The Impact of Emotion on the Information Diffusion Model in Online Social Network

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The Impact of Emotion on the Information Diffusion Model in Online Social Network

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Abstract. In order to characterize the information propagation accurately on online social network, we propose an optimized SEIR information diffusion model. Firstly, the model considers the emotional factor of every node, which is a dynamic parameter in propagation process. The model defines five possible states: susceptible, exposed, removed, positive and negative infected. Every node attached to a specific emotion value, the dynamic interaction among these emotion values is produced in the diffusion process. We analyse the new mechanism of information dissemination and establish the mean-field equations. As we all know, the information dissemination is affected by user’s emotion, user’s degree and other factors. By simulating information diffusion process on real social Weibo, we analyse the density of users and the effect of some factors in the diffusion process. Simulation results agree well with the theoretical analysis, and it shows that the optimized model fits the characteristics of online social networks.

1 Introduction

With the rapidly development of the Internet, significant events are usually firstly exposed and spread on online social network. Therefore, social media online become the main platform for the information formation and diffusion. As a typical representative, Weibo has already become one of the most popular social applications, fully demonstrating its strength as an effective medium. Weibo has 400 million registered users and over 184 million users post new information every day. A large number of people publish and share information on Weibo, and local discussions launched by several important users can cause public responses, and propagate via a global scope.

Most information diffusion models are based on the theory of complex networks [1] and the dynamics of infectious diseases. Starting with a simple information dissemination model, the susceptible-infected (SI) model [2,3] considers only two available states. A susceptible node can be infected by an infected neighbour permanently with a spreading rate, and thus all nodes become spreaders in the end. Then, the researcher proposed the susceptible-infected-susceptible (SIS) model [4,5], it allows nodes to recover and become susceptible again. The susceptible-infected-refractory (SIR) model [6,7] introduces a refractory state in which nodes cannot be infected. Infected nodes may enter the refractory state spontaneously with a refractory rate. The above method of dynamics not only used in infectious disease propagation, but also used in information propagation. As we all know, a user may not expression immediately after infection. Then the susceptible-exposed-infected-refractory (SEIR) model is proposed by Stehlé J et al. [8,9]. The node contacts the information or infects disease, but it remains in a latent state for a period of time before becoming infectious. Such node is called exposed nodes.

Now, people not only study the spread of information but also research the spread of emotions on social media. The spread of emotion on social media was extensively studied based on the data of...
Framingham Heart Study (FHS) [10]. With the shift in the usage of the Web from information consumption to information production and sharing, numerous online social network services have emerged. Simultaneously, due to more freedom of expression online, the online social networks have been the main platform for communication and emotional expression. Various contributions have been made based on the observation that emotion can be propagated via online interactions [11]. A recent study from Facebook suggests that emotional contagion occurs online even in absence of non-verbal cues typical of interpersonal interactions [12,13]. Aiming to show the detailed process and characteristics of emotional contagion within social media, an emotional independent cascade model is proposed [14].

Many research scholars have improved the SEIR model [15-17], but none of them considers the emotional factors. To solve this problem, we propose improved SEIR model. In the model, each node is attached emotion about the spreading topic. Unlike the previous SEIR model, we divide the infected node into positive and negative infected node according to the node’s emotion.

The rest of this paper is structured as follows. Section 2 presents a new diffusion model which concludes the diffuse rules and the mean-field equations of model. In section 3, we discuss simulation results on real social network for the model. At last, the conclusion and acknowledgment are depicted.

2 The Model

2.1 The Diffuse Rules of Model

In this paper, we assume that the network structure does not change and the user's heterogeneity other than emotion is ignored. According to the complex network and graph theory, the online social network can be abstracted into a directed graph \( G=(V, E) \), where \( V \) is the set of users (or nodes), and \( E \) is the concerned relationship among users. We divide the users into five states: susceptible, exposed, removed, positive and negative infected. Susceptible users refer to those that have never read the information. When users read the topic and have not yet decided to forward the information right away but have own emotion about the topic, they are changed to the exposed state. The users that forward the information and spread it to their neighbours are considered as infectors or spreaders. If the infected user’s emotion about the topic is positive (or negative), the infector is positive (or negative) infector. When users completely lost interests about the information, they have no feelings about the information and become removed users.

Based on the mechanism of information propagation on microblog websites, our model is defined in the following way. Consider a population of \( N \) users located on a social network, and only these users that connect with each other can have interactions. The emotional value of the user is -1 to 1. Emotional value is less than zero, which means that the user’s emotion about the information is negative. Conversely, the user’s emotion is positive. We define \( o(t) \) and \( \psi(t) \) as value and the absolute value of the user’s emotion at time \( t \). When user \( i \) interacts with infected user \( j \), the emotion update rule is:

\[
o_{i}(t+1)=o_{i}(t)+\eta(o_{i}(t)-o_{j}(t))\tag{1}
\]

In Eqs. (1), \( \eta \) is the influence of the user \( j \)'s emotion on user \( i \)'s, which is related to the authority of the infected users \( j \) and the intimacy between them. At each time step, interactions between spreaders and other users are governed by the following set of rules:

1. When each susceptible user meets an infected user, then the susceptible user has emotion about information. If the emotional value less than zero, the susceptible user is infected and become a negative spreader at a rate \( \lambda_{\psi}(t) \). On the contrary, it become a positive spreader at a rate \( \lambda_{\psi}(t) \).

2. Exposed user loses its interests in learning more about the information, and becomes removed user at a rate \( \lambda(1-\psi(t)) \) spontaneously. Otherwise, the exposed user has the opportunity to be spreader by infected again. The exposed user meets an infected user, then it update own emotion according to Eqs.
we can write the corresponding change rate transition rate of the reason of its decrease is that negative infected users change into removed ones. Therefore, the probability

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\( i_{\text{neg}}(k,t) \) increases with the susceptible or exposed users changed into negative infected users. Similarly, the reason of its decrease is that negative infected users change into removed ones. Therefore, the transition rate of \( i_{\text{neg}}(k,t) \) is given by

we can write the corresponding change rate \( s(k,t), e(k,t), i_{\text{neg}}(k,t) \) and \( r(k,t) \) as follows

(1) Similarly, If the emotional value less than zero, the exposed user becomes a negative spreader at a rate \( \mu \psi (t) \). On the contrary, it becomes a positive spreader at a rate \( \mu \psi (t) \).

(3) Infected user lose its interest in sharing and spreading the information gradually, and becomes removed users at a rate \( \delta (1-\psi (t)) \) spontaneously.

(4) When an infected user meets other infected user, their emotional value update if their emotional values is consistent. Conversely, they don’t interact if their emotional values is inconsistent.

On social media, the parameters \( \delta_1 \) and \( \delta_2 \) depend on the content of the information, the authority of the spreader and the susceptible users interest in this topic. The parameters \( \mu_1 \) and \( \mu_2 \) rely on the intimacy and the meeting times between users. The parameters \( \delta_1 \) and \( \delta_2 \) depend on the users lost interest rate. There is only one absorbing states in the model, that is the removed state. Infected and exposed users will lose their interests to become removed users and cease to spread the information.

2.2 The mean-field equations of model

We define \( s(k,t), e(k,t), r(k,t), i_{\text{neg}}(k,t) \) and \( i_{\text{pos}}(k,t) \) as the density of the susceptible, exposed, removed, negative and positive infected users belonging to connectivity class \( k \) at time \( t \). The probability that a susceptible users or an exposed users with degree \( k \) becomes negative infected user in the interval \([t,t+\Delta t] \) is given by \( p_{\text{neg}}(k,t) \) and \( p_{\text{neg}}(k,t) \), respectively. The probability, a susceptible user whose emotion is negative becomes a negative spreader during \([t,t+\Delta t] \) is \( \lambda \psi (t) \sum_k P(k|k)\dot{e}(k,t) \).

Considering the user has \( k \) neighbors, the probability \( p_{\text{neg}}(k,t) \) is given by

\[
p_{\text{neg}}(k,t) = \lambda \psi (t)k \Delta t \sum_k P(k|k)\dot{e}(k,t)
\]

Similarly, the probability \( p_{\text{rem}}(k,t) \) is given by

\[
p_{\text{rem}}(k,t) = \mu \psi (t)(1-\delta (1-\psi (t)))k \Delta t \sum_k P(k|k)\dot{e}(k,t)
\]

\[
\partial_t i_{\text{neg}}(k,t) = \lambda \psi (t)s(k,t) \sum_k P(k|k)\dot{e}(k,t) - \delta (1-\psi (t)) i_{\text{neg}}(k,t)
\]

\[
- \mu \psi (t)(1-\delta (1-\psi (t)))k \cdot e(k,t) \sum_k P(k|k)\dot{e}(k,t)
\]

\[
\partial_t i_{\text{pos}}(k,t) = \lambda \psi (t)s(k,t) \sum_k P(k|k)\dot{e}(k,t) - \delta (1-\psi (t)) i_{\text{pos}}(k,t)
\]

\[
+ \mu \psi (t)(1-\delta (1-\psi (t)))k \cdot e(k,t) \sum_k P(k|k)\dot{e}(k,t)
\]
$$\partial r(k,t) = \delta_1(1-\psi(t))i_{neg}(k,t) + \delta_2(1-\psi(t))i_{pos}(k,t) + \delta_1(1-\psi(t))e(k,t)$$ (6)

3 Evaluations
To further evaluation this model, we next compare this simulation result on Sina Weibo. The users and their interactions are used as the interacting topology. Assuming a group of $N$ users that interact with each other for a topic, time step is increased by 1 after $N$ users update their states according to the rules of our model.

3.1 Time Plots for Density of Users
At beginning of simulation, initial infected nodes are picked from the nodes whose degree is relatively large. The initial emotion of the users is based on the history information of the users. We assume that the initial emotional value follows a normal distribution of -1 to 1. We only set one initial positive and negative infected node in each realization.

Fig. 1.1

Fig. 1.2

Fig. 1.3

Fig. 1. Time plots for density of susceptible users, exposed users, removed users, positive and negative infected users. $\lambda_1=0.1, \lambda_2=0.1, \mu_1=0.2, \mu_2=0.2, \delta_1=0.5, \delta_2=0.1$ and $\eta=0.5$.

Fig. 1 illustrates that the node densities in different states changed over the time. It mainly depicts three situations distinguished by the densities of positive and negative nodes. The first case is that $i_{pos}(k,t)$ approximately equals to $i_{neg}(k,t)$ in Fig. 1.1. In Fig. 1.2 shows that $i_{pos}(k,t)$ is greater than $i_{neg}(k,t)$. In Fig. 1.3, $i_{pos}(k,t)$ is less than $i_{neg}(k,t)$. Clearly, the density of susceptible users declines quickly at beginning, and it reaches to zero gradually. That is because more susceptible users meet spreaders and change their own state. The density of exposed users rises quickly at first. While the density of infected users rises slowly compared with the density of exposed users. The reason we can
see from the time to peak and the values in Fig. 1. The peak of exposed users precedes the peak of infected users. After the peak, they both begin to decline and eventually tend to zero. Due to it is the absorption state, the density of removed users continues to rise until it approaches to 1.

3.2 The Impact of $\lambda$ and $\mu$ on the Information Dissemination Process

As shown in Fig. 2 and Fig. 3, the larger the value of $\lambda_i$ (or $\lambda_x$), the larger the peak value of $i_{neg}(k,t)$ (or $i_{pos}(k,t)$), and the shorter the time to reach the peak. The larger value of $\lambda$, the easier it is for a susceptible user to become an infected user. It means that the content of the contacted information is more attractive, the susceptible user is very interested in this information, and the authority of the spreader is relatively large.

As shown in Fig. 4 and Fig. 5, the larger the value of $\mu_i$ (or $\mu_x$), the larger the peak value of $i_{neg}(k,t)$ (or $i_{pos}(k,t)$). The exposed user interacts with spreader and updates their own emotion. As the number of exposed user’s neighbors which are spreader increasing, the contact information times of exposed user increases, which leads to that the chance of exposed user becoming infected user increases. This is a true portrayal of “A repeated slander makes others believe” in the information dissemination. Obviously, exposed users are easy to accept and spread information when $\mu$ is large, which means that there exsits high intimacy between users and spreader has greater authority.

Therefore, we can take some measures to change the value of $\lambda$ (or $\mu$) to prevent or promote the spread of the information. For example, by reducing the value of $\lambda$ and increasing the value of $\lambda_x$, the number of positive infected users increase and the number of negative infected users decrease. That is a measure to guide the topic toward to a positive direction.
4 Conclusions
In this paper, we analysis the impact of emotion on the information diffusion model in online social network to propose a new propagation model with two infected state, the positive and negative infected state. To estimate the diffuse rules of our model, we establish the mean-field equations. By simulating information diffusion process on the real networks, we analyse the influence of various parameter. From the simulation results, we can draw the following conclusions: The authority of the infected users and the attractiveness of the topic affect the early dissemination of information. The intimate relationship and meeting times between users affect the subsequent propagation process. In total, the simulation results are well agreement with the theoretical analysis. The model accurately reflects the information diffusion process. As future work, we are planning to study the specific methods to control the information spread from our model.

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