A Study of Positive and Negative Information Dissemination Model on Multiple Networks of Awareness and Information under the Influence of News Media

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Abstract. For the public management of online information, this paper proposes an optimization model to study the impact of news media. This paper constructs a network model of the awareness layer and the information layer. An external global influence is set to influence whether the awareness layer is conscious or not, dividing the nodes in the awareness layer into aware nodes and unaware nodes. Setting the internal intention of the nodes to classify the attitude of the nodes in choosing to accept different information as positive or negative when faced with the same topic information. Taking the degree of nodes into account, the interactions between high- and low-influence nodes are added to the information layer. We investigate the effect of news media nodes on the interactions among high-influence aware nodes, low-influence aware nodes, high-influence unaware nodes, and low-influence unaware nodes in a social network by using the micro-Markov method. Our study contributes to the research on the news media's ability to control information and the reaction of the masses to complex information.

Keywords: Information dissemination; Layered social network; Micro Markov; News media

1 Introduction

With the rapid development of the Internet, online social networks have undeniable importance in society. And information dissemination on online social networks is the most concerning part. We can know from the previous research that the dissemination of information is not a single one but the role of various information[1]. So we introduce the heterogeneity of information in this thesis to study the dissemination of information with different tendencies under the influence of different factors in social networks. Attitudes towards information dissemination in social networks tend to form two parts: one part shows positive attitudes, and the other part shows negative attitudes towards the same information content. In this paper, we set up a positive-negative relationship between different pieces of information.

Previous scholars have proposed to assess the impact of social media on the fight against the Indian COVID-19 and found that information disseminated by social media changes public attitudes and behaviors [2]. Research has shown that social media plays an increasingly important role in disseminating both correct information and misinformation [3][4][5]. So the change in

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attitude is not only related to one's own perceptions but also to external influences, like whether one is aware of the news about the event or not. Nodes that are already aware of the news have a high probability of favoring the attitude held by the news media due to the authority of the news node[6], but this tendency is not certain. The nodes of information dissemination also exist as nodes with high influence besides ordinary users, such as the big V nodes[7]. Media messages work differently for each individual, and the effects are influenced by the individuals themselves[8]. After knowing the news information, ordinary users and big V users do not behave the same way; most of the ordinary people speak freely, even after knowing the news, but also dare to express different ideas[9]. The big V nodes, on the other hand, are different from the general public; as influential nodes, it is difficult to oppose the tendency of authoritative news and often have a stronger effect in the process of information dissemination[10]. In order to better simulate the information dissemination in this situation in reality, this paper sets up a positive and negative information dissemination model between the awareness layer under the influence of news media and the information layer with high- and low-influence.

2 Model

With the continuous development of technology, social networks consisting of a large number of users have become very popular due to their ease of access to information. There is an endless variety of information in the network, and messages from different users play very different roles; nodes are heterogeneous; some users are trustworthy; some users are appealing; and some users are wavering. In this paper, we consider the heterogeneity of nodes and categorize nodes according to their degree into high-influence nodes with high appeal and ordinary nodes with low influence. The ones with the greatest influence and the greatest appeal on social networks are news media users with an official nature, who not only have strong appeal but also have unique and convincing authority. In order to reflect the uniqueness and authority of the news media, we in this paper make the news media nodes independent of the high-influence nodes and become external news media nodes with a global nature. As shown in Figure 1, the information released by the news media node affects the whole network. As long as the news information is received, regardless of whether the node chooses the same tendency or not, the node transforms from an unaware state to an aware state, which is the transformation process of the awareness layer.

For the transformation of the information layer, the states of the nodes are distinguished into S, P, N, and R to denote susceptible nodes, positive nodes, negative nodes, and removed nodes. Additionally, nodes are classified into high- and low-influence layers within the information layer according to their heterogeneity, and the information exchanges within the information layer are impacted by the various roles that the awareness layer plays in the high- and low-influence layers.

The external node shown in Figure 1 represents the news media node with global influence that connects to every node. The upper gray layer shows the network structure of the awareness layer. Purple nodes indicate aware nodes, which know news information; cyan nodes indicate unaware nodes, which are in a state of ignorance of news information. The transformation of aware nodes can be achieved not only through the global influence of the news media node but also through the dissemination of the aware nodes in the awareness layer. The lower blue layer denotes the information layer, which represents the four states of SPNR through four colors: yellow, red, blue, and green. The high- and low-influence nodes distinguished by the information layer are represented by their size, with large ones having high influence and small ones having low influence.

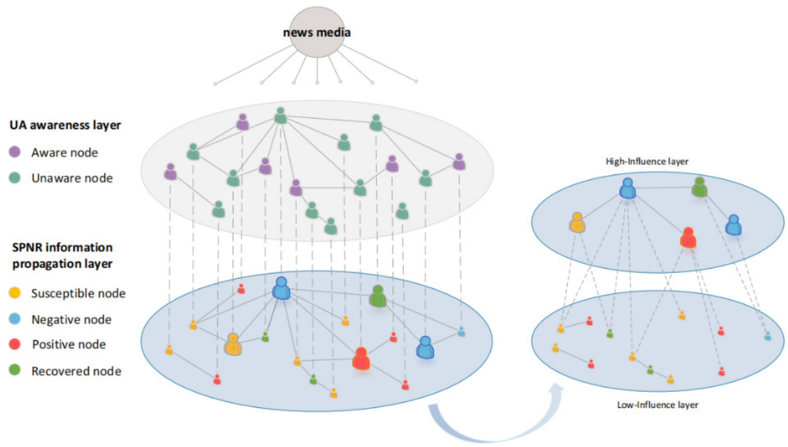

Fig. 1. Network structure figure represents the nodes in different states in a multiple network to make connections.

2.1 Model mechanism

We use A and U to denote the aware and unaware states in the awareness layer. The news media node is globally infected at each time step with probability m. Neighbors have a probability η to disseminate news information. From the left panel of Figure 2, we can see that unaware nodes can be transformed in two ways: through neighbors and through the news media.

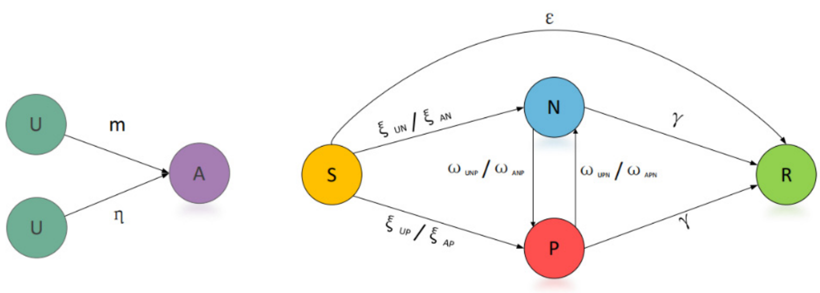

Fig. 2. State Transfer in the awareness layer and the information layer. The left panel shows the awareness layer and the right panel shows the information layer.

For the information layer, we denote the susceptible, positive, negative, and removed states by S, P, N, and R, respectively. As shown in the right panel of Figure 2, a node in the S state is transformed with a certain probability when it comes into contact with P or N information from its neighbors, and an S node in the U state is transformed with a probability of ξ_P^U or ξ_N^U. The choice of parameters for propagation within the information layer is decided based on the U-A state of the upper layer affecting the lower layer. The same is true for other state transformations; the probabilities of N and P transforming into each other are similarly chosen as ω_{AN}, ω_{UN} or ω_{AP}, ω_{UP} depending on the U-A state. ε denotes the probability that S is not interested in this topic and transforms directly to the removed state. γ denotes the probability that the P or N state loses interest in the information and transforms to the removed state.

2.2 Markov state transfer tree

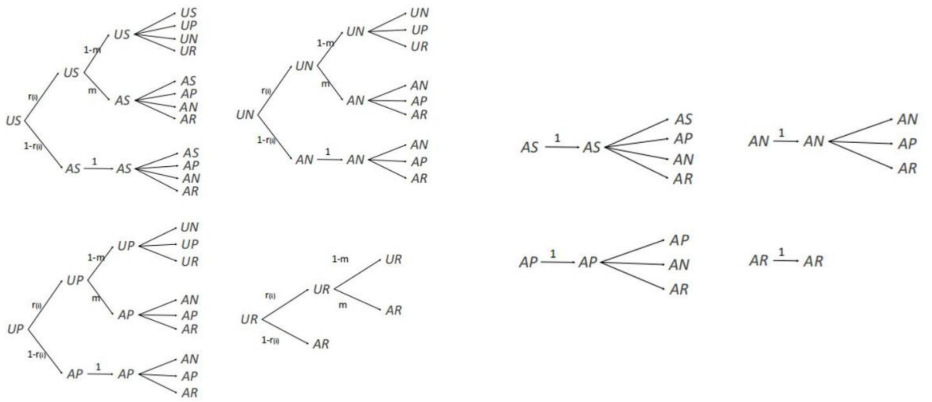

Fig. 3. State transfer trees for different states.

$$r_i(t) \;\; = \prod\nolimits_j [1 - a_{ji} P_j^x(t)\eta] \tag{1}$$

where $P_j^x(t)$ denotes the probability that node j is in state x and η denotes the probability that a neighbor disseminates information. m as shown above denotes the probability of being transformed by the news media node. Equation (1) represents the probability that node i is not informed by any neighbor.

Other state transfer equations not labeled in Figure 3 are denoted as:

$$\begin{cases} \mathrm{US} \rightarrow \mathrm{US} = \mathrm{q}_{\mathrm{iP}}^{\mathrm{U}}(\mathrm{t})\mathrm{q}_{\mathrm{iN}}^{\mathrm{U}}(\mathrm{t}) \\ \mathrm{US} \rightarrow \mathrm{UP} = \left(1 - \mathrm{q}_{\mathrm{iP}}^{\mathrm{U}}(\mathrm{t})\right)\mathrm{q}_{\mathrm{iN}}^{\mathrm{U}}(\mathrm{t}) \\ \mathrm{US} \rightarrow \mathrm{UN} = \left(1 - \mathrm{q}_{\mathrm{iN}}^{\mathrm{U}}(\mathrm{t})\right)\mathrm{q}_{\mathrm{iP}}^{\mathrm{U}}(\mathrm{t}) \\ \mathrm{US} \rightarrow \mathrm{UR} = \left(1 - \mathrm{q}_{\mathrm{iP}}^{\mathrm{U}}(\mathrm{t})\right)\left(1 - \mathrm{q}_{\mathrm{iN}}^{\mathrm{U}}(\mathrm{t})\right) \end{cases} \tag{2}$$

$$\begin{cases} \mathrm{AS} \rightarrow \mathrm{AS} = \mathrm{q}_{\mathrm{iP}}^{\mathrm{A}}(\mathrm{t})\mathrm{q}_{\mathrm{iN}}^{\mathrm{A}}(\mathrm{t}) \\ \mathrm{AS} \rightarrow \mathrm{AP} = \left(1 - \mathrm{q}_{\mathrm{iP}}^{\mathrm{A}}(\mathrm{t})\right)\mathrm{q}_{\mathrm{iN}}^{\mathrm{A}}(\mathrm{t}) \\ \mathrm{AS} \rightarrow \mathrm{AN} = \left(1 - \mathrm{q}_{\mathrm{iN}}^{\mathrm{A}}(\mathrm{t})\right)\mathrm{q}_{\mathrm{iP}}^{\mathrm{A}}(\mathrm{t}) \\ \mathrm{AS} \rightarrow \mathrm{AN} = \left(1 - \mathrm{q}_{\mathrm{iP}}^{\mathrm{A}}(\mathrm{t})\right)\left(1 - \mathrm{q}_{\mathrm{iN}}^{\mathrm{A}}(\mathrm{t})\right) \end{cases} \tag{3}$$

$$\begin{cases} \mathrm{UP} \rightarrow \mathrm{UP} = 1 - \gamma - \omega_{\mathrm{UPN}} \\ \mathrm{UP} \rightarrow \mathrm{UN} = \omega_{\mathrm{UPN}} \\ \mathrm{UP} \rightarrow \mathrm{UR} = \gamma \end{cases} \tag{4}$$

$$\begin{cases} \mathrm{UN} \rightarrow \mathrm{UN} = 1 - \gamma - \omega_{\mathrm{UNP}} \\ \mathrm{UN} \rightarrow \mathrm{UP} = \omega_{\mathrm{UNP}} \\ \mathrm{UN} \rightarrow \mathrm{UR} = \gamma \end{cases} \tag{5}$$

$$\begin{cases} \mathrm{AP} \rightarrow \mathrm{AP} = 1 - \gamma - \omega_{\mathrm{APN}} \\ \mathrm{AP} \rightarrow \mathrm{AN} = \omega_{\mathrm{APN}} \\ \mathrm{AP} \rightarrow \mathrm{AR} = \gamma \end{cases} \tag{6}$$

$$\begin{cases} \mathrm{AN} \rightarrow \mathrm{AN} = 1 - \gamma - \omega_{\mathrm{ANP}} \\ \mathrm{AN} \rightarrow \mathrm{AP} = \omega_{\mathrm{ANP}} \\ \mathrm{AN} \rightarrow \mathrm{AR} = \gamma \end{cases} \tag{7}$$

The group of equations (2)-(7) represents the state transfer equations for different branches of the state transfer tree.

$q_{iP}^{U}(t)$ denotes the probability that an unaware node i won't be infected by P information. The q(t) formula is expressed as equations (8)-(11).

$$q_{iP}^{U}(t) = \prod_{j}[1 - b_{ji}(p_j^{UP}(t) + p_j^{AP}(t))\xi_P^U] \tag{8}$$

$$q_{iP}^{A}(t) = \prod_{j}[1 - b_{ji}(p_j^{UP}(t) + p_j^{AP}(t))\xi_P^A] \tag{9}$$

$$q_{iN}^{U}(t) = \prod_{j}[1 - b_{ji}(p_j^{UN}(t) + p_j^{AN}(t))\xi_N^U] \tag{10}$$

$$q_{iN}^{A}(t) = \prod_{j}[1 - b_{ji}(p_j^{UN}(t) + p_j^{AN}(t))\xi_N^A] \tag{11}$$

For the U state: $\xi_N^U = \xi, \xi_P^U = \xi$. For the A state, when news media publish N information : if node belongs to high-influence layer, $\xi_N^A = T_1\xi$, $\xi_P^A = T_2\xi$; if node belongs to low-influence layer: $\xi_N^A = FT_1\xi$, $\xi_P^A = (1 - F)T_2\xi$, where $T_1>1$, $0<T_2<1$ and F randomizes out random numbers. When news media publish P information: if node belongs to high-influence layer: $\xi_N^A = T_1\xi$, $\xi_P^A = T_2\xi$; if node belongs to low-influence layer: $\xi_N^A = (1 - F)T_1\xi$, $\xi_P^A = FT_2\xi$, where $T_2>1$, $0<T_1<1$ and F follows normal distribution.

2.3 State transfer equation

The transfer equations for the eight states expressed by the micro-Markov method are as follows:

$$p_i^{US}(t+1) = p_i^{US}(t)r_i(t)(1-m)q_{iP}^{U}(t)q_{iN}^{U}(t) \tag{12}$$

$$p_i^{AS}(t+1) = (p_i^{US}(t)(r_i(t)m + 1 - r_i(t)) + p_i^{AS}(t))q_{iP}^{A}(t)q_{iN}^{A}(t) \tag{13}$$

$$\begin{aligned} p_i^{UP}(t+1) = {} & p_i^{US}(t)r_i(t)(1-m)(1-q_{iP}^{U}(t))q_{iN}^{U}(t) \\ & + p_i^{UP}(t)r_i(t)(1-m)(1-\gamma-\omega_{UPN}) \\ & + p_i^{UN}(t)r_i(t)(1-m)\omega_{UNP} \end{aligned} \tag{14}$$

$$\begin{aligned} p_i^{AP}(t+1) = {} & [p_i^{US}(t)(r_i(t)m + 1 - r_i(t)) + p_i^{AS}(t)](1-q_{iP}^{A}(t))q_{iN}^{A}(t) \\ & + [p_i^{UP}(t)(r_i(t)m + 1 - r_i(t)) + p_i^{AP}(t)](1-\gamma-\omega_{APN}) \\ & + [p_i^{UN}(t)(r_i(t)m + 1 - r_i(t)) + p_i^{AN}(t)]\omega_{ANP} \end{aligned} \tag{15}$$

$$\begin{aligned} p_i^{UN}(t+1) = {} & p_i^{US}(t)r_i(t)(1-m)(1-q_{iN}^{U}(t))q_{iP}^{U}(t) \\ & + p_i^{UN}(t)r_i(t)(1-m)(1-\gamma-\omega_{UNP}) + p_i^{UP}(t)r_i(t)(1-m)\omega_{UPN} \end{aligned} \tag{16}$$

$$\begin{aligned} p_i^{AN}(t+1) = {} & [p_i^{US}(t)(r_i(t)m + 1 - r_i(t)) + p_i^{AS}(t)](1-q_{iN}^{A}(t))q_{iP}^{A}(t) \\ & + [p_i^{UN}(t)(r_i(t)m + 1 - r_i(t)) + p_i^{AN}(t)](1-\gamma-\omega_{ANP}) \\ & + [p_i^{UP}(t)(r_i(t)m + 1 - r_i(t)) + p_i^{AP}(t)]\omega_{APN} \end{aligned} \tag{17}$$

$$\begin{aligned} p_i^{UR}(t+1) = {} & p_i^{US}(t)r_i(t)(1-m)(1-q_{iN}^{U}(t))(1-q_{iP}^{U}(t)) \\ & + p_i^{UR}(t)r_i(t)(1-m) + (p_i^{UN}(t) + p_i^{UP}(t))r_i(t)(1-m)\gamma \end{aligned} \tag{18}$$

$$\begin{aligned} p_i^{AR}(t+1) = {} & [p_i^{US}(t)(r_i(t)m + 1 - r_i(t)) + p_i^{AS}(t)](1-q_{iN}^{A}(t))(1-q_{iP}^{A}(t)) \\ & + (p_i^{UN}(t) + p_i^{UP}(t))(r_i(t)m + 1 - r_i(t))\gamma \\ & + (p_i^{AN}(t) + p_i^{AP}(t))\gamma + p_i^{UR}(t)(r_i(t)m + 1 - r_i(t)) + p_i^{AR}(t) \end{aligned} \tag{19}$$

The equation(12)-(19) represents the probability that node transforms into the state. The complexity of the equation is O(n). $p_i^X(t)$ denotes the probability that node i is in state x. $r_i(t)$

denotes the probability of not being informed by any neighbor. m denotes the probability of being influenced by the media node. $q_{iy}^{x}(t)$ denotes the probability that an x state node i won't be infected by y state information. ω_{Axy} denotes the probability that an A state node transforms from x to y state.

3 Simulation and analysis

In order to check the feasibility, we verify the accuracy of this MMCA by conducting a large number of Monte Carlo simulations and also analyze the influence of news media nodes in the model[11]. The Monte Carlo method is used to simulate the real information dissemination process and is compared with this paper's model. The results of the two methods shown in Figure 4 are comparatively fitted, indicating that the model proposed in this paper is feasible in reality. Compared with the previous SIR model, it is not only more in line with the real situation but can also better study the interaction of different information.

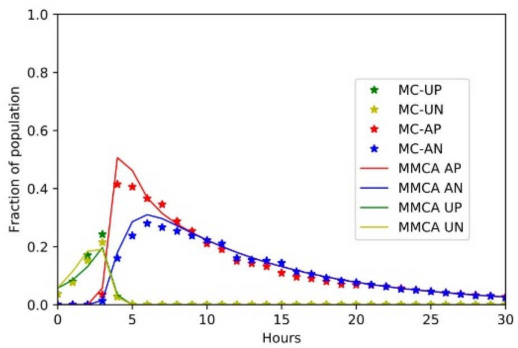

Fig. 4. Comparison of Monte Carlo results with micro-Markov results. At 2 hours, the news media release positive information.

From Figure 5, we can see that the earlier the news media information is released, the wider the spread of positive information is, and the influence of the news media is more effective in the rising process of information dissemination. And we also find that the addition of the news media not only guides the tendency of the information but also increases the scope of the whole information dissemination, so that the information on this topic is more widely known.

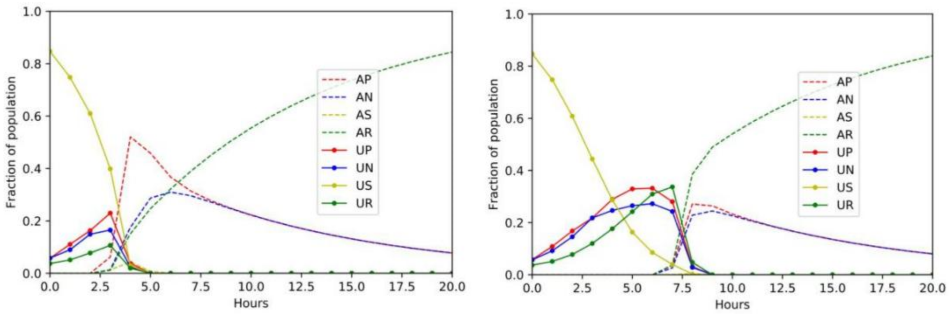

Fig. 5. Left: At 2 hours, the news media release positive information. Right: At 5 hours, the news media release positive information.

Figure 6 illustrates how inaccurate information distributed by the news media can have a detrimental impact on public opinion and influence. And in some cases, such as when the news media release negative information during the rising period of information dissemination, even if the negative information is denied, it still continues to affect public opinion. The first tendency of the news media to report has a very large role, even if the second tendency to report the reversal of the negative impact is difficult to undo.

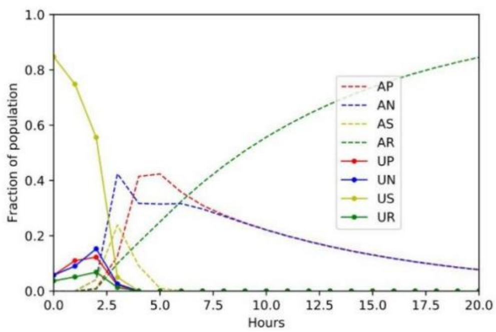

Fig. 6. At 1h, the news media released negative information, and at 2h, the news media released positive information to dispel rumors.

From the simulation, it can be seen that news media play an important role in the network and can influence the tendency and scope of information dissemination. The news media node should have a sense of social responsibility and should be cautious in making statements due to its great influence. If misinformation is published in error, the negative impact should be mitigated by promptly debunking the rumor, increasing the exposure of the debunked information, or adding evidence to prove its credibility.

4 Conclusion

In this paper, we study the propagation dynamics of a complex network of awareness and heterogeneous information under the influence of news media and propose and simulate one model of positive and negative information propagation under the influence of mainstream media. By distinguishing between high- and low-influence nodes, we simulate reality through the heterogeneity of low-influence nodes. The influence of the news media node on information dissemination is expressed through the awareness layer, and the situation that the news node does not always issue positive information and has a certain probability of being negative is also considered. The negative impact of news media nodes wrongly sending out negative information reminds us that, as influential news media, even timely dispelling rumors after sending out negative information can still cause a lot of harm, and that the news media should be more socially responsible and strictly control the news they release. The next research will focus on proposing the optimal control strategy for information based on the model, etc.

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