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Sentiment contagion in complex networks

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HIGHLIGHTS

- The transition probabilities of the binary emotional state are defined.
- Sentiment contagion model is established and transition equations are derived.
- The assimilation and weight combination exert influences on sentiment contagion.
- The crowd is more likely to achieve consistent sentiment.

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ABSTRACT

Sentiment contagion such as the spread of panic in emergencies is a common phenomenon in human society. Considering the difference between sentiment contagion and epidemic contagion, we define the transition probabilities of the binary emotional state (optimism, pessimism) and establish a sentiment contagion model. Transition equations are given in a homogeneous network and the stability of the zero solution is discussed. Also the Monte Carlo method is used for numerical simulation in the inhomogeneous networks. Simulation results show that the overall tendency of sentiment variation in the BA scale-free network is similar in the homogeneous network. Furthermore, the assimilation and weight combination exert influences on sentiment contagion.

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1. Introduction

As many complex systems in the real world can be described by complex networks, the complex network as a tool is widely used to model a variety of complex issues [1–4]. One of the representative applications is modeling the spread of a virus in complex networks [5–7]. The spread of a virus here is a general phenomenon and the transmission of infectious diseases should be the closest to human life. At present, the SIS epidemic model and the SIR epidemic model are the most widely investigated and employed models in infectious diseases [8,9]. In the SIR model, the population can be divided into three categories: "S" are the susceptible individuals who are not contagious; "I" are the infected individuals who are contagious; and "R" are the removed individuals who may be cured and acquired immunity or may die. However, for some diseases such as the common cold, when the patients were cured but without obtaining immunization, the SIS model will be found suitable to work. The SIS model is similar to the SIR model, but the only difference is that in the SIS model when patients were cured they automatically translated into susceptible individuals (the second "S"). In addition to the above

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models, some other relevant epidemic models [10–14] were also investigated depending on the characteristics of different diseases.

Another important application is the public opinion dissemination in complex networks. The public opinion here mainly focuses on the harmful rumors and panic sentiment. The earlier classic rumor spreading models were the DK model [15,16] and MK model [17]. As the rumors can somehow be referred to as diseases, Sudbury [18] firstly employed the SIR epidemic model to study rumor propagation and established the SIR rumor spreading model. In the SIR rumor model (compared with the SIR epidemic model), "S" represents the spreaders who know the rumor and disseminate it; "I" represents the ignorant people who do not know the rumor; and "R" represents stiflers who know the rumor but do not transmit it. Afterwards, scholars considered the topological characteristics of networks and established rumor models on small-world networks, scale-free networks, etc. [19–21]. The basics of emotional information mining on the internet is to divide the text into words which can represent the text information. The optimistic attitude, pessimistic attitude or neutral attitude of the individuals can be accurately distinguished through words which are obtained from the text, however, subtle emotions like sadness are not easily differentiated by the text [22]. Zhang et al. [23] used system dynamics modeling to analyze the online public opinion trend and emotional attitude change. Sunstein [24] found out the group polarization phenomenon of public opinion transmission, i.e., at first the group members have some bias, upon consultation among them, they continue to move forward in the bias direction and finally achieve the extreme view.

According to the above methods of categorization among groups of people, we study a 2-state emotional contagion model. One state is the optimistic state denoted by "$+$", and the other one is the pessimistic state denoted by "$-$". These two states of the sentiment contagion model are similar to the SIS epidemic model, with respect to the optimistic state ("$+$") similar to the susceptible (S) and the pessimistic state ("$-$") similar to the infective (I). However, in the SIS epidemic model, when an "S" contacts an "I", only the "I" can affect the "S", the susceptible person shifts into an infective state with a certain probability, while the "S" does not affect the "I", i.e., the infective individual is not cured to change its state to "S" through contacting the susceptible. In the novel sentiment contagion model, two states can affect each other. In addition, the contacts between the "$+$" would enhance the optimistic emotion to make it more optimistic. Similarly, the contacts between the "$-$" would also provoke the pessimistic emotion to make it more pessimistic.

However, individuals' emotional transformation in sentiment contagion is not only affected by the assimilation and the dissimilation of the surrounding people who directly contact him/her, but is also influenced by the external general information. Taking the event as an example that college students fled out of cities during SARS in China in 2003, if one college student at the worst-hit areas knew that the SARS explosion in his/her hometown is not so serious, he/she might have the idea of going home. Thus it is a binary choice (stay or go) for every student. If one student was in the stay state, he/she would return to his/her hometown when he/she saw a few (e.g. two) of his classmates or friends had already left. However, when the student learnt that only two students went home in the whole campus, he is more likely to stay. Another student found that his/her classmates or friends all stayed at school, but he/she also learned that half of the students had left school. He might immediately pack up for going home. The studies that external information influence an individual's sentiment contagion are mostly about the sentiment contagion models for investors in stock markets [25–27]. M. Baker and J. Wurgler [28] used a set of empirical results to demonstrate that the investor sentiment affects the cross-section of stock returns. They found when sentiment is estimated to be high, many stocks tend to earn relatively low subsequent returns and vice versa. M.P. Bowden [29] combined the sentiment and the network and obtained that the size of the investment return depends on the network structure and the number of agents that do not engage in any form of learning from neighbors. Inspired by Lux [25] who investigated the stock market, we can use the external general information to study the transition rate between the two states.

In this paper, we investigate a kind of imitative behavior in population awareness. Considering that the individual's state change will be comprehensively influenced by social direct contacts and external general information, we describe the process of the crowd sentiment contagion, and establish the group sentiment contagion model in complex networks. A series of numerical simulation experiments are conducted to characterize the sentiment contagion process. Quantitative results are analyzed and can serve as the theoretical decision-making basis for policymakers. In Section 2 we build a 2-state sentiment contagion model and derive equations that illustrate the dynamics of the model. In Section 3 numerical simulation is conducted to analyze the impact factors under different network topology structures and parameters. Conclusions and discussions are given in Section 4.

2. Sentiment transformation rate and sentiment contagion model

We consider a closed and homogeneously mixed population consisting of N individuals as a network where individuals are vertices and contacts between people are edges. Then, an undirected graph $G = (V, E)$ can be obtained, where V is the set of vertices (individuals) and E is the set of edges (contacts). Assuming in this network there are two states: one is the optimistic state ("$+$"); the other is the pessimistic state ("$-$"). The optimistic individuals are more rational and will not generate aggressive behaviors, while the pessimistic individuals are prone to produce aggressive behaviors. At time t, the total number of the optimistic group is denoted by $n_+(t)$, and the total number of the pessimistic group is denoted by $n_-(t)$, so $n_+(t) + n_-(t) = N$.

In the process of sentiment contagion, the optimists would impact the connected pessimists to change them into the optimistic and would impact the connected optimists to enhance the optimistic state. Likewise, the pessimistic would impact

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