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Evolutionary accumulated temptation game on small world networks

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ABSTRACT

The temptation in the traditional prisoner's dilemma is constant. To explore the evolution of temptations, the accumulated temptation game is proposed, where the temporal temptation is of heterogeneity among agents according to historical strategies. Agents accumulate the temptations by cooperation but consume the temptation by defection. The accumulation factor is introduced to measure the amplitude of the variation of temptations. During the evolutionary process, the density of cooperators and the average temptation may move towards the same direction. Cooperative behaviors will be eliminated if the accumulation factor is large enough. As an interesting result, a fraction of agents may keep cooperation constantly for accumulating temptations and they instantaneously defect at a certain time. The higher accumulation factor accelerates the instantaneous defection of agents. The completely random networks play an essential role in motivating cooperation when the temptation is small.

1. Introduction

Game theory plays a vital role in the dissection of personal behaviors [1,2], which emphasizes the interactions among actions of different agents. As one of the most crucial assumptions, agents in the game theory are always egoistic. It indicates that strategies of agents are almost driven by higher self-payoffs. There is no doubt that such hypothesis is consistent with humans in reality. Meanwhile, social relationships among humans cannot be neglected, which may determine partners in the game [3]. With the integration of game theory and social network, networked evolutionary game is studied. Researchers attempt to explore mechanisms that motivate cooperations within some classical models, including prisoner's dilemma game [4–10], snowdrift games (SG) [11–14], public goods games (PGG) [15–18] and so on. These canonical models are foundations of the description of human behaviors in society.

More investigations focus on the heterogeneity in the evolutionary game process. Heterogeneity may be reflected by diversified games among the system [19,20]. Szolnoki et al. considered multigames in the structured population [21–24]. In multigames, specific types of games among agents depend on the features of agents and the environment. Namely, different kinds of canonical games are allowed to coexist in their system. Some scholars concern the heterogeneity through feedback effects in the evolution. Tomochi and Kono studies the temporal payoff matrices [25], which characterize the effects of feedbacks on agents' behaviors [26,27]. Meanwhile, Lee et al. [28] propose a multiadaptive game, where the temptation in their prisoner dilemma is adjusted according to the cooperators' frequency. Szolnoki and Chen [29] explore

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how higher cooperation level change the environment through the effect of feedback. Most of the current systems connect the heterogeneity with specific scenarios, in which some phenomena are illustrated concretely. For characterizing the relationship among investors in financial markets, the power-based game and investor sharing game are proposed in [30–33] where entries of payoff matrix are heterogeneous in terms of agents' degrees and funds on networks. Following these works, the accumulated temptation game is presented in this paper. In this model, payoff matrices are related to behaviors and the local networks of agents.

Motivated by the references above, the accumulated temptation game is introduced concretely in Section 2. Rules about agents' payoffs and strategy updating are shown in Section 3. Section 4 investigates the evolutionary process of accumulated temptation games on WS small world game. Finally, Section 5 makes conclusions.

2. Accumulated temptation game

The spatial prisoner's dilemma game (PDG) is a classical model for illustrating the evolution of egoists' cooperative behaviors. In the prisoner's dilemma game, the temptation for defectors, which is usually denoted by $b > 1$, is the key parameter. Traditionally, the temptation is exogenous and constant according to assumptions. In other words, how the scale of temptation forms and evolves is not under consideration.

In our spatial model, agents are placed on the network $G(\mathcal{N}, E)$. The set $\mathcal{N}$ collects N agents, that is to say, $\mathcal{N} = \{1, 2, \ldots, N\}$. Edges in E characterize interactions among agents. Normally, the degree of agent $i \in \mathcal{N}$ is represented by d_i, which signifies the public power of an agent [30]. As we mentioned above, temptations in prisoner's dilemma game (PDG) are constant and exogenous. In this work, the case that temptations become higher (lower) as agents cooperate (defect) is studied. With the combination of agents' degrees, the payoffs of the accumulated temptation game are written in a rescaled matrix as follow:

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} 1 & 0 \\ b_i^t & 0 \end{pmatrix} \end{array}$$

and

$$b_i^{t+1} = \begin{cases} b_i^t \times \bar{d}^{\alpha}_{n_i,t}, & s_i^t = C \\ b_i^t / \bar{d}^{\alpha}_{n_i,t}, & s_i^t = D \end{cases}$$

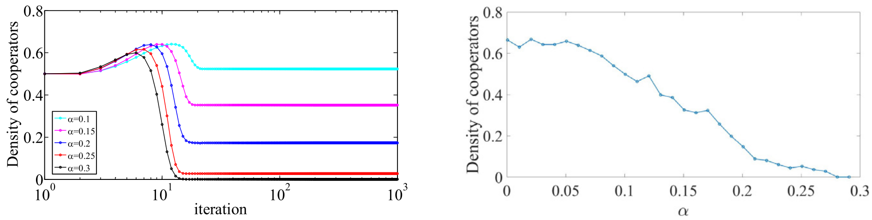
where

$$\bar{d}_{n_i,t} = \frac{1}{|\Omega^c_{i,t}|} \sum_{j \in \Omega^c_{i,t}} d_j$$

and $\Omega^c_{i,t}$ is the set of cooperators in agent i's neighborhood. Here, $|\Omega^c_{i,t}|$ indicates the scale of cooperators in agent i's neighborhood. Similar to the traditional prisoner dilemma game, as both of two agents choose cooperation, they gain the same payoff that equals to 1. Particularly, b_i^t refers to what a defector gets when the other agent chooses to be a cooperator, which depends on different agents and may vary with time t. It indicates that the temptation is nonconstant and reflects heterogeneity.

Furthermore, the accurate rule of how we fetch the value for the temptation b_i^t is displayed as follow. As mentioned above, $\bar{d}_{n_i,t}$ refers to the average degree of all cooperators among the neighbors of agent i. It is the essential factor that controls the way b_i^t evolves. In our case, defection may be inhibited by the reduction of temptation after previous defections. Meanwhile, the temptation is enhanced for prior cooperators. We assume that the evolution of temptation is correlated to the agent and cooperators in his/her neighborhood. Actually, according to the payoff matrix, agents capture positive payoffs only when encountering cooperative neighbors. In other words, cooperators in the neighborhood attend games with agents currently and achieve positive payoffs of agents, who may witness agents' current behaviors. As such, cooperators in the neighborhood may be essential for the evolution process of temptation of agent. This is also why $\bar{d}_{n_i,t}$ is introduced in our model. Here, the participation of cooperative neighbors in the evolution of temptation is represents by $\bar{d}_{n_i,t}$. On the one hand, if agent i chooses to cooperate currently, $s_i^t = C$, according to the accumulated temptation game, the temptation of agent i is accumulated by multiplying with $\bar{d}^{\alpha}_{n_i,t}$. Obviously, the temptation b_i^{t+1} will be larger at the next time $t + 1$ for the accumulation factor $\alpha > 0$, which will be explained in detail next. On the other hand, when agent i defects cooperators in his neighborhood, the temptation of agent i is discounted by $\bar{d}^{\alpha}_{n_i,t}$ at time $t + 1$. Therefore, current strategies of agents in the accumulated temptation game have feedback effect on their payoffs in the future [28].

With regard to the accumulation factor α, it controls the scale of the defector's payoff directly in the D–C pair and it is assumed to be positive by default. Mathematically, the larger the value of accumulation factor α, the more sharply b_i^t converts over time. Actually, α measures the feedback effect from cooperative neighbors. If α tends to zero, current cooperators in agents' neighborhoods may have little influences on temptations of agents. On the contrary, when α is big enough, temptations of agents are not stable and almost controlled by cooperative neighbors. Hence, $\bar{d}_{n_i,t}$ and α are closely linked in the formation of b_i^t. In fact, the value of α may be different when the temptation is enhanced and discounted. For example, to restrain more defection, the value of α in the discount of temptation may be larger than that in the growth



(a) Density of cooperators with iteration

(b) Density of cooperators with α

Fig. 1. (a) presents the density of cooperators during the evolutionary process on WS small world networks with 1000 agents. Initially, 50% cooperators (i.e. 50% defectors) randomly distribute on networks. Meanwhile, the temptation of the population is initialized to 1, $b_i^0 = 1, i \in \mathcal{N}$. Curves with different colors correspond to diverse accumulation factors α. (b) shows the density of cooperators in equilibrium states with different α. Note that 1000 agents are assumed and the rewiring probability of the WS small world network is 0.5.

of temptation. In this work, α is assumed to be unified in the evolution of temptation, for highlighting the effect of the evolutionary mechanism of temptation.

Theoretically, the accumulated temptation game is on the border between the prisoner's dilemma and stag-hunt game. When the temptation b_i^t is larger than 1, our game is similar to prisoner's dilemmas. If b_i^t is small enough, the accumulated temptation game resembles the stag-hunt game. However, we should note that b_i^t may become less than 1 and is not the true temptation. Here, b_i^t is called as temptation just because it may be regarded as the extension of social dilemma in form.

3. Strategy updating

In the networked evolutionary process, each agent i acquires gross payoffs in games with his neighbors on $G(\mathcal{N}, E)$. At the time step t, agent i's neighbor j with the highest payoff $P(j)$ is focused on. Concretely, the agent i will adopt the strategy s_j with a probability determined by Fermi function:

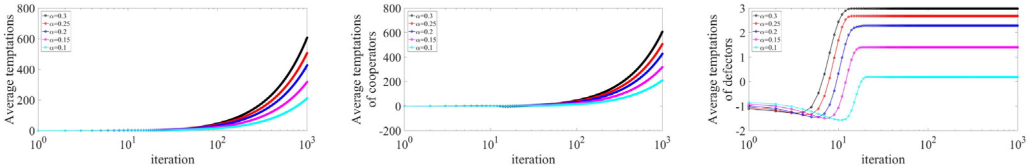
$$W(s_j \to s_i) = \frac{1}{1 + exp[(P(i) - P(j))/\kappa]}$$

where $P(i)$ represents the payoff of agent i, and κ characterizes the noise effects. In fact, to avoid the noise effect originated from the variation of κ, we have explored the sensitivity to the noise effect [34–37]. Through our simulations, when κ ranges from 0.1 to 10 000, the system shows robustness about the noise κ. It indicates that irrational errors of agents may not affect the choice of strategies around the population. In what follows, κ is set to 0.1 in the simulation.

4. Simulation

In this section, we will simulate the evolutionary process on WS small-world network. The WS small-world network is generated by the classical mechanism in [38], which is also called randomly rewiring. Based on the nearest-neighbor network, each edge is randomly rewired with the given rewiring probability. Here, the average degree of the nearest-neighbor network is fixed to 4. The rewiring probability is set to 0.5. We generate the WS small-world network with 1000 vertices. Half of the agents are cooperators while the others are defectors. The temptation of the population is initialized to 1, $b_i^0 = 1, i \in \mathcal{N}$. The evolutionary dynamics is simulated with Monte Carlo method. After each full Monte Carlo step, all agents will update their strategies simultaneously. Per data point has been averaged with 40 independent Monte Carlo simulations containing 1000 steps respectively, in order to overcome the impact of randomness.

Fig. 1a shows how the density of cooperators varies after iterative simulations. For comparison, the variation with different values of accumulation factor α is also displayed. As we can see, the density of cooperators increases slightly in the first place but drops before long, which reaches an equilibrium at last. In fact, according to the payoff matrix of accumulated temptation game, cooperation behaviors are beneficial for the accumulation of temptations. Consequently, after accumulating temptations for a certain period, the initial cooperators may convert to be defectors. Once their defections occur, their temptations will decline though payoffs may still be huge currently. There is no doubt that temptations of defectors decrease constantly with their defection strategies, which may be less than what a cooperator gets finally. It implies that the tradeoff between cooperations and defections is realized and then an equilibrium state occurs in the end. Comparatively, when the accumulation factor α is at a higher level, the density of cooperators in the network will decline more sharply. Initially, the frequency of cooperators increases at a similar speed with disparate values of α. After a period of time, with the larger α, cooperators may accumulate much more temptations, which makes them realize that being a defector is more beneficial than choosing cooperation. Hence, more defective behaviors prosper and almost occupy the whole population as α is great ($\alpha = 0.3$). In shorts, agents will find defection easier to perform so the density of cooperators decreases more sharply in the end. It suggested that higher level of the accumulation factor α leads to more violent volatility of temptations and less cooperation finally.



(a) Average temptation of agents (b) Average temptation of cooperators (c) Average temptation of defectors

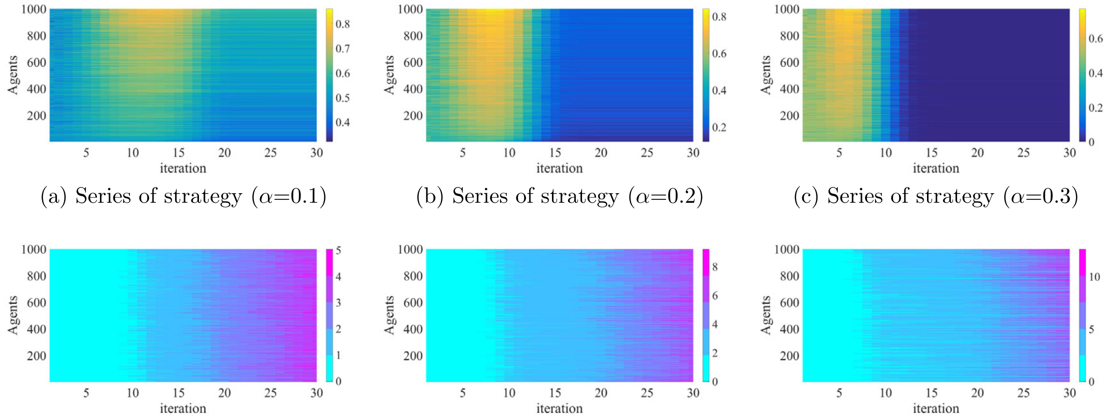
Fig. 2. The simulation is held on WS small world networks with 1000 agents. (a) records the evolution of average temptations among the population. (b) and (c) exhibit the average temptation for cooperators and defectors respectively. The natural logarithmic scale is applied here for value adjustment. The initial states of agents are the same as that in the figures above. Curves with different colors denote different accumulation factors α. Apparently, the average temptations of cooperators is much higher.

The effect of accumulation factors on the density of cooperators in the equilibrium state is shown in Fig. 1b. When α is lower, according to the accumulated temptation game, the variation of temptation at each time step diminishes. In other words, the accumulation of temptations slows down, which represses defections and motivates cooperation to some extent. As α approaches to 0.3, cooperation will vanish finally. Note that α controls the impact of cooperative neighbors on the evolution of agent's temptation. With the large α, cooperators in agent's neighborhood may have greater effect on the evolution process of agent's temptation. However, it is not beneficial for the level of cooperation around the system. In fact, the excessive interfere may result in the case that players accumulate more temptations by temporary cooperation and defect in the short period.

In the accumulated prisoner dilemma game, the temptation varies with times and it plays an essential roles during the evolutionary process. The result of the average temptations of all agents on networks is displayed in Fig. 2a. Note that the logarithmic scale is applied here. At the beginning, no matter what the accumulation factor α is, there is no great change in the average temptation of agents and it is extremely close to zero. As time evolves, strong increment appears especially for larger α. Mathematically, the accumulation factor α controls the amplitude of variation of temptations each time. Specifically, temptations will increase or decrease more rapidly when α is larger. Firstly, the average temptations of agents have hardly fluctuated at the early stage. In terms of our payoff matrix, what the defector can get in the next defection will decline as he chose defection before that. At the early stage, if one chooses defection time after time, he will get less and less payoffs as a result. Realizing that defection becomes a relatively disadvantageous strategy, agents will tend to select cooperation at a certain time, which is able to accumulate temptations and bring stable payoffs. However, as time evolves, with the combination of Fig. 1a, the density of cooperators is lower if α is higher. It implies that defection is much easier to boost if temptations become enormous.

To be specific, the average temptations of cooperators and defectors will be discussed separately as Fig. 2b and c. In the accumulated temptation game, temptations are of heterogeneity among the population. Note that the logarithmic scale is also adopted here. Fig. 2b shows that the average temptation of cooperators maintains a lower level at the early stage. But it gradually raises and keeps increasing at a high pace later. This pattern is similar to Fig. 2a, which demonstrates that the average temptation is mainly driven by cooperators. When α goes up, the temptation increases faster accordingly. Fig. 2c exhibits how the average temptation of defectors swings in the process of iteration. At first, the average temptation of defectors declines slightly. Before long, however, it goes up notably and remains at a certain level in the equilibrium state. In fact, without the accumulation of historical cooperation at the initial state, defectors' temptations are discounted and become small enough. As the matrix shows, defection will cause the decrease of agents' payoffs. Thereafter, defectors on networks will ultimately tend to be cooperators due to the loss of temptations, in order to accumulate their temptation again. It indicates that groups of defectors may be faced with agents' quits as the temptation declines. However, with a break, agents with accumulated and higher temptations return to groups of defectors, pulling up the average temptation of defectors. At this time, the lower accumulation factor α means slower velocity of accumulation, which accounts for the inflection point coming later. By comparison, the average temptation of cooperators is much larger than that of defectors. Particularly, cooperators' average temptation is increasing continuously, which means that several cooperators may keep cooperation over a long period. It will be illustrated in detail next.

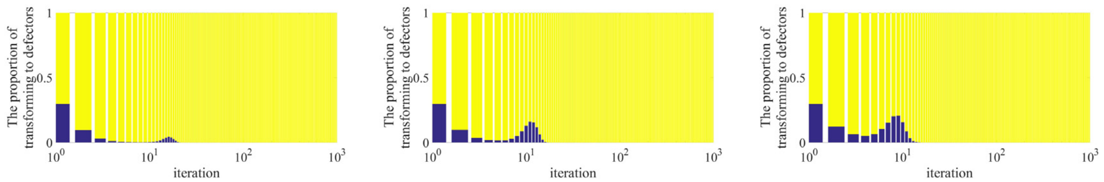
Here, we will observe agents' strategies at the micro level in Fig. 3, which gives strategies and temptation series of all agents. In the first row of Fig. 3, series of strategies of 1000 agents from $t = 1$ to $t = 30$ under different accumulation factors are shown. Concretely, numbers of the vertical axis correspond to agents. For each agent $i \in \mathcal{N}$, his strategy s_i^t during the period is displayed by colors in the sub-figures (Fig. 3a, b, c), where grids in much lighter yellow means agents may cooperate with higher probability at the points-in-time. Meanwhile, grids in much darker blue means agents may cooperate with lower probability at those points-in-time. The similar signification is applied in the second row of Fig. 3. Series of temptations of 1000 agents from $t = 1$ to $t = 30$ are investigated in Fig. 3(d, e, f). Analogously, numbers of the vertical axis represent agents. The evolution of their temptations is presented by heatmaps, where grids in much lighter pink means agents may hold more temptations while grids in much lighter cyan means agents may hold less temptations at the points-in-time. Intuitively, as the accumulation factor α increases, cooperative behaviors emerge earlier and more intensively (Fig. 3a, b, c). Obviously, temptations of different agents tend to rise as time evolves (Fig. 3d, e, f). More



(a) Series of strategy (α=0.1) (b) Series of strategy (α=0.2) (c) Series of strategy (α=0.3)

(d) Series of temptation (α=0.1) (e) Series of temptation (α=0.2) (f) Series of temptation (α=0.3)

Fig. 3. Series of agents' strategies and temptations as time evolves from $t = 1$ to $t = 30$. Note that states of agents' strategies mainly converge around $t = 30$. In each subfigure, numbers of the vertical axis denotes agents (1000 agents totally). Colors of grids that correspond to different t and agents represent the various probabilities of cooperation strategy (a–c) or scales of temptations (d–f). Specifically, as for sub-figures a,b,c, grids in much lighter yellow means agents may cooperate with higher probability at the points-in-time. Grids in much darker blue means agents may cooperate with lower probability at those points-in-time. As for sub-figures (d–f), grids in much lighter pink means agents may hold more temptations while grids in much lighter cyan means agents may hold less temptations at the points-in-time.



(a) Transform to defection (α=0.1) (b) Transform to defection (α=0.2) (c) Transform to defection (α=0.3)

Fig. 4. The transformation of strategies among 1000 agents. As for subfigures, the detailed proportion of agents with different strategies at $t-1$ who transform to defection at time t is exhibited. Each yellow bar of these sub-figures tells us the proportion of defections that are transformed from defectors at time $t-1$. The bar in purple counts the proportion of defectors who are transformed from cooperators at time $t-1$.

outcomes are implied in the figures. Actually, in the region that approaches to the top of each sub-figure (Fig. 3a, b, c), a number of grids in lighter yellow clusters horizontally before about $t = 15$. After that, colors of grids become blue immediately. Such occurrence indicates that a fraction of agents may cooperate with higher probability constantly before $t = 15$. According to our model, the constant cooperation creates more temptations. As temptations become larger, the instantaneous defection occurs for capturing higher payoffs and unchanges forever. When α is lower, the instantaneous transformation from cooperation to defection probably happens around $t = 17$. At this time, temptations of agents reach about 2 in the natural logarithmic scale. With the higher accumulation factor ($\alpha = 0.3$), the timing for instantaneous defections is advanced at $t = 10$, where temptations of agents are close to 5 in the natural logarithmic scale. Notably, the instantaneous defection after constant cooperations arises with higher probability as α rises. Totally, the higher α not only pulls up temptations but also accelerates the instantaneous defection of agents. In reality, it indicates that too much temptations and benefits cause defective behaviors.

Fig. 4 makes a discussion about the transformation of agents' strategies. In our accumulated temptation game, there are exactly two strategies including cooperation and defection. During the evolutionary process, agents are allowed to transform their strategies in term of Fermi rules. Fig. 4a, b, c explore the detailed proportion of agents with different strategies at $t-1$ who transform to defection at time t. Each yellow bar of these sub-figures (Fig. 4a, b, c) calculates the proportion of defectors who are transformed from defectors at time $t-1$. The bar in purple means the proportion of defectors who are transformed from cooperators at time $t-1$. At the beginning, few cooperators would like to transform to be defectors. However, as α augments, more cooperators convert to be defectors during the evolution. As we mention in Fig. 3, the higher α motivates the accumulation of agents' temptation. Note that the simple x-axis is applied in Fig. 3 while the logarithmic one is used in Fig. 4. With the constant cooperation, cooperators store more temptations which may entice their instantaneous defections. It is also evident in Fig. 4. Over certain periods, a fraction of cooperators transform to defectors abruptly. With the simple calculation, when $\alpha = 0.3$, nearly 20% defectors comes from cooperators at about $t = 10$ (Fig. 4). At the same time, 70% defectors occupy the population (Fig. 1), which means approximately $20\% \times 70\% = 14\%$ cooperators turn to defect. Under the circumstance with higher α, not only the magnitude of defection from cooperators is larger but also the timing of that is earlier. This result is consistent with the implication of Fig. 3.

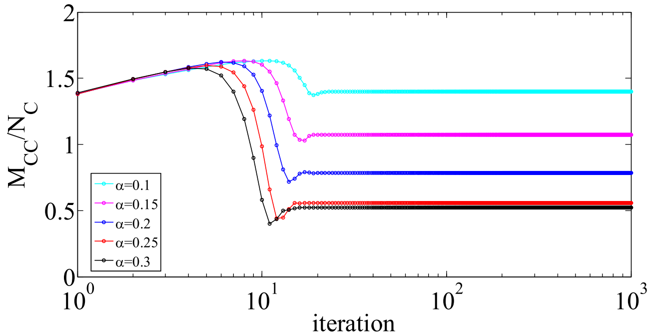
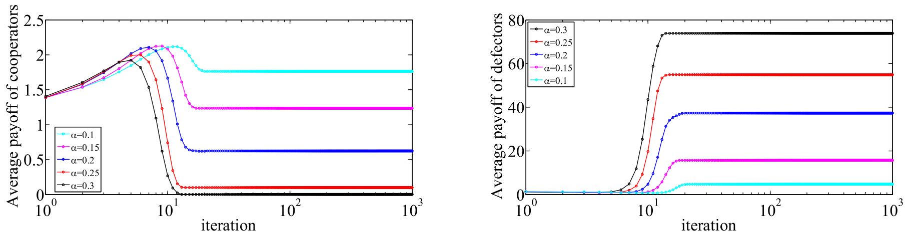


Fig. 5. The M_{cc}/N_c with varied accumulation factors α. M_{cc} is defined as the number of C–C pairs, the same as the number of links that connect both of cooperators at each time step. N_c denotes the total number of cooperators at each time step. As an alternative of snapshot, this ratio investigates how cooperative behaviors cluster. The initial states of agents are the same as that in the figures above. 1000 agents are assumed in the system. Curves with different colors denote different accumulation factors α.



(a) Average payoffs of cooperators (b) Average payoffs of defectors

Fig. 6. Simulations are executed on the WS small world network with 1000 agents. (a) and (b) show the average payoffs of cooperators and defectors in the evolutionary process. The initial states of agents are the same as that in the figures above. Curves with different colors denote different accumulation factors α.

In square grids, snapshots are used to characterize the clustering of strategies in the iteration process, which cannot be introduced to small-world network directly. Therefore, the ratio M_{cc}/N_c between M_{cc} and N_c is applied as an alternative [30], where M_{cc} signifies the quantity of C–C pairs and N_c stands for the total number of cooperators in each period of time. As for the higher level of the accumulation factor α, the clustering of cooperators is certain to decline (Fig. 5). With the larger α, Fig. 1a reveals that the density of cooperators on the network falls off at the equilibrium state. Meanwhile, the average temptation of cooperators gradually increases over time (Fig. 2b). Totally, in fact, cooperators may accumulate more temptations by clustering with other cooperators during the initial iteration. Their behavior will probably be imitated because of their stable payoffs, giving rise to the higher ratio M_{cc}/N_c. However, the increase of cooperation clustering does not keep up for a long time. As we mention above, it is easier for defection to occur with the larger α, which entices cooperators to change their strategies to be defectors. In other words, the invasion of defections isolates the clusters of cooperators, resulting in the reduction of M_{cc}/N_c.

In accordance with the trend displayed in Fig. 6a, the average payoff of cooperators obtains a slight increase in the first place, but declines to an equilibrium state finally. The internal logic is shown as follows. When agents choose to be cooperators, the strategies of their neighbors will directly determine what they acquire as payoffs. As the frequency of cooperators on the network increases initially (Fig. 1a), the probability of cooperation from neighbors increases as well. According to the payoff matrix, the clustering is the unique approach for the rise of cooperators' payoffs. On the contrary, the drop of the density of cooperators accounts for the decline of a cooperator's payoff, especially for the higher level of accumulation factor α. For further illustration, we analyze the average payoff of defectors in Fig. 6b. As what is presented in Fig. 2b, the average temptation of cooperators keeps increasing over time. That is to say, if agents with accumulated temptations become defectors, their payoffs will be extremely high accordingly. Particularly, when the accumulation factor α grows larger, it leads to more dramatical increase of the payoff of defection with accumulating high temptations. For comparison, the average payoff of defectors is much larger than the one of cooperators.

The range of the density of cooperators as rewiring probability varies is exhibited in Fig. 7. For the lower level of accumulation factor ($\alpha = 0.1$), the density of cooperators shows an upward tendency approximately with the growth of rewiring probability. To be specific, the density of cooperators almost reaches 1 on the extremely random network. The similar results under the condition of other different accumulation factors imply that agents on completely random networks will show more active responsiveness to cooperation. As an extreme case ($\alpha = 0.3$), the density of cooperators slightly fluctuates around zero. The studies about the traditional prisoner dilemma have suggested that long-range edges restrain the emergence of cooperation as the temptation is low, which is analogous to the high accumulation factor here.

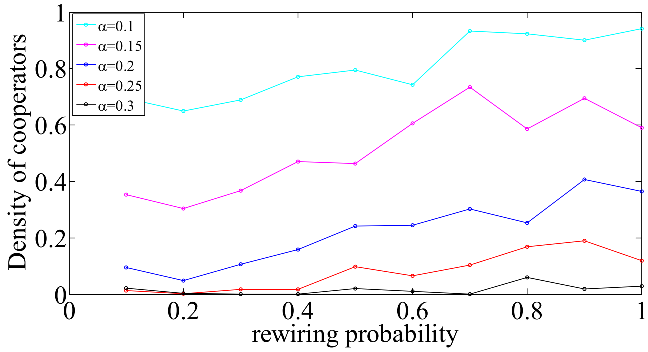


Fig. 7. The relationship between the rewiring probability and the density of cooperators in the equilibrium states. Note that rewiring probability is the key parameter for WS small world networks, controlling the proportion of long-range edges. Meanwhile, we also consider the influence of accumulation factors α that are denoted by different colors. The size of the network is set to 1000 .

It shows that the effect of long-range edges is different in our accumulated temptation games. Actually, when the value of α goes down, cooperators prefer clustering. It may be promoted by the greater rewiring probability, because more long-range connections are beneficial for enlarging social areas.

5. Conclusion

To model the formation of temptation in traditional prisoner's dilemma games, the evolutionary process of accumulated temptation games is studied in this paper. In the accumulated temptation games that we propose, the temporal temptation is of heterogeneity among agents, which may be evolving as time goes by. Agents accumulate the temptation by cooperation but consume the temptation by defection. Meanwhile, the accumulation factor α controls the amplitude of the variation of temptations. The simulation shows that the density of cooperators and the average temptations may move towards the same direction. Cooperative behaviors eliminate if the accumulation factor is large enough. Interestingly, a fraction of agents may keep cooperation constantly for accumulating temptations and instantaneously defect at a certain time. The higher α accelerates the instantaneous defection of agents. The defection strategy brings more payoffs than cooperation at the equilibrium state. Furthermore, more long-range connections promote cooperation on completely random networks as the temptation is small, which is different from the result in the traditional prisoner's dilemma. However, our result may be affected by the finite-size effect that is mentioned in [24,29,39], which is not considered in this paper. It will be our future directions about this model. In addition, our result is relevant to the value of α. On the one hand, more studies have illustrated that when α is high, the evolution becomes sensitive to the initial state [40,41]. On the other hand, α in the discount of temptation may be larger than that in the growth of temptation in actual. The future researches will work on these topics.

CRediT authorship contribution statement

Zhiqi Lin: Conceptualization, Methodology, Software, Writing-review & editing. **Hedong Xu:** Conceptualization, Software, Visualization, Formal analysis, Writing-review & editing. **Suohai Fan:** Formal analysis, Funding acquisition, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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