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Structure optimization based on memetic algorithm for adjusting epidemic threshold on complex networks☆

Jianan Yan, Maoguo Gong*, Lijia Ma, Shanfeng Wang, Bo Shen

Key Laboratory of Intelligent Perception and Image Understanding of Ministry of Education of China, Xidian University, Xi'an 710071, China

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ABSTRACT

Many social spreading phenomena can be modeled as epidemic spreading models over networks, and the studies of these phenomena are important to avoid epidemic outbreaks. Epidemic threshold of the network, which fundamentally depends on the network structure itself, is a critical measure to judge whether the epidemic dies out or results in an epidemic breakout. In this study, epidemic threshold is regarded as the objective function to control the spreading process. In addition, an efficient structure optimization strategy based on memetic algorithm is proposed to adjust the spreading threshold without changing the degree of each node. Lowering the threshold can promote the spreading process whereas heightening the threshold can prevent the spreading process. In the proposed algorithm, genetic algorithm is adopted as the global search strategy and a modified simulated annealing algorithm combined with the properties of networks is proposed as the local search strategy. Experiments on computer-generated and real-world networks demonstrate that the proposed algorithm has superior performances for both the threshold minimization and maximization problems.

1. Introduction

The investigations of epidemic spreading have a long tradition [1,2]. In recent years, complex network has become an important tool for the studies of epidemic spreading. Each node in the network represents an individual, and each edge denotes a route for spreading between two individuals. Various epidemic spreading models have been proposed to reveal how epidemics, rumors, viruses, and information spread over social and computer networks [3–5]. In spreading models, we use β to denote the probability of a node infecting its neighbors and δ to denote the probability that the infected node can be cured. Among these spreading models, the susceptible-infected-susceptible (SIS) [6,7] and susceptible-infected-removed (SIR) [8,9] models have received wide acceptance. Each individual in SIS model is either susceptible (S) or infective (I). A susceptible individual will be infected by its infective neighbors with a probability β, and an infective individual can be cured to be susceptible again with a probability δ. SIR model is a little different from SIS model. Once an infective individual is cured, it is removed (R) and never gets further infection. The models for epidemic spreading have been successfully employed to express many social spreading phenomena, such as the spread of email and computer viruses [3,10], the propagation of failure in power grid [11], the epidemic dissemination in peer-to-peer and ad hoc networks [12], and the diffusion of information in the online networks [4,13]. A simple epidemic would result in a massive outbreak in a complex network [14].

In recent years, there are many studies focusing on the prevention of epidemics. The immunization strategy is a commonly used method. Cohen et al. [15] proposed an immunization strategy for scale-free networks to immunize some random individuals. Kobayashi et al. [16] prevented the contagions in financial networks by combining the immunization strategy with the possibility of serious side effects. And Gong et al. [17] proposed a strategy to prevent epidemic outbreaks by vaccinating the bridge nodes in community networks. These immunization strategies are effective when there is vaccine and it works. Moreover, a few works [18,19] studied the effect of the network topology on the spread of epidemics to avoid cascading failures. Risau-Gusmn et al. [18] studied the effects of switching contacts on the controlling of epidemic outbreaks. At each time step, it breaks connections between susceptible and infective individuals, which works effectively only when the epidemic spreads slowly. Another work [19] addressed

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* Corresponding author.
E-mail address: gong@ieee.org (M. Gong).

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the impact of the network topology on the viral prevalence, and showed that the maximum eigenvalue of a network is a key factor to determine the prevalence of the virus. Changing the topology of the network may be difficult, especially for the relationship networks and the road networks. However, structure optimization method has some advantages over the vaccination strategy. First, the structure optimization method is effective for some networks whose topologies are easy to be changed, especially when there is no valid vaccine. Second, the application of structure optimization method can serve to design a robust network [20]. For example, an Internet worm is spreading in the web server whose connections are easy to be rewired and there is no effective way to kill the worm. Now, changing the topology of the web server network is necessary [19]. Moreover, the structure optimization method can be used to the design of some networks, such as the power grid networks, the ad hoc networks, and the road networks.

We prevent the spreading process in a unique way by adjusting the epidemic threshold which is an important property of epidemic spreading [21,22]. For each spreading model, there is an effective spreading rate β/δ. If $\beta/\delta \le \tau$, the epidemic dies out, otherwise the epidemic survives in the network and the infected number increases sharply with the increase of β/δ, where τ is the epidemic threshold of a network. The main advantages of the proposed method are that it requires no vaccine and it can improve the robustness of the network essentially. By optimizing the network structure with low cost (i.e., redesigning some connections in web server networks), the cascading failures can be effectively prevented.

The epidemic threshold fundamentally depends on the network structure itself [14], so an effective strategy for structure optimization is necessary. A rewiring method [20] was introduced to optimize the network structure without changing any nodal degree under the assumption that changing the degree of a node can be more expensive than changing edges. Based on the rewiring method, Buesser et al. [23] introduced hill-climbing and simulated annealing strategies to enhance the network robustness, and in our previous work [24], we devised a greedy algorithm to protect the structural integrity from the malicious attack. Motivated by these ideas, we try to adjust the epidemic threshold by a hybrid intelligent algorithm.

In recent years, intelligent algorithms for solving real-world engineering problems have attracted increasing attentions. Compared with traditional algorithms, intelligent algorithms can solve problems and find a high quality solution in a reasonable time. Memetic algorithm (MA) is a hybrid global–local search technique, which has been successfully applied to solve various non-deterministic polynomial time complete problems [25–29]. For example, Moscato et al. [25] introduced a memetic algorithm by integrating evolutionary algorithm with Tabu Search techniques for ordering microarray data. Our previous works [27,28] proposed some memetic algorithms for community detection in complex networks. Gong et al. [27] used hill-climbing strategy as the local search and Ma et al. [28] presented a multi-level learning as the local search strategy. Lacroix et al. [29] used the memetic algorithm with niching strategy for real-parameter optimization. In general, the global search can find the promising search space, while local search is to refine the local optima. Memetic algorithm combines the advantages of global search with local search.

In this paper, we present a structure optimization strategy, which is based on memetic algorithms and the rewiring method, to control the epidemic outbreaks. The proposed algorithm is termed as memetic structure optimization strategy, or MSOS for short. In MSOS, genetic algorithm is adopted as the global search strategy, and a modified simulated annealing algorithm combining network property (MSACN) is adopted as the local search procedure. Experiments on 5 scale-free (SF) and 6 real-world networks demonstrate that MSOS can not only prevent the spreading of epidemics by heightening the epidemic thresholds, but also expand the scope of spread by lowering the thresholds. Moreover, comparison experiments with other algorithms show the effectiveness and efficiency of the proposed method.

The rest of the paper is structured as follows: Section 2 gives a description of the related backgrounds including the introductions of epidemic spreading model, epidemic threshold and structure optimization strategy. In Section 3, the framework of MSOS is described and its detailed operations are given. In Section 4, experiment results on SF networks and real-world networks are given. Section 5 shows the concluding remarks.

2. Related background

In this section, the related backgrounds about the epidemic spreading models, epidemic threshold and structure optimization are given. Both SIS and SIR models are commonly used in epidemic spreading. However, with the increase of the time step, the number of infected node in SIR model tends to 0, while the number in SIS model converges to a constant. The converged constant represents the number of infected nodes of a network, so we consider SIS model as our epidemic spreading model. Here, a classical SIS model in discrete time [7] is introduced. A simple formula of epidemic threshold [14] is introduced as our objective function. Structure optimization shows a basic rewiring method to change the topological structure [20].

2.1. Epidemic spreading model

The spreading process can be modeled from the probability view, and the probabilities are considered independent. During each time interval, a susceptible node i gets infection from its infective neighbors $\{j|e_{ij}=1\}$ with probability β. At the same time, an infective node can be cured with probability δ. $p_{i,t}$ denotes the probability of node i being infected at time t. Here the probability that a node i at time t will not receive infections is denoted as $\zeta_{i,t}$, which just happens when each neighbor of node i has not been uninfected so far, or node i is not infected with the probability $(1-\beta)$. Moreover, Chakrabarti et al. indicated that the model considers infinitesimal time steps, so the probability of multiple events within the same Δt can be ignored. Therefore, $\zeta_{i,t}$ can be calculated as follows.

$$\zeta_{i,t} = \prod_{j|e_{ij}=1} (p_{j,t-1}(1-\beta) + (1-p_{j,t-1})) = \prod_{j|e_{ij}=1} (1-\beta \cdot p_{j,t-1}) \qquad (1)$$

Node i is susceptible at time t if: (i) i was susceptible before time t and did not get infections from its neighbors at time t; and (ii) i was infected before time t, and cured at time t. Here $(1-p_{i,t})$ represents the probability of node i being susceptible at time t, which can be calculated as follow.

$$1-p_{i,t} = (1-p_{i,t-1})\zeta_{i,t} + \delta p_{i,t-1}\zeta_{i,t} \qquad (2)$$

For a network, given infected rate β and cured rate δ, the number of infected nodes at each time can be calculated as the sum of the infected probability of each node, and the number of infective nodes can be computed as $\eta_t = \sum_{i=1}^{N} p_{i,t}$.

Fig. 1 shows the spreading process of SIS model. At each time step t, a susceptible node i gets infected from its neighbors with a probability $1-\zeta_{i,t}$, and keeps susceptible state with a probability $\zeta_{i,t}$. An infective node can be cured with a probability δ, and keeps infective state with a probability $1-\delta$.

The time evolution of infected nodes on a SF network with different parameters is shown in Fig. 2. The result shows that the number of infected nodes increases with the increase of β/δ value.