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Health behavior spreading with similar diminishing returns effect

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HIGHLIGHTS

- We model the spreading of health behavior in real-world online social network.
- The model captures the similar diminishing returns effect of health behavior spreading.
- The model's contagion threshold is merely decided by the spreading rate and the logout probability.
- The augmentation of the similar diminishing returns factor can increase the spreading speed and coverage.

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ABSTRACT

Nowadays the propagation of human activity, especially health behavior, has become a significant issue in the study of online social network. Considering the effect of human behavior on information diffusion in social networks (Centola, 2010), we propose a simple "susceptible–adopted–susceptible" model with several interpretable parameters. This model shows a similar diminishing returns effect, in which the adoption probability of a susceptible individual grows less quickly as the number of his or her adopted neighbors increases. Surprisingly, the model's contagion threshold is merely decided by the spreading rate and logout probability, not affected by the similar diminishing returns effect in real cases. Moreover, we find that the augmentation of the similar diminishing returns factor can increase the spreading speed and coverage. Our model captures properties of the real spreading of health behavior in real online networks and can provide instructions for fast propagation of new health behavior.

1. Introduction

As an important issue which people are concerned about, there have been considerable studies in social networks and collective behaviors [1–4]. Unlike epidemic spreading in population networks [1,5], the spreading of ideas, innovations and behaviors via social contact [6–9] in social networks have some interesting and significant properties [10,11], such as weak ties [12], and homophily [13]. Online social networks, as a typical and special example of social networks, has attracted much attention in the field of complex network [14–16]. In reality, much information originates from a few "early adopters" and diffuses in the online social networks fast and largely, such as, Twitter, and Facebook [17–20].

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Different from the traditional epidemic spreading, the spreading of information can be affected by people's behavior or decision. For example, H.P. Young discusses how agents interact in a small local cluster that can have influence on the dynamics of social innovation in social networks [21]. J. Watts tries to find appropriate cascading model which can well describe the spreading process [22]. J. Kleinberg shows us a similar diminishing returns effect, which means that the adoption likelihood of joining a LiveJournal community grows less quickly as the number of adopted friends [18]. D. Centola demonstrates the effects of network constructions on diffusion and the influence of reinforcing signals on adoption likelihood by experimental methods [23]. Though several phenomena of information spread affected by people's behavior have been demonstrated in experiments and numerical simulations [18,23], no model can exactly describe the similar diminishing returns (SDR) effect [18] of the behavior spreading in online social network, which captures the relationship between the number of reinforcing signals and the adoption probability of behavior or other information.

In order to delineate the SDR effect of health behavior spreading more precisely, in this paper we propose a simple "susceptible–adopted–susceptible" model with several significant parameters: spreading rate, logout probability, and SDR factor. The spreading rate and the logout probability are the factors which affect an individual to join in a behavior or to log out from the behavior, respectively. The SDR factor is used to reflect the SDR effect. This means, the first signal received by a susceptible individual from one of her or his adopted neighbors has the most important influence on her or his decision whether or not to adopt the health behavior. When the individual has known the behavior but not yet joined in it, another reinforcing signal about the same behavior will bring her or him less freshness, so that it will accumulate less likelihood of adoption.

By theoretical derivation and numerical simulations, we find that the model can report and explain the similar diminishing returns effect and the existence of contagion threshold during the behavior spreading. Due to the SDR effect, the adoption likelihood does not increase with the reinforcing signals linearly. We find that the SDR factor has no influence on the contagion threshold, but the augmentation of the factor can increase the spreading speed and range. The existence of the model's contagion threshold is only decided by its spreading rate and its logout probability. The model is further investigated in Erdős–Rényi (ER) networks [24] and Barabási–Albert(BA) networks [25] to compare the impacts of different topologies on the spreading process. The spreading speed of the health behavior in the ER network is slower than in the scale-free network, but the spreading range in the ER network is wider than in the scale-free network. In addition, we apply the model in two real online social networks to verify the behavior properties.

In brief, by presenting the logout probability, the similar diminishing returns effect and the contagion threshold, we verify that the proposed model can appropriately describe the real spreading of health behavior in a way, which provides more possibilities for our future study. Section 2 will introduce the model, the results of different networks will be presented in Section 3. And Section 4 will give us a final conclusion for the whole study.

2. "Susceptible–adopted–susceptible" model

The model, which evolves from the susceptible–infected–susceptible [26] (SIS) model, is described as follows. We consider a large population of individuals in an online social network as a connected and undirected network with N nodes, each of whom has some connected neighbor-nodes. We introduce one of health behaviors in the network, for example, joining in a sport forum, giving up smoking, etc., in order to study the behavior spreading in online social network. We divide the whole nodes into two classes: "susceptible" individuals and "adopted" individuals. We define a "susceptible" [1] individual (S) as an agent who has not yet learned the new behavior, or who has already logged out from the behavior with a likelihood of rejoining in this behavior. In other words, here the susceptibles mean "non-adopters". And an "adopted" individual (I) is an agent who has participated in the health behavior and who is able to spread it.

At beginning, all individuals are susceptible for one health behavior. We randomly choose a susceptible individual as the contagion source to spread the health behavior. Their decisions about whether or not to adopt a behavior depend explicitly on the adoption patterns of their neighbors [1]. The probability that a susceptible vertex acquires the infection from any given neighbor in an infinitesimal time interval $\mathrm{d}t$ is $\beta \mathrm{d}t$, where $0 < \beta < 1$ defines the health behavior spreading rate. At the same time, an adopted individual may turn back to be susceptible with a logout probability λ because of some internal or external causes, and this re-susceptible individual can again join in the behavior. We choose a random vertex as the first adopted individual who has known and joined in a health behavior, then the behavior will spread in the network through contacts/edges. The evolution of the model is therefore defined by the adoption density $i(t) = I(t)/N$ and the susceptible density $s(t) = S(t)/N = 1 - i(t)$. $I(t)$ and $S(t)$ present the number of adopted individuals and that of susceptible ones in the system, respectively. After a long enough period, the spreading process will turn into a steady state (see Fig. 1).

Specifically, considering that the spreading rate β we care about here is different from the constant parameter in traditional epidemic models, we define the health behavior spreading rate as the following function form:

$$\beta = \beta_0 q^{n-1}, \tag{1}$$

where q is the SDR factor that governs how much the likelihood to adopt the behavior is reduced each time with increasing number of adopted neighbors. The number of an individual's adopted neighbors is n. β_0 is an initial and constant spreading rate ($0 < \beta_0 < 1$). And $\langle k \rangle$ is the average degree of the social network. For homogeneous networks, n is approximately equivalent to $i\langle k \rangle$. Then, Eq. (1) reads

$$\beta = \beta_0 q^{n-1} = \beta_0 q^{i\langle k \rangle - 1} \approx \beta_0 q^{i\langle k \rangle}. \tag{2}$$