Promoting cooperation through fast response to defection in spatial games

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Abstract

Recent experimental research has revealed that the cooperation in dynamic social networks, has significant scope for enhancement because individuals in a social system break the links with defective neighbours. To investigate how the length of defection tolerance affects the cooperation of prisoner’s dilemma game in dynamic ring networks, we study evolution of breaking and rewiring operations for social interaction as a response to the defection strategy. Defection tolerance is measured in terms of the time length that an individual tolerates a defector who continuously adopts the defective strategy. The results show that the dynamic nature of human social networks plays an essential role in promoting cooperation. Interestingly, there exists a critical value of the temptation to defect, below which the system is entirely dominated by cooperators, and a lower value of defection tolerance induces a larger threshold of temptation.

Natural and social systems, composed of a large number of interacting individuals, can be represented by networks. The emergence of cooperation in networked systems is widely observed, and understanding the cooperative behavior among selfish individuals has attracted considerable research attention [1–5]. Game theory has become a powerful method for analyzing cooperation behaviors. To mimic the strategy selection of individuals in dilemma situations, some models, such as the prisoner’s dilemma game (PDG) [6–11], the snow-drift game (SG) [12–15], the stag-hunt game [16–18] and the public goods game [19–23] have been explored. Individuals in games gain specific fitness, relating to the strategies of coplayers and itself, and update the coming strategy on the basis of information from the last round.

In the original PDG, two individuals can choose one of two strategies, cooperation (C) or defection (D). They both receive the reward, R, upon mutual cooperation and the punishment payoff, P, upon mutual defection. If one defects while the other cooperates, the defector receives the ‘sucker’s’ payoff, S, while the defector gets the temptation payoff, T. In the PDG, the ranking of the four payoff values is \(T > R > P > S\) and \(2R > T + S\), while in the SG, \(T > R > S > P\). The only Nash equilibrium for the PDG is the pure strategy \((D, D)\), whereas for the SG, the pairs of pure strategies \((C, D)\) and \((D, C)\) are both Nash equilibria of the game.

For a well-mixed population, cooperators in PDG can easily become extinct due to the advantage of defectors; however, for a structured population, local networked clusters promote cooperation. Previous studies showed that scale-free networks can significantly enhance cooperation [24], and several cooperation maintaining mechanisms have been proposed, for example, migration [25, 26], aspiration induced cooperation [27–29], punishment [30, 31], reputation [32] and social diversity [33–35]. In many empirical cases, the social relationship of individuals is not fixed, and individuals are free to choose with whom to interact, which induces the topology of the network to evolve with time, such as the time scale separation between strategy and network dynamic [36], payoff-induced random linking [37], and strategy-independent adaptations of random interaction networks [38]. Therefore, the strategy coevolves with the structures of networks [39–42]. Recent experimental studies also demonstrated that cooperation can be significantly enhanced in dynamic social networks, where a fixed percentage of players were chosen randomly to decide whether to add a new link or to
break a link. It was found that an intermediate percentage of link change can lead to the optimal levels of cooperation \[43, 44\]. Thus, breaking and rewiring processes that reflect the response to defection are easier to contribute to the high cooperation level.

Here, we focus on the pattern of response to defection induced by continuous defection behaviors, while an occasional defection is neglected. This setup is used because the limitations of social relationships that help determine the candidate whom the individuals can establish the new links with, are relatively fixed. Individuals have low tolerance to continuous defection behaviors, and may choose to break links and refuse to interact with neighbors with which they face long-term defection. A question arises about how the speed of the response to defection affects cooperation in dynamic networks. To address this question, we investigate cooperation in dynamic networks induced by continuous defective behaviors. The simulation results show that cooperation level is enhanced significantly in dynamic networks by passively isolating the defectors. The breaking and rewiring operations induce networks that can retain a pure cooperation state even for large value of temptation to defection. In particular, it is found that faster response to defect is more effective to promote cooperation on dynamic networks with constrained rewiring compared to that of random rewiring.

Results

1. Cooperation on dynamic networks with constrained rewiring

We focus on the effect of response to defection on cooperative behaviors in dynamic networks with discrete time step, where nodes correspond to players and links to social contacts. At each time step, there are two processes: strategy adoption and link updating. In the first process (strategy adoption), each individual plays the PDG with its nearest neighbors (starting with a regular ring network with average degree \(k = 4\)). The total payoff of a player is the sum of all the payoffs obtained from the neighbors. Then, each player simultaneously updates the strategy of a randomly selected neighbor with the probability defined as the Fermi rule: \(w_{xy} = 1/(1 + \exp((P_x - P_y)/K))\), which results in players learning the strategies of the neighbor with high payoff. Parameter \(K\) represents uncertainty in strategy adoptions and \(P_x\) and \(P_y\) are payoffs of player \(x\) and randomly selected neighbour \(y\), respectively. In the second process (links updating), players break the links with neighbours who have continuously defected for \(L\) steps to avoid potential continuous loss. The broken links are rewired again after \(L\) steps by the one who has selected breaking operation, which is so called constrained rewiring because it is implemented between player and its inherent neighbours rather than randomly selected ones. For example, a player \(i\) has a neighbour \(j\) who has continuously defected for \(L\) steps. According to the rule of constrained rewiring, \(i\) will break the link of \(j\), and \(i\) will unconditionally link to \(j\) after the \(L\) time steps. Therefore, tolerance strength is used to control the evolution of networks structures, which is quantified by parameter \(L\).

We first examine the cooperation level as a function of \(L\) for different values of temptation to defect \(b\) (the only parameter in rescaled payoff matrix of PDG), as shown in figure 1. Additionally, figure 1 shows that an appropriate \(L\) can significantly enhance cooperation behavior. In particular, the intermediate tolerance to defection leads the systems to the phase where cooperation is dominating for a small \(b\). Consequently, systems that need a larger \(b\) to maintain the complete cooperation phase should have a lower \(L\). As such, the two strategies (C + D) can coexist for large enough \(b\), which is almost irrespective of \(L\). In other words, the
cooperation level depicts the transition from complete C phase to the C + D coexistence phase with the increasing of \( b \).

To study the effects of \( b \) more comprehensively, we present how the temptation to defect, \( b \), impacts the cooperation level by incorporating the tolerance parameter \( L \) in figure 2(a). It shows that dynamic networks greatly support cooperation compared to non-evolving networks (the cooperators go extinct around \( b = 1.1 \) for the latter). Interestingly, there exists a critical value \( b_c \) below which the system is fully cooperative. The lower the \( L \), the larger the threshold \( b_c \). That is to say, the lower the tolerance to the defection, the easier it is to hold the cooperation level. Beyond the critical \( b_c \), the cooperation level begins to decline. For a larger \( L \), evolving of strategy and link updating makes the estimation of \( b_c \) difficult. However, we can approximately evaluate the critical \( b_c \) for the extreme case of \( L = 1 \). Under this novel setup, the decrease in the cooperation level is mainly caused by cooperators adopting the defection strategy, while the increment of cooperation level for the initial steps is mainly contributed by the isolated individuals’ cooperation adoption who select strategy randomly. Hence, if the fraction of isolated individuals who will adopt cooperation strategy from \( t + 1 \) to \( t + 2 \) is larger than the decrement of the cooperation level from step \( t \) to \( t + 1 \), then the system tends to evolve into the cooperation dominant phase. Based on these simple analysis, we obtain the following critical condition for the case of \( L = 1 \):

\[
\frac{f_C(t) - f_{C\rightarrow D}(t) + f_{D\rightarrow C}(t) + \frac{p_b(t + 1)}{2}}{f_C(t) + f_{C\rightarrow D}(t) + f_{D\rightarrow C}(t) + \frac{p_b(t + 1)}{2}} = f_C(t + 2).
\]

The first term of the left-hand side denotes the fraction of cooperators at step \( t \), and the second term of left-hand side denotes fraction of cooperators who will adopt defection strategy at \( t + 1 \). The third term of the left-hand side denotes the fraction of defectors who will adopt cooperation strategy at \( t + 2 \) and the fourth term of left-hand side denotes the fraction of isolated individuals at step \( t + 1 \) who will adopt cooperation strategy. The right-hand side denotes the fraction of cooperators at step \( t + 1 \). The constant factor 1/2 denotes that the coming strategies of isolated players are selected randomly. We have also examined the results by choosing kinds of probability for isolated players to cooperate in the next step, finding that the larger probability is in favor of maintenance of pure cooperation phase C. The term \( f_{C\rightarrow D} \), representing the fraction of non-isolated cooperators in step \( t \) who will select the defection in \( t + 1 \), is calculated by using the mean-field approximation:

\[
f_{C\rightarrow D}(t) = (1 - p_b(t))(1 - f_C(t))w,
\]

where \( p_b \) is the fraction of isolated players and \( w = 1/[1 + \exp(P_C - P_D)/K] \) is the probability of cooperators with payoff \( P_C \) adopting the strategy of defective neighbour with payoff \( P_D \). The expected payoff \( P_C = k[1 - p_b(t)]f_C(t) \) and \( P_D = kb[1 - p_b(t)]f_C(t) \) is also obtained by the mean-field approximation. And \( k = 4 \) is the average degree of each player. By combining equations (1)–(2) and critical condition \( f_C(t) = f_C(t + 2) \), we obtain the equation of the fraction of cooperators and isolated individuals:

\[
f_C(t)(1 - f_C(t))(1 - p_b(t))^2w + f_{D\rightarrow C}(t) = \frac{p_b(t + 1)}{2}.
\]

For simplicity, we set \( t = 1 \) to obtain the approximate critical \( b_c \). We also neglect the effect which defectors will adopt a cooperation strategy, which is quite small in simulations. In this case, \( f_C(t = 1) = f_D(t = 1) = 0.5 \),

![Figure 2](attachment:image.png)

**Figure 2.** Cooperation level as a function of temptation to defect \( b \) for different values of \( L \) (left) and the first 200 time evolution of the cooperation level (right) for different tolerance strength \( L \). The results are averaged over last 2000 time-steps of a total of 40000 time-steps of evolution. Each data point results is obtained from the average over 200 different realizations. The cooperation level and fraction of isolated individuals in the former steps shows strong oscillation evolving with tim, and \( b = 1.48 \) for panel (b).
They found that if the players with more successful strategies are likely to keep the links, the cooperation level exhibits the oscillations as the rate of rewiring. If the defectors have not been isolated at the beginning of evolution, it is difficult for them to be isolated. Owing to the advantage of defection, cooperators must form the tight clusters to resist the invasion of defectors.

Second, the cooperation level does not always satisfy the condition of \( R > T \). The presence of a rewiring process in this interval increases the fraction of isolated individuals, which, in turn, leads to the expansion of cooperation. Similar oscillation of the worst cooperation environment becomes isolators. The existence of link updating can be divided into the following two elementary processes by \( L \): (i) \( t < L + 1 \) (absence of link updating), where, similar to the traditional PDG, the cooperation level decreases with time because of the defection advantage; (ii) \( L + 1 < t < 2L + 1 \) (presence of link updating), where the individuals who have adopted the defection strategy in \( t - L \) and do not alter strategy in the next \( L - 1 \) steps will be dismissed by neighbors. Especially at \( t = L + 1 \), all of the defectors, as well as cooperators who have the worst cooperation environment become isolators. The presence of a rewiring process in this interval increases the fraction of isolated individuals, which, in turn, leads to the expansion of cooperation. Similar oscillation of cooperation level has also been observed in the Snow-drift games on adaptive networks, where one link is randomly selected to rewire with probability \( p \) or one of linked players adopts the other’s strategy with probability \( 1 - p \). They found that if the players with more successful strategies are likely to keep the links, the cooperation level exhibits the oscillations as the rate of rewiring exceeds a critical threshold [45]. Repeating processes (i) and (ii), the oscillation disappears and the system reaches the final stable state, where the fractions of cooperators and isolated individuals remain unchanged. In time, the probability for individuals to be isolated decreases, because the rewiring and dismissing processes usually happen simultaneously.

Subsequently, we focus on the phase diagrams of cooperation levels and fraction of isolated individuals as functions of \( b \) and \( L \). On comparing figure 3(a) with figure 3(b), it is clear that the pattern with \( f_c = 1 \) in figure 3(a) is nearly the same as the pattern with \( p_0 = 0 \) in figure 3(b), but the most important result is that the conditions for \( f_c = 1 \) and \( p_0 = 0 \) are not equivalent. First, if the cooperation level is \( f_c = 1 \), we always have the condition of \( p_0 = 0 \). As for the full cooperation phase, the system might never have isolated individuals. Second, the cooperation level does not always satisfy \( f_c = 1 \) as \( p_0 = 0 \). Such as the case of \( L = 1 \), the fraction of isolated individuals is \( p_0 = 0 \) for large \( b \), while the cooperation level is also \( f_c = 0 \). The reason is that, even though the entire system consists of defectors for \( L = 1 \) in case \( b > b_t \), the short period of rewiring makes the defectors impossible to isolate.

For the case \( b > b_t \), the isolated individuals exist in the system, coexisting with cooperators and defectors. Owing to the advantage of defection, cooperators must form the tight clusters to resist the invasion of defectors. If the defectors have not been isolated at the beginning of evolution, it is difficult for them to be isolated in the following steps, which is caused by the simultaneous breaking and rewiring links. Hence, the defectors and cooperators isolated at time \( t \) are typically the ones who are isolators at time \( t - L \).

Based on the above discussion, it can be concluded that: (i) the proper tolerance to defection can enhance the cooperation level, and (ii) domination of cooperation is related to the structure of networks. Previous studies show that the spontaneous emergence of clusters hinders the extinction of cooperation strategies on structured networks.

\[ p_0(t = 1) = 0 \text{ and } p_0(t = 2) = f_c' + f_c'' \]

Replacing these terms into equation (3), we obtain \( b_t = 1.48 \) which is close to the simulation result of \( b_t = 1.50 \) as shown in figure 2(a). Below \( b_t \), the frequency of cooperators gradually increases and reaches full cooperation state eventually. On the contrary, above the \( b_t \), it leads to the full defection phase, which is consistent with the result in figure 2(a).
populations. The fraction of individuals who have four neighbours adds the half of \( p_0 \) is nearly equal to the cooperation level at the stable state

\[
f_C = p_s + \frac{p_0}{2}.
\]

In this, we simply assume the fraction of individuals with degrees \( k = 0, 1, 2, 3 \) are the same, that is \( p_0 = p_1 = p_2 = p_3 \). By combining with the constraint condition \( \sum_{j=0}^{4} p_j = 1 \), we can obtain the relationship between \( f_C \) and \( p_0 \) as the following:

\[
p_0 = \frac{2(1 - f_C)}{7}.
\]

equation (5) indicates that if \( f_C = 1 \), then \( p_0 = 0 \), which is consistent with the former discussion. In addition, we can find that the fraction of isolated individuals has the upper bound \( p_0 < 2/7 \) from equation (5), and it is smaller than the simulation result \( p_0 = 0.37 \) as shown in figure 3(b). That is because we assume \( p_0 = p_1 = p_2 = p_3 \).

Since temptation to defect \( b \) is the only parameter in PDG, we want to examine the robustness of the results under other possible parameterizations. For this purpose, we introduce another parameter \( a \) into original PDG, which denotes the cost of maintaining the link. Therefore, elements of the payoff matrix are \( R = 1 - a \), \( T = 1 + r - a \), \( S = -r - a \), and \( P = -a \), where \( r = c/(b - c) \) indicates the ratio of the costs of cooperation to the net benefits of cooperation. Then, we examine the cooperation as a function of \( a \) with different \( L \) and \( r \), as shown in figure 4(a). It is found that \( a \) does not affect the cooperation in two situations: both small \( L \) and \( r \) as well as both large \( L \) and \( r \). In this sense, cooperation can also be promoted by players choosing fastest response to defection, even the cost of maintaining the links is high. However, the level of cooperation decreases with the increasing of \( a \) in the condition of large \( L \) and small \( r \).

Actually, link rewiring can be treated as a form of costly punishment. The players who break the links with neighbors for \( L \) steps will lose the potential payoffs obtained from those ones. Meanwhile, these neighbors also cannot receive the payoffs from the players for \( L \) steps. The loss of payoffs for a player and its neighbors can be seen as the cost of punishment and penalty suffering from the punisher, respectively. Hence, we examine whether the cooperative behavior on the adaptive networks with constrained rewiring is consistent with results for non-evolving networks with punishments. To keep the rule of potential payoffs in the constrained rewiring model, \( \beta \) denotes the cost of punishment and the penalty is defined as \( \gamma \). In this way, punishment occurs if a player continuously adopts the defect strategy for \( L \) steps. Players with \( L \) continuous defect strategy have to pay the penalty of punishment in the following \( L \) steps, and their neighbors will pay the cost of punishment as well. The loss of payoffs for a player and its neighbors can be seen as the cost of punishment and penalty suffering from the punisher, respectively. Hence, we examine whether the cooperative behavior on the adaptive networks with constrained rewiring is consistent with results for non-evolving networks with punishments. To keep the rule of potential payoffs in the constrained rewiring model, \( \beta \) denotes the cost of punishment and the penalty is defined as \( \gamma \). In this way, punishment occurs if a player continuously adopts the defect strategy for \( L \) steps. Players with \( L \) continuous defect strategy have to pay the penalty of punishment in the following \( L \) steps, and their neighbors will pay the cost of punishment correspondingly. Thus, there are four cases for the cost of punishment \( \beta \) for player \( i \) with strategy \( s_i \) and penalty \( \gamma \) of \( i \)’s neighbour \( j \) with strategy \( s_j \) as the following: (i) \( \beta = 1, \gamma = 1 \) (\( s_i = C \) and \( s_j = C \)). (ii) \( \beta = 1, \gamma = b \) (\( s_i = C \) and \( s_j = D \)). (iii) \( \beta = b, \gamma = 0 \) (\( s_i = D \) and \( s_j = C \)). (iv) \( \beta = 0, \gamma = 0 \) (\( s_i = D \) and \( s_j = D \)). We examine the cooperation level as a function of \( L \) with different temptation to defect \( b \) for PDG on regular ring networks with punishment, as shown in figure 4(b). Comparing results of constrained link rewiring in figure 1, one can find that cooperation level with costly punishment on non-evolving networks is similar to that of...
adaptive networks with constrained link rewiring, which demonstrates that link rewiring can be seen as form of costly punishment.

2. Cooperation on dynamic networks with random rewiring
Motivated by opinion dynamics on adaptive networks, where players build new links with others [46–50], we further compare cooperative behaviors on dynamic networks with constrained rewiring to that of randomly rewiring. The former refers to players rewiring their inherent links to their neighbors, while the latter involves the player rewiring links to a randomly selected one. In both processes, players break the links to a neighbour who continuously defected within $L$ time steps. Here, we have paid more attention on tolerance to defect on cooperative behavior, rather than success probability of adding new links on cooperation, which is different from the models of opinion dynamics on adaptive networks. Therefore, we explore cooperative behaviors on dynamic networks with random rewiring, as shown in figure 5. It is found that cooperation levels can be enhanced slighted by the fast response to defect for low temptation to defect $b$. While for large $b$, i.e. $b = 1.4$, cooperators cannot resist the invasion of defectors. Figure 5 demonstrates that, compared to randomly rewiring, faster response to defect is more effective to promote cooperation on dynamic networks with constrained rewiring.

**Discussion**

Previous studies [43, 44] have demonstrated that the adaptive networks can support cooperation and the rewiring of links is mainly implemented among the randomly selected players, where a fixed percentage of individuals pairs were chosen at random to decide whether to rewire or break the links at each step. Motivated by the fact that in many empirical cases, players do not easily create new links with strangers, we study a mechanism that individuals may temporarily stop to play games with their opponents who continuously adopt the defect strategy. If some neighbors have continuously adopted the defect strategy for $L$ steps, the player chooses to break the links with these and the broken links will be rewired again after $L$ steps. In this manner, we mainly focus on the response to continuous defection, while the discontinuous defect strategy is considered as an occasional defect that is not considered for response.

It is found that the repeated rewiring processes isolated the defectors, which not only prevents the spreading of defection, but also gives the isolated individuals the chance to choose cooperation strategy. The results show that the cooperation level is enhanced greatly in dynamic networks, and the lower defection tolerance strength induces the networks to remain in the pure cooperation phase for a larger temptation to defect $b$, which is consistent with the experimental results [44]. Our finding also indicates that the faster breaking operation is conductive to cooperation.
Methods

The individuals are located on the regular ring networks with periodic boundary conditions, in which each one is linked with its four nearest neighbors before the evolution. Initially, each individual is designated either as a cooperator or defector with equal probability. A full Monte Carlo step (MCS) consists of two processes: strategy adoption and link updating, respectively. Results are obtained after the

(i) Strategy adoption. For each MCS, individual $x$ plays the PDG with its nearest neighbors. Its payoff $P_x$ is the sum of all the payoffs acquired from the neighbors. Consequently, $x$ adopts the strategy of a randomly selected neighbor $y$ with the probability [51, 52]:

$$w_{x \rightarrow y} = \frac{1}{1 + \exp[(P_x - P_y)/K]},$$

where $K$ represents uncertainty in strategy adoptions and $P_y$ is the payoff of $y$. We set $K = 0.1$ and network size $N = 20000$ for all simulations. For simplicity but without loss of generality, the payoff matrix for the PDG are rescaled such that $R = 1, S = 0, T = b, P = 0$, where $1 < b \leq 2$ represents the advantage of defectors over cooperators.

(ii) Links updating. A parameter $L$ is introduced to control the time scale of link updating. Each player, once some neighbors have continuously adopted the defection strategy for $L$ steps, chooses to break the links with these. We introduced two rewiring mechanisms: constrained rewiring and random rewiring, respectively. (a) Constrained rewiring. The broken links at step $t$ will be rewired at step $t + L$ by players who have chosen breaking operation. (b) Random rewiring (motivated by [49]). Player $i$ breaks the links with number of $n_b$ neighbors at step $t$ who have continuously defected for $L$ steps, then they rewire the new links to randomly selected ones. In this sense, $L$ is called the tolerance strength to defection. First, this setup determines the rewiring as an active behavior, which means it is implemented by the one who chooses to break links. Second, the rewiring and dismissing operation happen in the same individual pairs, rather than randomly selected ones. To an individual who has no neighbors (isolated), the strategy adopted in the next step is randomly chosen and parameter $L$ quantifies the tolerance strength of the continuous defection. A larger $L$ indicates that the individuals will not change the current interaction environment easily when facing the continuous defection, while the rewiring also requires a significant amount of time. For the case of $L = 0$, the cooperators are dismissed by neighbors, but the rewiring is executed immediately, thus the model is the same as the original PDG. Without loss of generality, we set $L \geq 0$ in our model. Note that for $L \to \infty$ the model reduces to the original PDG, because the individuals never alter the neighborhood.

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Competing financial interests

The authors declare no competing financial interests.

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