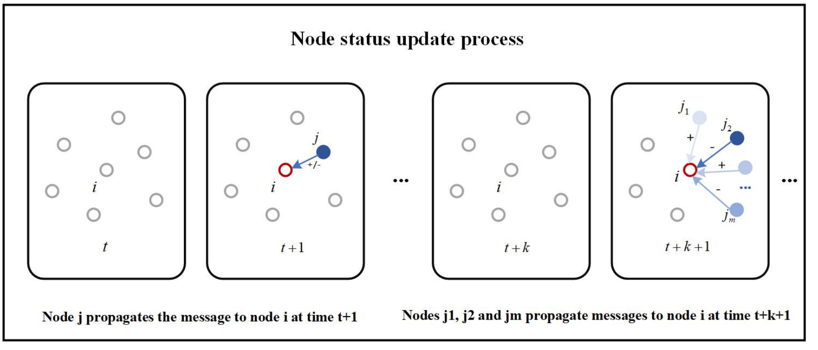


Figure 5. Schematic diagram of attitude update of a single node

B. Propagation rules description

As mentioned in the previous introduction, both information transmission and virus transmission have similar premises and similar transmission patterns. The classical social network information dissemination models based on the principle of infectious diseases are mainly divided into Susceptible-Infected (SI) model, Susceptible-Infected-Susceptible (SIS) model, Susceptible-Infected-Recovered (SIR) model, etc. These models assume that when the propagation rate of information knowns to an unknown is greater than a certain threshold, the information knowns will propagate information to the unknown until the entire network of information knowns is in some stable state. In this paper we improve the traditional SIR model and further describe the propagation rules.

As a classical information dissemination model, the SIR model classifies the nodes in the network into three main categories: the healthy S state, which has never received a message; the I state, which has the ability to disseminate; and the immune R state, in which no more dissemination behavior occurs. The SIR model can be simply described as follows: a user publishes a message at a point in time and becomes the initial infection source node. Next, neighboring nodes infected with the source node will accept this message and may complete the forwarding behavior with probability $p1$, the neighboring node state is converted from S state to I state. The node with I state will end the whole propagation process by switching from I state to R state with probability $p2$ after propagating the information. The state transition is shown in Figure 6.

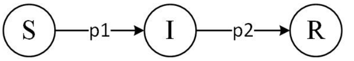


Figure 6. Traditional SIR model propagation diagram

The traditional SIR model keeps both the infection probability $p1$ and immunity probability $p2$ constant during the transmission process. In an actual online social network, the attitude of nodes is constantly updated over time. The update of node attitudes also leads to a consequent change in the transfer probability between individual states. And the different polarities of the nodes' attitudes lead to a relatively positive and negative influence on the disseminated information. Thus, based on the SIR model, this paper assumes that the nodes in the network may be in one of the five states S, I^+, I^-, R^+, and R^-. And the states of the nodes may change. The specific propagation model state transitions are shown in Figure 7. Since state changes are directly and closely related to the possibilities of transition between states, this paper will assume that the probability of infection from the S state to the I^+ state is $p1^+$ and from the S state to the I^- state is $p1^-$; the probability of immunity from the I^+ state to the R^+ state is $p2^+$ and from the I^- state to the R^- state is $p2^-$. Table 4 describes the states and parameters of this section in detail.

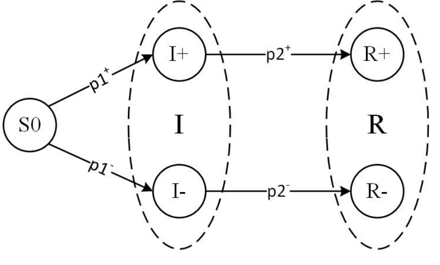


Figure 7. Transformation diagram of information transmission model based on node attitude change

Based on the above analysis, this paper quantifies the node attitudes on and redesigns the corresponding new propagation rules by combining the different propagation influence caused by the different polarity of node attitudes, as described below:

1. There are three major classes of states for nodes in the network, and the three classes of states can be further subdivided into five specific states, which are S state, I^+ state, I^- state, R^+ state, and R^- state. The I state can be subdivided into I^+ state and I^- state, which represent the communication states with positive and negative emotions towards the message, respectively. The R state can be subdivided into the R^+ state and the R^- state, which

Notation	Description
S	The health state that has never received a message
I	The state with the ability to spread
I^+	The state with a tendency to spread positive influences
I^-	The state with a tendency to spread negative influences
R	The immune state with loss of transmission capacity
R^+	The state of maintaining a positive influence but no longer disseminating
R^-	The state of maintaining a negative influence but no longer disseminating
$p1$	The probability of infection from S state to I state
$p1^+$	The probability of infection from S state to I^+ state
$p1^-$	The probability of infection from S state to I^- state
$p2$	The probability of immunization from I state to R state
$p2^+$	The probability of immunization from I state to R^+ state
$p2^-$	The probability of immunization from I state to R^- state

Table 4. Description of node state and transformation probability

indicate the immune state with positive and negative emotions towards the message, respectively.

2. If a node in S state receives the influence of the propagated information from the propagating node, then the attitude value of the current state node will also complete further update operations according to the attitude update principle. A node in S state may switch with probability $p1^+$ to the propagation I^+ state with positive attitude tendencies, or switch with probability $p1^-$ to the propagation I^- state with negative attitude tendencies, $p1 = p1^+ + p1^-$.
3. Once a node becomes immune to the R state, it will not be affected by the propagation node or propagation behavior, but will remain in the R^+ or R^- state until the end of propagation.
4. During propagation, a propagation node in the I^+ state may switch with probability $p2^+$ to the immune R^+ state with positive attitude tendency, or a propagation node in the I^- state may switch with probability $p2^-$ to the immune R^- state with negative attitude tendency, $p2 = p2^+ + p2^-$. It is also stipulated that nodes in propagation states cannot be transformed between specific propagation I^+ state and I^- state.

C. Node state transition

The propagation dynamics of the classical SIR information propagation model are:

$$\frac{\mathrm{d}S(t)}{\mathrm{d}t} = -p1S(t)I(t), \tag{4}$$

$$\frac{\mathrm{d}I(t)}{\mathrm{d}t} = p1S(t)I(t) - p2I(t), \tag{5}$$

$$\frac{\mathrm{d}R(t)}{\mathrm{d}t} = p2I(t) \tag{6}$$

where the network size is the total number of nodes as N and $S(t)$ denotes the total number of nodes in the network in S state at moment t, $I(t)$ denotes the total number of nodes in the network that are in I state at time t, $R(t)$ denotes the total number of nodes in the network that are in R state at moment t, and satisfies $S(t) + I(t) + R(t) = N$. The parameter $p1$ denotes the probability that an S state node makes contact with an I state node and becomes a new I state node. The parameter $p2$ indicates the probability that a node in I state becomes a node in R state during the propagation process.

In this paper, we model the node attitude updating process of inter-node relationships based on non-Bayesian social learning principles, and consider negative relations to define new variable transfer probability calculation methods. The relevant parameters and descriptions are shown in Table 5.

Notation	Description
p_i^{SS}	The probability that node i remains in S state
p_i^{SI}	The probability of node i changing from S state to I state
p_i^{II}	The probability that node i remains in I state
p_i^{IR}	The probability of node i changing from I state to R state
β	Non-autonomous factors of node transition from S state to I state
γ	Non-autonomous factors of node transition from I state to R state
$\Gamma_m^I(i)$	The set of $I-$state nodes that deliver information to node i in state S
$p1^{j_1^I}$	The infection probability of node i under the influence of propagating node j
$p1^{j_m^I}$	The infection probability of node i under the influence of m propagating nodes

Table 5. Description of transformation parameters and symbols

1. At moment t, the attitude value of healthy node i in S state is assumed to be u_t^i, and at moment $t+1$, the probability of node i maintaining healthy S state is assumed to be P_i^{SS}, while the probability of node i moving from healthy S state to propagation I state is P_i^{SI}, and $P_i^{SS} + P_i^{SI} = 1$. The transition is schematically shown in Figure 8.

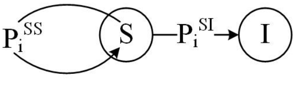


Figure 8. Schematic diagram of S state transition

If at moment $t+1$, healthy node i in S state receives information propagation from a single propagation node j in I state. A single propagation node j can be denoted j_1^I. The infection probability $p1^{j_1^I}$ can be expressed as:

$$p1^{j_1^I} = u_{t+1}^{j_1^I} + \left(1 - u_{t+1}^{j_1^I}\right) \times \beta \tag{7}$$

where $u_{t+1}^{j_1^I}$ represents the updated attitude value of node i at moment $t+1$ after being subjected to a message transfer from a single node j_1^I in I state. β represents the non-autonomous factors of the node's transition from S state to I state, such as the nature of the message, the self-attraction of the message, etc.; $(1-u_{t+1}^{j_1^I})\times\beta$ represents the proportion of the non-autonomous factors in the transfer probability.

At this point, the probability that node i remains healthy under the influence of a single propagating node j_1^I is then $1-p1^{j_1^I} = 1-\left[u_{t+1}^{j_1^I} + \left(1 - u_{t+1}^{j_1^I}\right) \times \beta\right]$. If there exist m propagating nodes propagating messages to healthy node i at moment $t+1$, then node i will be under the joint influence of these m propagating nodes, and the probability of maintaining S state despite this joint influence can be expressed as:

$$\begin{aligned}
p_i^{SS} &= \left(1 - p1^{j_1^I}\right)\left(1 - p1^{j_2^I}\right)\dots\left(1 - p1^{j_m^I}\right) \\
&= \prod_{j_m^I \in \Gamma_m^I(i)} 1 - p1^{j_m^I} \\
&= \prod_{j_m^I \in \Gamma_m^I(i)} \left\{1 - \left[u_{t+1}^{j_m^I} + \left(1 - u_{t+1}^{j_m^I}\right) \times \beta\right]\right\} \\
&= \prod_{j_m^I \in \Gamma_m^I(i)} \left\{1 - \left[u_t^i + \alpha u_t^{j_m^I} \delta\left(i, j_m^I\right) \times (1-\beta) + \beta\right]\right\}.
\end{aligned} \tag{8}$$

where $\Gamma_m^I(i) = \left\{j_1^I, j_2^I, \dots, j_m^I\right\}$ denotes the set of I-state nodes that deliver information to node i of S state.

Therefore, the probability p_i^{SI} of a healthy node i changing from the original S state to the I state under the joint influence of m propagating nodes can be expressed as follows:

$$\begin{aligned}
p_i^{SI} &= 1 - p_i^{SS} \\
&= 1 - \prod_{j_m^I \in \Gamma_m^I(i)} \left\{1 - \left[u_t^i + \alpha u_t^{j_m^I} \delta\left(i, j_m^I\right) \times (1-\beta) + \beta\right]\right\}.
\end{aligned} \tag{9}$$

In this paper, we quantify the node i attitude value u_t^i at a certain t moment on the scale of $[-1,1]$. If the node attitude u_t^i is between $[-1,0]$ for negative state. And the node attitude u_t^i is between $[0,1]$ for positive state, which means node i has the intention of propagation behavior and both the propagation node in the positive state. The propagation node in the negative state has the same ability to influence the behavior state of other nodes. In calculating the probability when node transfer probability, according to the definition given before, the probability of a node transforming from a healthy state to a propagated state $p1$ is:

$$p1 = 1 - \prod_{j_m^I \in \Gamma_m^I(i)} \left\{1 - \left[\left|u_t^i + \alpha u_t^{j_m^I} \delta\left(i, j_m^I\right)\right| \times (1-\beta) + \beta\right]\right\}. \tag{10}$$

The probability of transitioning from the S state to the I^+ state to become a positively propagating node is $p1^+$. When the node attitude is positive, that is, when the node attitude value is greater than zero, $p1^+$ is calculated as follows:

$$\begin{aligned} p1^+ &= p_i^{SI} = 1 - p_i^{SS} \\ &= 1 - \prod_{j_m^I \in \Gamma_m^I(i)} \left\{1 - \left[u_t^i + \alpha u_t^{j_m^I} \delta\left(i, j_m^I\right) \times (1-\beta) + \beta\right]\right\}. \end{aligned} \tag{11}$$

Based on the derivation of Equations (9) and (10), the probability $p1^-$ of transitioning from the S state to the I^- state to become a negatively propagated node is obtained. The calculations are as follows:

$$\begin{aligned} p1^- =& p1 - p1^+ \\ =& \left\{1 - \prod_{j_m^I \in \Gamma_m^I(i)} \left\{1 - \left[\left|u_t^i + \alpha u_t^{j_m^I} \delta\left(i, j_m^I\right)\right| \times (1-\beta) + \beta\right]\right\}\right\} \\ &- \left\{1 - \prod_{j_m^I \in \Gamma_m^I(i)} \left\{1 - \left[u_t^i + \alpha u_t^{j_m^I} \delta\left(i, j_m^I\right) \times (1-\beta) + \beta\right]\right\}\right\}. \end{aligned} \tag{12}$$

2. At the moment $t+1$, the probability that the propagation node i originally in I state maintains the propagation state is assumed to be p_i^{II}, and the probability of node i moving from propagation I state to immune R state is p_i^{IR}, and $p_i^{II} + p_i^{IR} = 1$. The conversion schematic is shown in Figure 9.

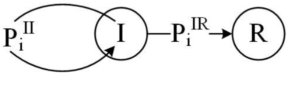


Figure 9. I Schematic diagram of state transition

At the moment $t+1$, if node i in I state is subjected to the influence of propagating node j_1^I, the probability that node i transforms from I state to

R state at this time is:

$$p_{i|j_1^I}^{IR} = \left(1 - u_{t+1}^{j_1^I}\right) + u_{t+1}^{j_1^I} \times \gamma \tag{13}$$

where γ denotes the non-autonomous factors of node transfer from the I state to the R state, such as encountering immune nodes, etc. $u_{t+1}^{j_1^I} \times \gamma$ represents the proportion of non-autonomous factors in the probability of transfer.

If there exist m propagating nodes propagating messages to node i at time $t+1$, the probability of node i moving from I state to R state is:

$$p_i^{IR} = \prod_{m=1}^{m} p_{i|J_m^I}^{IR} = \prod_{m=1}^{m} \left(1 - u_{t+1}^{j_m^I}\right) + u_{t+1}^{j_m^I} \times \gamma. \tag{14}$$

The transformation of a node from a propagation state to an immune state can also be divided into two specific cases:

(a) Transitioning from the I^+ state to the R^+ state becomes an immune state node that maintains a positive view with probability $p2^+$.
(b) The probability of switching from an I^- state to an R^- state and becoming an immune state node that maintains a negative view is $p2^-$.

In addition, considering the property of non-negative probability, this paper takes the absolute value of negative attitudes and uses the absolute value as its propagation probability. In summary, the probability $p2$ of a node transforming from the I state to the R state is:

$$p2 = \prod_{m=1}^{m} \left(1 - \left|u_{t+1}^{j_m^I}\right|\right) + \left|u_{t+1}^{j_m^I}\right| \times \gamma. \tag{15}$$

The probability of switching from the I^+ state to the R^+ state to become an immune state node that maintains a positive view is $p2^+$, when the node attitude is greater than zero:

$$p2^+ = \prod_{m=1}^{m} \left(1 - u_{t+1}^{j_m^I}\right) + u_{t+1}^{j_m^I} \times \gamma. \tag{16}$$

The probability of switching from an I^- state to an R^- state to become an immune state node that maintains a positive view is $p2^-$:

$$\begin{aligned} p2^{-} =& p2 - p2^{+} \\ =& \left\{ \prod_{m=1}^{m} \left(1 - \left|u_{t+1}^{j_m^I}\right|\right) + \left|u_{t+1}^{j_m^I}\right| \times \gamma \right\} \\ &- \left\{ \prod_{m=1}^{m} \left(1 - u_{t+1}^{j_m^I}\right) + u_{t+1}^{j_m^I} \times \gamma \right\}. \end{aligned} \tag{17}$$

The specific propagation rules of the propagation model constructed in this paper and the way of transition between states are described in detail above, which can reflect the update of node attitudes at each time step and its influence on the transfer probability of each state, as well as the dynamic changes in the state transfer process.

4 EXPERIMENT AND ANALYSIS

We use a subset of the symbolic social network dataset Bitcoin-Alpha as a test dataset. The Bitcoin-Alpha dataset [31] comes from a Bitcoin trading site where users are anonymous and therefore need to establish an online trust network to ensure their security. Bitcoin-Alpha members set other members' ratings to range from −10 (not at all trustworthy) to +10 (fully trustworthy), which helps prevent fraudulent transactions from occurring. In this paper, scores greater than 0 are considered positive and other scores are considered negative. The nodes in the network represent the users in the site, and the connected edges and labels between users represent whether the relationship between them is positive or negative. The total number of nodes in this dataset is 3 183, the number of edges is 14 124, the average degree is 7.3090, and the average aggregation coefficient is 0.1775. Next, this paper will conduct specific experiments on the proposed information dissemination model incorporating negative relations from the following aspects:

1. We analyze the overall process of propagation, focusing on the five types of node state change trends proposed in this paper, and then further analyze the influence of inter-node relationships in the network on propagation.
2. We compare the model proposed in this paper with the classical SIR model with the same parameters and two more mature propagation models based on the IC model and LT model, SC-B model and TG-T-B model, respectively, which are applicable to symbolic networks, to demonstrate the effectiveness of our proposed model in predicting the information propagation process and its applicability in symbolic social networks.

4.1 Analysis of Information Dissemination Process

At the beginning of the information dissemination process, an arbitrary "seed node" is selected as the dissemination state in the initial state, and all other nodes are temporarily in the easy-to-propagate state. The propagating node can disseminate information to its neighbors in a propagation-prone state, and may also be influenced by other nodes. After a period of time, the propagation nodes will lose their propagation interest and stop disseminating information, transforming into an immune state. Propagation nodes maintain their views even after switching to immune nodes. Based on the model proposed in this paper, the trend of the number of nodes in the network with time change for the three major categories of nodes is first analyzed, and the results are shown in Figure 10.

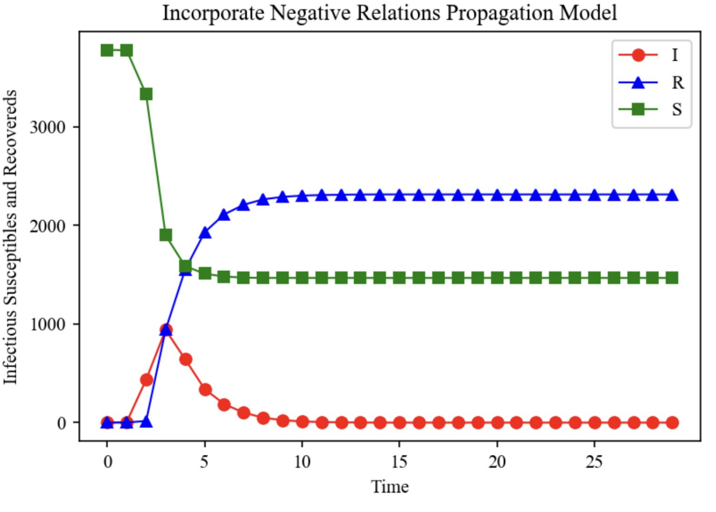


Figure 10. Node information transmission trend of the three categories

By observing the trend of the number of nodes in the three types of states in the figure, we can see that the number of immunity is zero in the initial condition, and after the seed nodes start to propagate, the number of nodes in the easy propagation state rapidly decreases and become nodes in the new propagation state, leading to a rapid increase in the number of propagation nodes. With the extension of time, some of the nodes in the propagation state lose their propagation interest due to a combination of factors, and thus make the number of nodes in the immune state increase. When the number of nodes in the propagation state reaches its peak, the nodes in the propagation state are still transformed into nodes in the immune state with a certain probability as time changes, that is, the number of nodes in the propagation state gradually decreases and the number of nodes in the immune state gradually increases until the nodes in the propagation state disappear and the number of nodes in the immune state stabilizes, and the propagation process ends. In summary, the propagation process is consistent with the characteristics of real propagation in which the number of propagation nodes rises sharply and then ends slowly, which can reflect the process of creation, development and extinction of information propagation in the network. Therefore, the information dissemination model incorporating negative relationships proposed in this paper is able to better reflect the information dissemination law in online social networks.

In addition, in order to more clearly and intuitively reflect the node state change trend in the model proposed in this paper, we further analyze the five possible states of S, I^+, I^-, R^+, and R^- of the nodes in the network on the basis of the above three types of node state analysis. The trend of the number of nodes in the network with time for five specific node categories is shown in Figure 11.

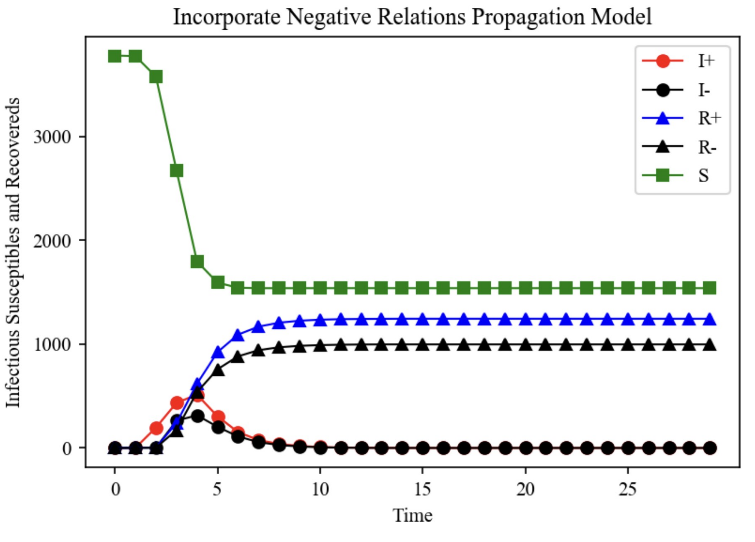


Figure 11. Information transmission trend diagram after node status is specified

We arbitrarily select the nodes in the I^+ state as seed nodes in the initial stage of propagation. If the conventional model is extrapolated, there will be only I^+ state propagation nodes during the propagation process, and after some time the I^+ state nodes slowly become R^+ state nodes. In fact, this inference is not reasonable. This is also demonstrated in our experiments, as shown in Figure 11. Since people are social in nature, each individual has his or her own attitude or viewpoint towards different information or specific events. And people will demonstrate positive or negative communication behaviors depending on the social environment and the influence of people around them. Therefore, the existence of positive attitudes in the communication process will inevitably lead to the opposite negative attitudes.

In addition, since there is no specific classification of the type of information or event itself in this paper, the information or event in this paper is neutral by default. As for neutral events, theoretically, there should not be a significant difference in the number of propagation state nodes for the two different attitudes. The specific state in which the number of propagating nodes is dominant may be related to the state of the first propagating seed nodes and the overall propagation preferences of the node community. This is also consistent with the results presented in Figure 11.

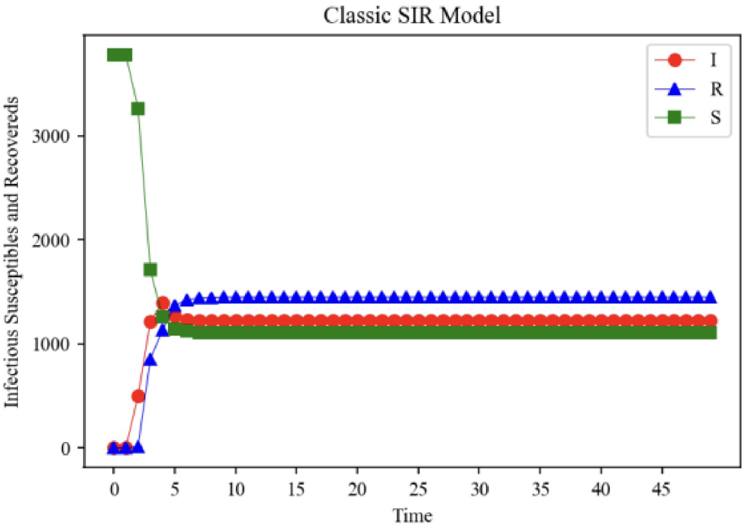
Therefore, the experimental results and analysis prove that the information dissemination model incorporating negative relations proposed in this paper can reasonably reflect the information dissemination law in online social networks, and also can more specifically show the change trend in the number of nodes with different attitudes of dissemination status. Our research can provide more specific directions for the government and other relevant public opinion monitoring departments to consider regarding the adjustment of the overall direction of public opinion to maintain social stability.

4.2 Comparison and Analysis with Other Models

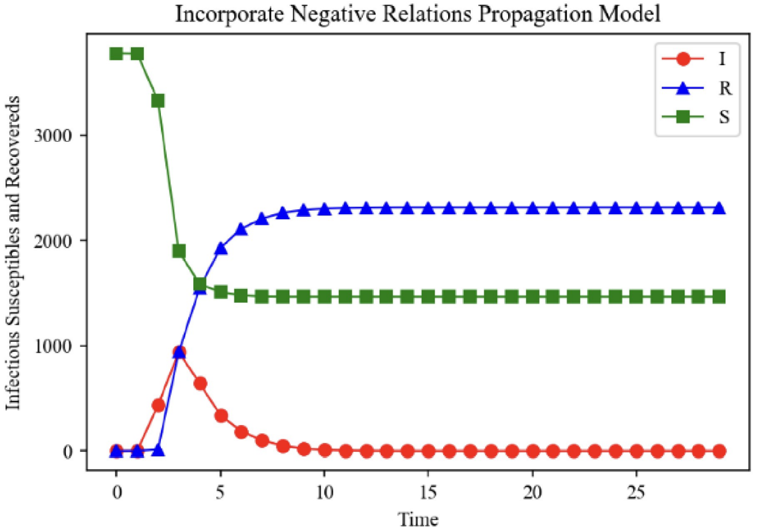
Next, we simulate the proposed information propagation model incorporating negative relations with the classical SIR model and the more mature IC-based propagation models SC-B model and TG-T-B model for symbolic networks in the same environment and with the same symbolic network data set.

Since the classical SIR model is still mainly applied to the information propagation prediction of unsigned networks at this stage, here we set the initial parameters of the model as follows: First, we use the SIR model to select an arbitrary "seed node" at the initial stage of the information dissemination process, and set the state of the seed node to the propagation state, and all other nodes are temporarily in the easy propagation state. At the same time, in order to consider the special characteristics of symbolic networks, we set the strength of any link randomly between the interval $(-1, 1)$ while considering the polarity of edges. In the process of propagation, based on the strength of linked edges, the propagating nodes may spread the information to their neighbors in the easy propagation state with a certain probability, or they may be transformed into immune nodes with a certain probability. Next, we compare the trend of the number of nodes in the SIR model with the number of nodes over time with the model proposed in this paper, as shown in Figure 12.

By observing and comparing Figure 12 a) and 12 b), we can find that the propagation process using the SIR model is consistent with the sharp increase in the number of propagation nodes in real propagation compared with using the model proposed in this paper, while the propagation process using the SIR model does not conform to the characteristics of real propagation in which the number of nodes in the propagation state reaches a peak and then ends slowly. The number of propagation nodes in Figure 12 a) eventually tends not to zero, but a constant, while in real life, the information dissemination process cannot always be in a state of intense propagation continuously. Therefore, the traditional SIR model does not reflect the extinction process of information dissemination in symbolic social networks. The proposed model reflects the process of creation, development and extinction of information dissemination in symbolic social networks. It also proves the applica-

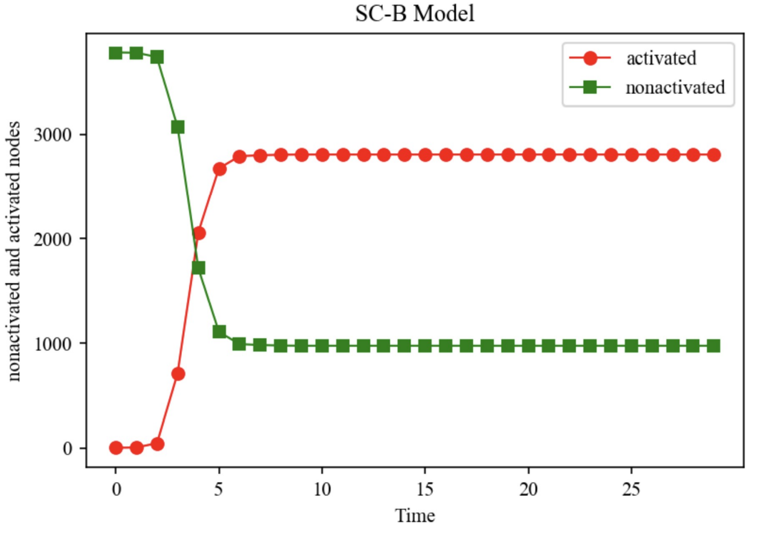


a) Evolution data graph of classical SIR model on symbolic network data set

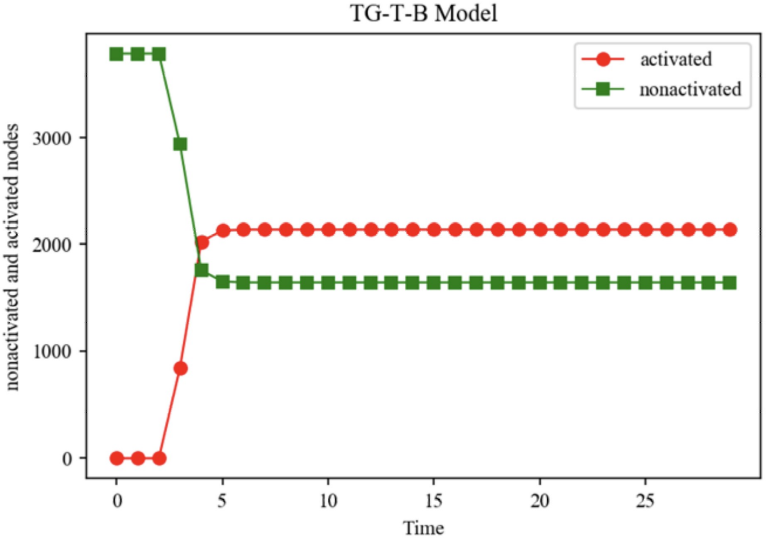


b) The evolution data graph of the proposed model on symbolic network dataset

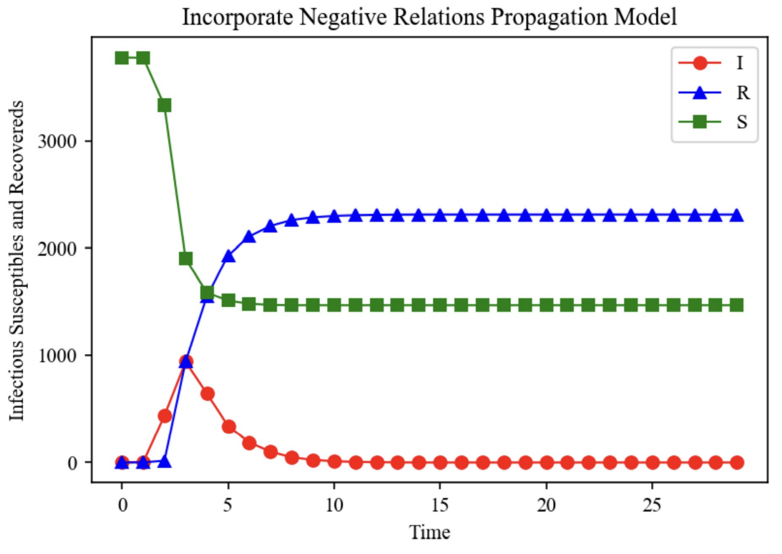
Figure 12. Comparison diagram of the propagation trend of the classic SIR model in the same environment



a) SC-B model evolution data graph on symbolic network dataset



b) Evolution data graph of TG-T-B model on symbolic network dataset



c) Model evolution data graph presented in this paper on symbolic network dataset

Figure 13. Comparison diagram of propagation trend with SC-B model and TG-T-B model designed based on symbolic network in the same environment

bility of the information dissemination model incorporating negative relationships proposed in this paper in compliance with social networks.

We simulate the SC-B model and the TG-T-B model, which are improved propagation models based on the IC model and the LT model applicable to symbolic networks, with the models proposed in this paper in the same environment and with the same symbolic network data set. And the trend of the number of nodes in the three models with the time change is shown in Figure 13.

By comparing and observing Figure 13 a), 13 b), and 13 c), we can see that using the SC-B model and the TG-T-B model remain basically the same as using the model proposed in this paper in terms of the time to reach the peak of propagation, i.e., all three models can evaluate the practice and the maximum propagation range of the propagation nodes in the network to reach the peak. However, the SC-B model and TG-T-B model cannot portray the propagation extinction time and extinction process, and have limitations in propagation prediction. The model proposed in this paper can well portray the process of communication extinction and give prediction of the time of communication extinction, which can better reflect the complete process of information communication and predict important communication characteristics.

In summary, we can see that the model proposed in this paper can better estimate the maximum possible coverage of propagation events, predict the earliest possible time to reach the peak of propagation and the total duration of the disappearance of propagation nodes. These are important for monitoring the development of public opinion and making corresponding preventive and emergency measures in time.

5 CONCLUSIONS

In this paper, we study the information dissemination model based on the attitude change of nodes from the relationship perspective, and propose a social network information dissemination model incorporating negative relationships. The conclusions of our study can be drawn as follows.

1. We analyze the influence of negative relationships on communication in the context of social research. The modeling of nodal attitudes is more reasonable.
2. We give a mathematical description and characterization of node attitudes and their changes, so as to construct an information dissemination model applicable to symbolic social network analysis.
3. The experiments prove that the model proposed in this paper can reflect the trend of nodes in the propagation process in terms of quantity and predict the important propagation characteristics.

Since the relationship evaluation mechanism in this paper does not specifically quantify the relationship strength and size, in the future, we will work on refining the evaluation mechanism of relationship polarity and relationship strength to further optimize the model to improve its performance in practice.

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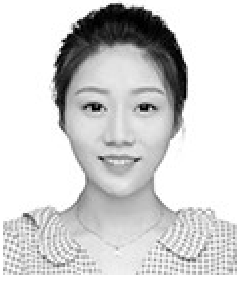
Meizi Li received her Ph.D. degree in computer science from the College of Electronics and Information Engineering, Tongji University, Shanghai, China, in 2021. She is currently Associate Professor with the College of Information, Mechanical and Electrical Engineering, Shanghai Normal University, Shanghai, China. Her current research interests include social network analysis, big data analysis and mining, and artificial intelligence education.

Xue Li received her bachelor's degree from the College of Information, Mechanical and Electrical Engineering, Shanghai Normal University, Shanghai, China, in 2021. She is currently pursuing her master's degree in the College of Information, Mechanical and Electrical Engineering, Shanghai Normal University, Shanghai, China. Her current research interests include link prediction in social networks and information dissemination.



Ya Zhang received her M.Sc. degree in computer science from the Shanghai Normal University, Shanghai, China, in 2021. She is currently pursuing the Ph.D. degree with the School of Management, China University of Mining and Technology, Beijing, China. Her current research interests mainly include link prediction in social networks and automated negotiation.

Jianguo Pan received his Ph.D. degree from the College of Computer Science and Technology, Shanghai University, Shanghai, China, in 2009. He is currently Associate Professor in the College of Information, Mechanical and Electrical Engineering, Shanghai Normal University, Shanghai, China. His current research interests include artificial intelligence and Internet of Things.

Ru Yang received her B.Sc. degree in computer science and technology from the Shandong University of Science and Technology, Qingdao, China, in 2013 and her Ph.D. degree in computer science and technology from the Tongji University, Shanghai, China, in 2020. She is currently Lecturer with the College of Information, Mechanical and Electrical Engineering, Shanghai Normal University, Shanghai, China. Her current research interests include mobile systems, formal engineering, big data analysis and mining, and machine learning.