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An environment aware epidemic spreading model and immune strategy in complex networks

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ABSTRACT

In the standard SIS model, each node has the same probability to be infected by its neighbors regardless of its surrounding environment. In the real world, the probability of a node to be infected is varying with the network environment; the prior model is not suitable for this scenario. In this paper, we consider an actual epidemic spreading model in which the probability of a node to be infected is related with the number of the infected nodes among its neighbors. We develop an analytical model for this epidemic spreading, named environment aware SIS model (EA-SIS) considering the heterogeneous infection rates, and analytically investigate the epidemic spreading in complex networks. We find that the threshold of EA-SIS is smaller than SIS which means the virus is easier to spread out in the EA-SIS model. In addition, we study several existing immune strategies on the EA-SIS model and propose a novel immune strategy which is based on expected infection time, ETB, of the nodes around the infected nodes for EA-SIS. The simulation results show that the EA-SIS model is more efficient that the SIS model, also, the proposed immune strategy, ETB, is more effective than the local information method and is close to the target immune strategy.

1. Introduction

Complex network has many properties, such as small world phenomenon, scale-free properties, and high clustering [1]. It can be classified into two main types by its connectivity property. One is the exponential network in which the connectivity distribution of node obeys the Poisson distribution and is exponential bounded [2]. The Erdős–Rényi (ER) model network [3] and Watts–Strogatz (WS) model network [2] are both included in this type. Another type is the Scale-free (SF) network whose degree distribution follows a power-law distribution and the Barabási–Albert (BA) model network is the famous one of this type [4].

Complex network has a very wide range of research contents, involving many disciplines, one of them is the transmission mechanism and dynamics analysis in complex networks. In view of the wide occurrence of complex networks in nature, it becomes a very interesting issue to inspect the effect of their complex features on the dynamics of epidemic and disease spreading [5]. Several models have been proposed for epidemic dynamics, differing in the disease stages, the dynamical parameters, and the underlying structure of contacts. In the 1920s, Kermack and McKendrick [6] first put forward SIR model in which the individuals are divided into three states: susceptible (S), infectious (I), removed (R). Here "removed" means individuals who are either removed from the disease and immune to further infection, or dead. The susceptible individuals that have connections with infective individuals can be infected at an average rate β per unit time and the infective individuals can recover to remove

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individuals at an average rate γ per unit time. The SIR model is a cornerstone model in epidemic spreading modeling where each individual in a population can be in one of three different compartments. There are extensive studies on the epidemic spreading in networks based on the SIR model [7–10].

In this paper, we focus on epidemic models of the susceptible-infectious-susceptible SIS type [11–20]. The SIS model can be easily derived from the SIR model by simply considering that the individuals recover with no immunity to the disease, that is, individuals could be immediately susceptible once they have recovered. In SIS models, the susceptible individuals can become infectious through a contact with infectious individuals and after a period of time, recover and return to the susceptible state. In [11], the authors studied the SIS epidemic spreading process on scale-free networks, finding the absence of an epidemic threshold and its associated critical behavior, which suggests that scale free networks are prone to spreading and the persistence of infectious at any spreading rate. Pastor-Satorras and Vespignani [12] studied the epidemic dynamics in bounded (finite size) scale-free networks with soft and hard connectivity cutoffs. They provided the expression for the infection prevalence and discussed its finite size corrections. In [13], Zhang et al. investigated an SIS epidemic model based on semi-directed networks where the networks are static and uncorrelated. They studied the effect of asymmetric and symmetric transmission on the steady-state fraction of infected individuals, and on the epidemic threshold. In [14], Li et al. proposed a novel SIS spreading model and mainly focused on the epidemic threshold and the steady fraction of infected nodes in networks with different degree distribution. The study concern the spread of epidemics on pure static networks is a well-developed field. Considering transmitting vector and the direct contacts of human beings, Wang et al. [15] proposed a modified SIS model on complex networks. They obtained the basic reproduction number and investigated the effects of various immunization schemes. Zhang et al. [16] proposed a model for an SIS epidemic process in a population of individuals in a complex network where the transmission of diseases can occur along the network links. The number of neighbors/degrees of individuals varies with the estimated risk of infection. So, they proposed an adaptive mechanism that adjusts the contact patterns of the individuals according to the perceived risk from disease. In [17], Jin et al. discussed the network epidemic models with demographics for disease transmission. They gave the formula of the basic re-production number of infection for an SIS model with births or recruitment and death rate. And they concluded that the degree distribution of the population varies with time before it reaches the stationary state. However, they only considered the case of the network models with constant recruitment rate. Recently, there are a few studies on heterogeneous transmission rink [18–24]. In [18], Miller provided the analytical results of disease outbreaks in large random networks with heterogeneous susceptibility and infectivity, where the transmission of infections is addressed on static networks. Considering mobile individuals, Li et al. [19] investigated the SIS model on a random dynamical network composed of mobile individuals and analytically studied the criticality of spreading dynamics under different distribution of individual susceptibility and infectivity. In [20], taking the location-specific heterogeneous human contact pattern into account, the authors studied the complex dynamic behaviors of spatial transmission of epidemics and analyzed the epidemic threshold of the system. However, how to evaluate the infection rate according to the degree of the node is not explicitly provided. In [21], the authors studied the effect of non-uniform transmission on the critical threshold of the SIRS epidemic model in SF networks. They concluded that the threshold depends on the topology of the underlying networks and the disease transmission mechanism, e.g., non-uniform transmission. In [22–24], the authors also considered the heterogeneous of transmission in complex network; however, they did not investigate the transmission mechanism based on the SIS model in their work.

In order to control the epidemic spreading in complex networks, the researchers have proposed several immune strategies. Random immune strategy [25] which is proposed by Anderson and May in 1992 is to choose some nodes from the network at random to immunize them. In 2002, the random immune strategy was proved to be not efficient on all the complex networks by Pastor-Satorras and Vespignani [26]. And they also put forward target immune strategy proved to be more efficient on the SF (scare-free) network. In 2003, Cohen et al. [27] presented the acquaintance immunization strategy and they found that it has good effect on the scale-free networks and networks having double kurtosis distribution. In 2008, Fu et al. [28] came up with an idea that they just took the nodes around the infected nodes into consideration and proved its effectiveness through theory analysis and simulations. Huang et al. [29] studied the influence of edge heterogeneity in disease spreading. They proposed an edge importance index based on the gravity model and improved the performance of immunization strategies by measuring the influence of edge heterogeneity for selecting vaccination nodes. Also, the difference of the infection rates on strong and weak ties is analyzed in [29]. Hadjichrysanthou and Sharkey [30] presented a deterministic SIS model of the dynamics on networks and designed effective targeted intervention strategies to mitigate and control the propagation of infections across heterogeneous contact networks.

As a matter of fact, it has been pointed out that the accurate epidemic modeling has many factors to be taken into account, and different transmission mechanisms can also lead to the distinct results on the critical threshold property in complex networks. In many realistic applications, the probability to be infected is varying according to the environment. For example, a person would be easier to be infected if many people around him have been infected by diseases than the case if few people around him infected. A computer node is more likely to be affected if most of its neighboring nodes are affected. So we changed the probability to be a variable which is a function of the number of the infected nodes around the current node and we propose a new propagation model which is called environment aware SIS model (EA-SIS) model. The main contributions of this paper can be summarized as follows.

In this paper, we propose an epidemiological model, EA-SIS model, taking the dynamic environment into consideration and analyze some immune strategies in EA-SIS model. In addition, we propose an immune strategy based on expected infection time, called ETB. In ETB, we not only take the nodes around infected nodes into consideration, but also we sort the nodes by expected infection time. At last, we do some simulation to evaluate our proposed schemes, which are more efficient than the traditional