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An evolutionary vaccination game in the modified activity driven network by considering the closeness

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HIGHLIGHTS

- The evolutionary vaccination game is considered in a modified activity driven network.
- A closeness parameter $p$ which is used to describe the connection between individuals is presented.
- The closeness $p$ may have an active role in weakening both the spreading of epidemic and the vaccination.
- Infected frequency increases with the increase of the individuals' activity.
- Results indicate some better hope (such as reducing the connection) may lead to backfire.

ABSTRACT

In this paper, we explore an evolutionary vaccination game in the modified activity driven network by considering the closeness. We set a closeness parameter $p$ which is used to describe the way of connection between two individuals. The simulation results show that the closeness $p$ may have an active role in weakening both the spreading of epidemic and the vaccination. Besides, when vaccination is not allowed, the final recovered density increases with the value of the ratio of the infection rate to the recovery rate $\lambda/\mu$. However, when vaccination is allowed the final density of recovered individual first increases and then decreases with the value of $\lambda/\mu$. Two variables are designed to identify the relation between the individuals' activities and their states. The results draw that both recovered and vaccinated frequency increase with the increase of the individuals' activities. Meanwhile, the immune fee has less impact on the individuals' vaccination than the closeness. While the $\lambda/\mu$ is in a certain range, with the increase of the value of $\lambda/\mu$, the recovered frequency of the whole crowds reduces. Our results, therefore, reveal the fact that the best of intentions may lead to backfire.

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1. Introduction

Infectious diseases, such as the MERS (Middle East Respiratory Syndrome), smallpox and human immunodeficiency virus, continue to significantly impact morbidity, mortality, and economic outcomes in many population [1–5]. The primary intervention method for preventing transmission of infectious diseases is vaccination. However, the decisions whether to vaccinate themselves can evolve in time depending on the epidemic incidence observed in the population [6]. That is because in deciding whether to vaccinate themselves, people consider the risk of morbidity from vaccination, the probability that...
they will become infected, and the risk of morbidity from such an infection [7–9]. However, the game theoretical approach could be suitable to describe the decision-making processes [10–15].

Game theory attempts to predict individual behavior in such a setting, where the payoff to strategies chosen by individuals depends on the strategies adopted by others in the population [16–19]. Zhang [20] et al. investigated Braess’s Paradox in epidemic game, the results indicated that improving the successful rate of self-protection does not necessarily suppress the epidemic or increase the whole society payoff. By using game theory, Timothy [21] investigated the social distancing in response to an epidemic. The results showed that social distancing is most beneficial to individuals for basic reproduction numbers around 2. Based on the probabilistic cellular automaton, Schimita [22] et al. proposed a vaccination game according to public health actions and personal decisions in which the players are the government and the susceptible newborns. The results supported showed the disease is not fully eliminated and the government implements quasi-periodic vaccination campaigns. Alessio [23] et al. analyzed the evolution of voluntary vaccination in scale-free networks and random networks. The results showed that if the vaccine is perfect, scale-free networks enhance the vaccination behavior, however, imperfection may lead to a cross-over effect. Eunha Shim [24] et al. investigated the game dynamic model of the vaccine skeptics and vaccine believers. They demonstrated that the pursuit of vaccine skeptics-interest among vaccine skeptics often leads to vaccination levels that are suboptimal for a population, even if complete coverage is achieved among vaccine believers. Han [25] et al. studied how the memory and conformism effect on epidemic processes. Their results indicated if the individuals make decision mostly depending on their own payoffs and do not believe too much in the celebrity, the final recovered number will be significantly reduced.

In many social, biological, and physical systems the interactions among the elements of the system are rapidly changing [26,27]. In recent years, there have been extensive research activities on time-varying networks, or called temporal networks, which evolve on a time scale comparable to the timescale of the propagation process [28,29]. The time-varying structure of link activations affects the network dynamics, from disease contagion to information diffusion [30,31]. The role of individual behavior in the spreading of epidemic diseases is becoming increasingly important due to increased travel activity on both short (commuting) and long (leisure or business trips) space and time scales [32,33]. Bhushan [34] et al. investigated the epidemics process on adaptive time varying networks. Their results showed the interaction patterns of the infected population play a major role in sustaining the epidemic. Michele [35] et al. explored the immunization strategies for epidemic processes in time-varying contact networks. Their results suggested that the strong variation of temporal networks, however, limits the efficiency of immunization strategy. Liu [36] et al. investigated the contagion processes in activity driven networks. They derived the critical immunization threshold and assessed the effectiveness of three different control strategies. However, the characterization and modeling of time-varying networks are still open and active areas of research [37,38]. On the other hand, the researchers often make an assumption on the activity driven network: each activated vertex connects with the other nodes randomly. However, this assumption sometime is unreasonable. That is because the link between the individuals is subject to some certain laws. For example, a Chinese person will connect the other Chinese more often than American people. Generally speaking, an individual may connect his old friends more frequent than other strangers.

Motivated by the above discussion, in this paper, we explore an evolutionary vaccination game in the modified activity driven network by considering the closeness. We set a closeness parameter \( p \) which is used to describe the way of connection between two individuals. We first investigate the case that vaccination is not allowed. The results show that under different closeness \( p \) the final density of recovered increases with the value of \( \lambda/\mu \). However, when vaccination is allowed, under different closeness \( p \) the final density of recovered individual first increases and then decreases with the value of \( \lambda/\mu \). Besides, the results point out that the closeness \( p \) may have an active role in weakening both the spreading of epidemic and the vaccination. In order to identify the relationship between the individuals’ activities and their states, we design two variables. The results indicate the recovered frequency increases with the increases of the individuals’ activities. Meanwhile, the immune fee has less impact on individuals’ vaccination than the closeness \( p \). With the increase of the value of \( \lambda/\mu \), the recovered frequency of the whole crowds reduces. From the perspective of human behaviors, our findings reveal that the best of intentions may lead to backfire.

The rest of the paper is organized into three sections. In Section 2, we describe the modified activity driven network. The evolution of vaccination game is detailed and illustrated in Section 3. In Section 4, we present the simulations results. Section 5 presents the conclusions and the relevant discussions.

2. The epidemic spreading in the modified activity driven network

In most social and information systems the activity of agents generates rapidly evolving time-varying networks. Activity driven models consider heterogeneous populations where each node \( i \) is characterized by a specific activity rate \( \alpha_i \). Variables \( \alpha_i \) do not change in time and are independent and identically distributed realizations of a random variable \( \alpha \), with a probability density function \( F(\alpha) \). In general, the density function is considered as a heavy-tailed form \( \alpha \sim \alpha^{-\gamma} \). Realizations \( \alpha_i \) of the random variable \( \alpha \) are constrained as \( \xi < \alpha_i \leq 1 \), where \( \xi \) is a cutoff value that is suitably chosen to avoid the possible divergences of \( F(\alpha) \) close to the origin.

Some researchers usually make an assumption when they investigate the activity driven network: each individual which becomes active will connect with the other nodes randomly. However, this assumption sometime is unreasonable. In general, the link between the individuals is subject to some certain laws. For example, a Chinese person may connect the other Chinese people more often than American people. More generally, an individual may connect with his old friends more
frequent than other strangers. The topology of the pattern of contacts between individuals plays a fundamental role in determining the spreading patterns of epidemic processes. In this paper, we research a modified activity driven network. We set a closeness parameter $p$ which is used to describe the way of connection between individuals. Considering a network with $N$ nodes, the epidemic processes in an epidemic cycle (the epidemic cycle is defined in the following) can be described as follows.

1. At each discrete time step $t$, a network $G_t$ with $N$ nodes and zero edges is generated.
2. Each vertex $i$ becomes active with probability $\alpha$, and generates $n$ links. Taking into account the two ways of connection in activity driven network: Each link is connected to the node which has been connected with probability $p$ (we assume if an activated individual has not connected with others, this node will select other nodes randomly). Otherwise, it will connect with an arbitrary node with probability $1 - p$. Note that when the closeness $p = 1$, all the individuals only connect with the individuals who have been connected, otherwise the individual select others randomly when the closeness $p = 0$.
3. The epidemic model rules are run on the obtained network. Considering the classical compartmental Susceptible–Infected–Recovered (SIR) model, there are three compartments which are susceptible $S$, infected $I$ and recovered $R$ in the population. At each time step, all individuals update their states in a synchronous way. More specifically, a susceptible node can be infected with a probability $\lambda$ if it is connected to an infected node. At the same time, the infected nodes may heal to a recovered state with a probability $\mu$. The epidemic process can be characterized by the following equations:

$$
\begin{align*}
S + I & \xrightarrow{\lambda} 2I, \\
I & \xrightarrow{\mu} R.
\end{align*}
$$

(1)

4. At time $t + 1$, all the links in the network $G_t$ are removed, and the process starts again from step (1).

3. The evolution of vaccination game

The primary intervention method for preventing transmission of infectious diseases is vaccination. However, under the complexity of human mobility and interaction, the individuals decide whether or not to vaccinate mainly results from a tradeoff between their cost and the potential risk. The decisions of individual can evolve in time depending on the epidemic incidence observed in the population. Therefore, the game theoretical approach could be suitable to describe the decision-making processes.

With respect to the epidemic model, our model is based on the evolution of the SIR epidemic dynamics. Some assumes and instructions for the vaccination game are given as follows:

1. An epidemic cycle $T$ is defined as lasting from the time the infection is first introduced to the time the last infection disappears from the population.
2. At the end of every cycle, each recovered individual loses natural immunity representing the effects of antibody loss and antigenic drift. At the same time, each vaccinated individual loses vaccine immunity.
3. The vaccine is fully effective but can only resist the disease for one cycle.
4. At the end of every epidemic cycle, we could calculate the neighbors set $N_i$ of individual $i$, that is defined as the node $j$ which has been connected with individual $i$ as least one time in a cycle.
5. At the beginning of each epidemic cycle, each individual forget all his links. In other words, each individual has no any neighbors. Therefore, a neighbor $j$ of individual $i$ in cycle $T$ may not be the neighbor of individual $i$ in cycle $T + 1$.

After each epidemic cycle, the individual $i$ will randomly choose one neighbor $j$ and imitate the strategy of neighbor $j$. We adopt the Fermi rule, namely an individual $i$ attempts to adopt the strategy from selected neighbor $j$ with a probability determined by the Fermi function

$$
U(s_i \leftarrow s_j) = \frac{1}{1 + \exp[-(f_j - f_i)/\kappa]}
$$

(2)

where $s_i$ and $f_i$ are the strategy and the payoff of an individual $i$, respectively. The parameter $\kappa$ quantifies the uncertainty related to the strategy adoption process. In general, for a large $\kappa$, individuals are less responsive to payoff difference, and the strategy of the individual with a high payoff becomes less likely to be adopted. In this paper, we let $\kappa = 0.1$.

An unvaccinated individual faces two different results: he will pay $b$ if he is infected, otherwise, he will pay none if he escapes from infection. Without loss of generality, we set the cost of infection $b = 1$. Meanwhile, once one takes vaccination, he needs to pay the cost of vaccination $c$ (in general $c < 1$), and the individuals can escape from contagion. The cost $c$ includes the immediate monetary cost for vaccine and the potential risk of vaccine side-effects. After the epidemic, people have the highest payoffs are the ones who neither take vaccination nor being infected, and they pay nothing, we usually call the lucky individuals as free-riders, as they payoff from others vaccination efforts. The proposed vaccination game in modified activity driven network is illustrated in Fig. 1.
Fig. 1. Schematic of the proposed model. In a cycle, the activated node connects the others according to the closeness $p$. After each epidemic cycle, the individuals decide whether or not to take vaccination in the following epidemic cycle mainly results from a tradeoff between their cost and the potential risk. The persons who are infected pay $b$, otherwise pay $0$. Once one takes vaccination, he needs to pay $c$.

Fig. 2. The evolution of the density of recovered with the change of $\lambda/\mu$. Considering $N = 2000$, $n = 6$, the distribution $F(\alpha) \propto \alpha^{-\gamma}$ with $\gamma = 1.63$ and a lower cutoff $\xi = 0.01$. Each data point is obtained by averaging 100 independent runs.

4. Results

We begin by presenting vaccination game on a network with the total population $N = 2000$. Initially, 1 percentage of vaccination and 1 percentage of infected are randomly distributed among the whole population. Let $\rho_V$, $\rho_R$, $\rho_S$ be the final density of vaccination, recovered and free-rides in the end of each cycle. Note that the final density of recovered $\rho_R$ is equal to the density of those have been infected. To alleviate the effect randomly, the equilibriums are obtained by averaging over 100 independent runs.

Generally speaking, the connection of face to face is more frequent than the phone connection or cooperation network. In Ref. [36], the exponents are taken $\gamma \in [2, 3]$, however, in this paper we used a deterministic power law distribution $F(\alpha) \propto \alpha^{-\gamma}$ with $\gamma = 1.63$ and the lower cutoff $\xi = 0.01$. We start our discussion by briefly reporting the behavior of the epidemic model when no vaccination is implemented.

Fig. 2 shows the epidemic diagram $\rho_R$ for the modified activity driven network when vaccination is not allowed. As illustrated in Fig. 2, the final density of the recovered increases with the value of $\lambda/\mu$. Moreover, a larger value of the closeness $p$ could help suppress the epidemic spreading. That is because a larger closeness $p$ means the individuals would like to connect with their old friends, which may effectively constrain the epidemic diffusion within localized groups of individuals. However, when the closeness $p$ is relative small, the individuals could connect more other people in a cycle.

The next, we are interested in studying on how the individuals’ decisions affect the final contagion densities in the modified activity driven network.

Fig. 3 illustrates the evolution of the final fraction of susceptible, recovered and vaccinated individuals with the cycle $T$. Obviously, one can see the vaccination density increases rapidly in the beginning, and then tends to be stable in the
last. However, the recovered density greatly declines. If people would like to vaccinate, the final size of an epidemic would significantly reduce. However, vaccinated individuals are tempted not to take the vaccine due to the benefits. Once people get know that their immune neighbor have more payoff than them, they will take vaccination soon, and then it will form a large-scale emergence of immunity so that the immune density fast rise. On the other hand, as time goes, people make the decision whether or not to take vaccination mainly according to comparing the payoff with their friends. With the immune number increasing, people who do not taking vaccination are more likely to connect to the vaccinated, so they will not be infected and their payoff will maintain a high level. In the next cycle, they will make decision not to take vaccination. However, the free-rides will have a higher risk of infection when they contact the infected neighbors. In this case, the free-rides will take vaccination again. Eventually the recovered density and free-rider density would stabilize.

The evolutions of the average fraction of recovered and vaccinated on the first 100 cycles for different closeness $p$ are shown in Fig. 4 (we do lots of simulations by choosing different parameters, the stable-state could be obtained in the first 100 cycles. Therefore, we just consider the first 100 cycles in the next). Interestingly, we find that a large closeness $p$ is responsible for not only constraining the epidemic diffusion within localized groups but preventing people to vaccinate. Also we may get, no matter how the immune cost is, the average final density of vaccination reduces with the increase of the closeness $p$. At the same time, the average final vaccination density minimum coincides with peaks in the average final recovered density. Although the individuals may feel crisis according to the outside information (such as TV, broadcast, Internet, newspaper, and so on), however, such crisis awareness is far less than that when they get know their friends are infected. Therefore, if the individuals only connect with limited people, that would weaken their crisis awareness. As a result, people would not take immune even if the disease exists in the network. That would sharply increase the probability of individuals to be infected. However, if the effective number of “acquaintance” becomes smaller and the closeness $p$ is bigger enough (in this paper the $p$ is close to 0.7), the total recovered individuals will reduce with the increase of the closeness $p$. Above all, the results point out that the closeness $p$ may have an active role in weakening both the spreading of epidemic and the vaccination.

In order to investigate the vaccination game processes in more detail, Fig. 5 shows the mean final density of recovered and vaccinated individuals as a function of the $p$ and $\lambda/\mu$ in the modified activity driven network. As shown in Fig. 5(a1)–(a3), we may observe some counterintuitive phenomena: under some certain closeness $p$, the final density of recovered individual first increases and then decreases with the value of $\lambda/\mu$. On the one hand, there are few higher activity individuals throughout the crowds which result in a few connections between individuals. On the other hand, the recovery rate is relatively larger when the value of $\lambda/\mu$ is smaller. Therefore, although some individuals are infected, the epidemic could not spread widely. However, once the value of $\lambda/\mu$ is larger enough, the probability that the susceptible to be infected increases. Due to the crisis awareness has been escalated, more individuals would like to take immune avoiding to be infected. Therefore, according to Fig. 5(b1)–(b3), we could observe that the density of vaccination increases with the $\lambda/\mu$.

In order to investigate the relation between individuals’ activities and their states, we set two variables named $F_R(\alpha)$ and $F_V(\alpha)$ that denote the frequency of the individual with activity $\alpha$ of becoming recovered or taking vaccination during some given cycles, respectively. The two variables also could be used to indicate the individuals’ attitude towards the surroundings. We express them by using the following equations:

$$F_R(\alpha) = \frac{C_R(\alpha)}{T},$$

$$F_V(\alpha) = \frac{C_V(\alpha)}{T}.$$
Fig. 4. The average final fraction of recovered and vaccinated individuals as the function of $p$ in activity driven networks on the first 100 cycles. Considering $N = 2000$, $n = 6$, the distribution $F(\alpha) \propto \alpha^{-\gamma}$ with $\gamma = 1.63$ and a lower cutoff $\xi = 0.01$. Other parameters: $\kappa = 0.1$, $\lambda/\mu = 10$, $b = 1$. Each data point is obtained by averaging 100 independent runs.

Fig. 5. The contour plots show the mean density of recovered and vaccinated individuals as a function of the $p$ and $\lambda/\mu$ in the activity driven network. The subgraphs (a1)–(a3) show how the density of recovered changes, their respective cost of vaccination $c = 0.1, 0.3$ and 0.5; (b1)–(b3) show how the density of vaccinated changes, their respective cost of vaccination $c = 0.1, 0.3$ and 0.5. All results are implemented with $\kappa = 0.1$, $b = 1$, $N = 2000$, $n = 6$, the distribution $F(\alpha) \propto \alpha^{-\gamma}$ with $\gamma = 1.63$ and a lower cutoff $\xi = 0.01$. Each grid point is made by averaging the first 100 cycles and over by averaging 100 independent runs.

and

$$F_V(\alpha) = \frac{C_V(\alpha)}{T}$$

(4)
Fig. 6. The recovered and vaccinated frequency for different values of $p$ in the modified activity driven network. Considering $N = 2000$, $n = 6$, the distribution $F(\alpha) \propto \alpha^{-\gamma}$ with $\gamma = 1.63$ and a lower cutoff $\xi = 0.01$. Other parameters: $\kappa = 0.1$, $\lambda/\mu = 10$, $c = 0.1$, $b = 1$, $T = 100$. Each data point is obtained by averaging 100 independent runs.

Fig. 7. The recovered and vaccinated frequency for different values of $c$ in the modified activity-driven network. Considering $N = 2000$, $n = 6$, the distribution $F(\alpha) \propto \alpha^{-\gamma}$ with $\gamma = 1.63$ and a lower cutoff $\xi = 0.01$. Other parameters: $\kappa = 0.1$, $p = 0.5$, $\lambda/\mu = 10$, $b = 1$, $T = 100$. Each data point is obtained by averaging 100 independent runs.

where $T$ denotes the total cycles of the epidemic process, $C_R(\alpha)$ and $C_V(\alpha)$ are the times of an individual with activity $\alpha$ of becoming recovered or taking vaccination during $T$ cycles, respectively.

As shown in Fig. 6(a), as expected, the frequency of recovered becomes larger with the increase of the individuals’ activity. For the case of $p = 0$, which means the activated individuals connect with others randomly, the gap of recovered frequency for the individuals with maximum and the minimum activity approaches to $F_R(\alpha_{\text{max}}) - F_R(\alpha_{\text{min}}) \simeq 0.1$. However, for the case of $p = 1$, which means the activated individuals only connect with the one who have been known, the gap of recovered frequency for the individuals with maximum and the minimum activity approaches to $F_V(\alpha_{\text{max}}) - F_V(\alpha_{\text{min}}) \simeq 0.5$. The results indicate the difference of recovered frequency becomes smaller with the decreases of the closeness $p$. According to Fig. 6(b), the frequency of vaccination becomes larger when $p$ is larger. However, the disparity of vaccination between the maximum and the minimum activity individuals is not obvious.

As one can see from Fig. 7(a), the recovered frequency for the same individual increases with the immune cost. Interestingly, under different immune cost $c$, the recovered frequency for the individuals with maximum and the minimum activity is almost the same $F_R(\alpha_{\text{max}}) - F_R(\alpha_{\text{min}}) \simeq 0.3$. Fig. 7(b) shows that the vaccinated frequency increases with the individuals’ activity. Moreover, under different immune cost $c$, the vaccinated frequency for the individuals with maximum and the minimum activity is almost the same $F_V(\alpha_{\text{max}}) - F_V(\alpha_{\text{min}}) \simeq 0.2$. The results indicate the immune cost has less effect on the vaccination than the closeness $p$.

As illustrated in Fig. 8(a), the recovered frequency, counterintuitive, declines with the increase of the value of $\lambda/\mu$. Meanwhile, as shown in Fig. 8(b), more people would like to take immune while the value of $\lambda/\mu$ becomes larger. This remarkable result suggests that better hope sometimes means backfire. We can call this situation as Braess’s Paradox, which have been detailedly described in Ref. [20].
Fig. 8. The recovered and vaccinated frequency for different values of \( \lambda/\mu \) in the modified activity-driven network. Considering \( N = 2000, n = 6 \), the distribution \( F(\alpha) \propto \alpha^{-\gamma} \) with \( \gamma = 1.63 \) and a lower cutoff \( \xi = 0.01 \). Other parameters: \( \kappa = 0.1, p = 0.5, c = 0.1, b = 1, T = 100 \). Each data point is obtained by averaging 100 independent runs.

5. Conclusion and discussion

We explore an evolutionary vaccination game in a modified activity-driven network by considering the closeness. We set a closeness parameter \( p \) which is used to describe the connection between individuals. Firstly, when vaccination is not allowed, under different closeness \( p \) the final density of recovered increases with the value of \( \lambda/\mu \). However, when vaccination is allowed, under different closeness \( p \) the final density of recovered individual first increases and then decreases with the value of \( \lambda/\mu \). Moreover, our results point out that the closeness \( p \) may have an active role in weakening both the spreading of epidemic and the vaccination. In order to identify the relationship between the individuals’ activity and the recovered and vaccinated density, two variables are designed. The results indicate recovered frequency increases with the increase of the individuals’ activity. Meanwhile, the immune fee has less impact on individual than the closeness \( p \). With the increase of the value of \( \lambda/\mu \), the recovered frequency of the whole crowds reduces.

Although the epidemic may be suppressed within localized groups if an individual only connect with their old friends, the available information become less. Because the crisis awareness can influence the individuals’ attitude towards epidemic, some better hope (such as reducing the connection) may lead to backfire.

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