An evolutionary game with memory-based reputation in networked populations

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***Abstract*—The networked evolutionary game theory investigates the emergence of cooperative behaviors in the real world possible. Many reputation-based studies have made significant progress. However, reputation is easily forgotten in the real world, and only the reputation of loyal individuals remains. Therefore, in this paper, we focus on a reputation updating mechanism based on forgetting and explore how it influences the emergence and maintenance of cooperative behavior in complex networks. We creatively introduce a behavior threshold that influences the memory of reputation. In the simulation, we show the evolution of cooperation density over time, discuss the influence of behavior threshold on cooperation density, and further show the evolution of cooperators and defectors over time under different thresholds, which helps us understand the formation of cooperation. Results show that the mechanism we propose helps to overcome social dilemmas.**

***Index Terms*—Evolutionary game, Reputation, Cooperation, Behavioral threshold**

I. Introduction

Cooperation typically refers to the behavior of individuals or groups working together and supporting each other in order to achieve their common goals. It is considered a pro-social behavior [1], involving interdependence and reciprocity among different individuals. According to Darwin's theory of evolution [2], cooperation is not sustainable in nature and human society. Individuals often exhibit selfish tendencies, and betrayal for maximum gain appears to be the optimal strategy. However, numerous instances of cooperative behaviors exist in the real world [3]. For instance, worker ants willingly sacrifice themselves to protect the queen and the nest, and antelopes relinquish their hiding places, exposing themselves to provide additional escape time for other members of the herd. Therefore, comprehending cooperation within competitive environment is crucial for elucidating the emergence and perpetuation of pro-social behaviors in nature. This topic has aroused significant attention from researchers across diverse fields [4] [5].

Evolutionary game theory on complex networks provides a theoretical and powerful framework for investigating this dilemma. It employs various game models, including the Prisoner's Dilemma (PDG) [6], the Snowdrift Game (SDG) [7] [8], and the Public Goods Game (PGG) [9] [10], to describe different types of social dilemmas and characterize the game process between individuals. Notably, Nowak and May were first to introduce spatial structure to the Prisoner's Dilemma, aiming to study the impact of network connectivity on cooperative behavior [11]. The research found that although defection has an evolutionary advantage in the PDG, the existence of spatial structure can still promote the evolution of cooperation through local interactions and clustering between individuals. This study has inspired many scholars to study the game behavior in networks [12]. Since then, people have been working to explore evolutionary game models in various complex network topologies [13] [14], such as small-world network [15] [16] and scale-free network [17] [18].

In 2006, Nowak proposed five well-known mechanisms, namely kin selection, direct reciprocity, indirect reciprocity, group selection, and network reciprocity [19], which effectively promote cooperation. Furthermore, as evolutionary game theory has continued to develop, other mechanisms such as submissive behavior [20] [21], memory mechanisms [22] [23], rewards [24], punishments [25] [26], and reputation [27] have also been proven to play important roles in maintaining cooperation. Among these mechanisms, reputation is a pervasive, spontaneous, and efficient social control mechanism in natural societies. Unlike direct reciprocity, any altruistic behavior that helps others will be rewarded under the reputation constraint system. Therefore, cooperation will emerge in order to maintain a high reputation score [28] [29] [30]. Consequently, researchers have proposed many interaction scenarios based on reputation. For instance, Nowak and Sigmund [31] argued that the emergence of indirect reciprocity was a pivotal step in the evolution of human societies. Liu and Chen [32] introduced reputation into different models and discussed the impact of reputation on evolutionary games from different perspectives. Wang [33] proposed a model assuming that reputation affects individual strategy updating. Li [34] found that reputation heterogeneity has an impact on cooperative evolution.

In real life, we have to face different people every day, and it is difficult to remember the characteristics of each of them. Most people will gradually be forgotten over time, and only those who frequently cooperate will be remembered [35] [36]. Just like in the long river of history, only the great people who have made outstanding contributions to the country will be remembered by posterity. Therefore, in this paper, we

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suppose that reputation is easy to be forgotten, and only those individuals who have accumulated enough cooperation times can obtain the lasting reputation, which is also consistent with the situation in the real world. We assume that the frequency of cooperation between individuals in the network has an important influence on the formation of reputation. When an individual frequently cooperates with other individuals and exhibits reliable behavior, its reputation will gradually be established. This reputation will become a reference basis for other individuals in strategy updates, making those individuals who have good reputation more likely to be imitated and adopted.

The rest of this paper is organized as follows. In Section II, we describe our model in detail, including the node revenue computation, the reputation update rule and the strategy update rule. In Section III, we outline the simulation methodology, give relevant simulation experimental results, and reveal the hidden information in the results. Eventually, we conclude our work and give the prospect in Section IV.

II. Model

In this section, we introduce our model details, including node's payoff, reputation update rule and strategy evolution.

A. Game model

In this paper, we utilize the PDG model for dynamic evolution. There are two available strategies for participants, cooperation (C) and defection (D). If both participants choose cooperation, they both receive the same reward (R). If both participants choose defection, they both receive the same punishment (P). However, when facing opposite strategies, the cooperator receives the sucker's payoff (S), while the other adopting defection receives the temptation (T). In the PDG, the payoffs R, P, S, and T satisfy the following conditions: $T > R > P > S$, and $2R \geq T + S$. There exists a Nash equilibrium (D, D), which means that once both participants choose defection (D), there is no incentive for anyone to change anymore. In other words, for an individual, defection is always the best strategy regardless of the opponent's choice. For simplicity, we set $R = 1$, $P = 0$, $S = -r$, and $T = 1+r$, where r represents the cost-to-benefit ratio and $0 < r \leq 1$ is a regulable parameter. The payoff matrix for the PDG is as follows

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} 1 & -r \\ 1+r & 0 \end{pmatrix} \end{array}. \tag{1}$$

B. Reputation update rule

We assume that the reputation of a node can only be retained until the next iteration in proportion to β. The reputation of a node at time step t ($t \geq 1$) depends on the historical memory and the current strategy selection. Therefore, the reputation update formula for a node is as follows

$$R_i(t) = \beta R_i(t-1) + \Delta R, \tag{2}$$

where $R_i(t)$ represent the reputation of node i at time steps t. ΔR denotes the reputation increment of the node based on its strategy. β is the decay factor, which primarily depends on the node's behavior score N,

$$\beta = \begin{cases} \frac{N-T}{N}, & N > T \\ 0, & N \leq T \end{cases}. \tag{3}$$

For each cooperation, the node's behavior score increases by 1, and decreases by the same value for each defection. To investigate the impact of the behavior score on the decay factor β, we introduce a threshold value T. Specifically, if N exceeds the threshold T, β increases with the growth of N, which signifies that the node is considered reliable, and a portion of its reputation is preserved for the next iteration. Moreover, the larger the value of N, the higher the proportion of reputation preserved for the next iteration. If N does not exceed the threshold T, we consider the node unreliable, and β is directly set to 0, implying that the node's reputation is completely forgotten. The reputation increment ΔR is determined by its current strategy selection, following the rules outlined below

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} \frac{\xi}{2} & \xi \\ -\xi & -\frac{\xi}{2} \end{pmatrix} \end{array}, \tag{4}$$

where ξ represents the magnitude of reputation fluctuation. We assume that even when nodes make the same choice to cooperate, the strategy selections of their neighbors can have a certain influence on the reputation increment of a node. For instance, if a node chooses to cooperate while its neighbor defects, it should gain a higher reputation increment, while it would lose more reputation if the neighbor also chooses to cooperate. We found that different values of ξ do not affect the experimental results. For simplicity, we set $\xi = 1$ in this paper.

C. Strategy evolution

Individuals are more likely to adopt the strategy of another individual with the higher payoff. However, unlike previous research, we assume that when individuals select and update their strategies with another individual, they have a higher probability of selecting an individual with a higher reputation. In other words, the probability of individual i selecting individual j is determined by

$$W_i = \frac{R_j^{'}}{\sum_{r \in \Gamma_i} R_r^{'}}. \tag{5}$$

Here, Γ_i is the set of neighbors of individual i. Since there are negative values for the reputation of nodes, we use the Sigmoid function to map the reputation positively before normalization,

$$R_j^{'} = \frac{1}{1 + e^{-R_j}}, \tag{6}$$

where R_j is the reputation of node j and $R_j^{'}$ is the mapped reputation.

For strategy updating, if individual i selects neighbor j, the probability that i adopts j's strategy at the next time step is

$$P(S_i \leftarrow S_j) = \frac{1}{1 + e^{(\Pi_i - \Pi_j)/\kappa}}, \tag{7}$$

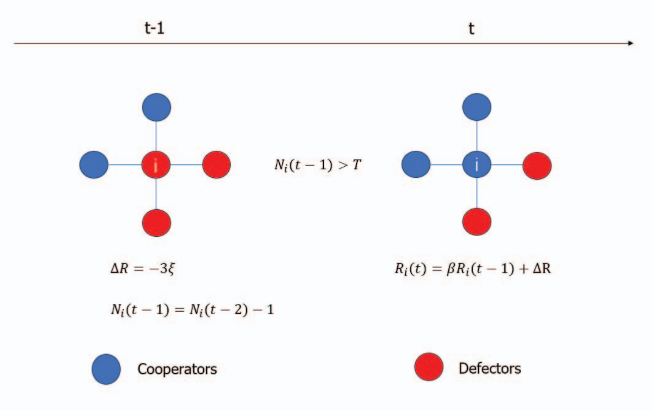


Fig. 1: **An example of the proposed model.** This figure illustrates the reputation updating rule in a randomly generated regular network. The red nodes represent defectors, and the blue nodes represent cooperators. The time axis from $t-1$ to t represents an iteration process. In the left panel, the defector i plays the game on each of the four surrounding nodes, and the reputation gained increases by $\Delta R = -3\xi$, while the behavior scores $N_i(t-1) = N_i(t-2) - 1$ due to the fact that the node i chooses to defect in the last round. We assume that $N_i(t-1) > T$ in this case, thus the reputation of the node in this iteration is updated as $R_i(t) = \beta R_i(t-1) + \Delta R$. Node i selects a neighbor for strategy updating with a probability proportional to its reputation, and finally, in the $t-th$ iteration, node i becomes a cooperator.

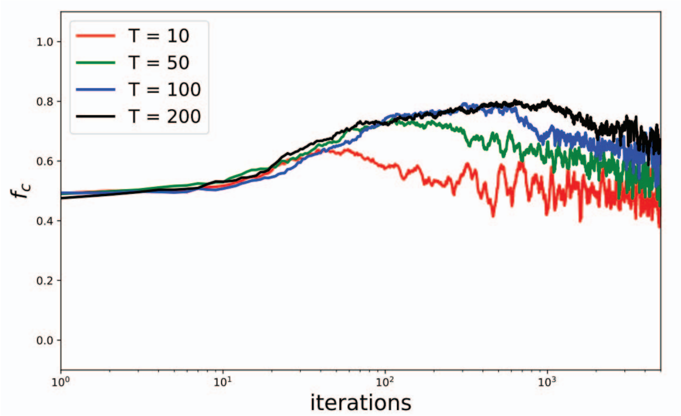


Fig. 2: **The evolution of cooperation against time.** The horizontal axis is iterations which uses a logarithmic(log) scale, and the vertical axis is f_c. The experiments are conducted on the 50×50 square lattice. We set $r = 0.4$, and different colors represent different thresholds. As time evolves, the cooperation frequency gradually tends to stabilize.

where S_i and Π_i represent the strategy and payoff of individual i, respectively κ represents the noise factor used to describe the irrational selections of individuals in the game. Specifically, the greater the difference in payoff between i and j, the more likely i is to adopt the strategy of j, and vice versa. For simplicity, we set $\kappa = 0.5$.

In order to better describe our model, we briefly summarize the modeling section here. Firstly, we introduced the traditional PDG and its payoff matrix. Next, we explained our reputation updating rule, which states that only individuals who have cooperated above a threshold number of times can accumulate reputation, otherwise reputation will be forgotten. Finally, in the strategy updating phase, we select a neighbor with a probability proportional to reputation and use the Fermi function for strategy updating. We provides an example of our model in Fig. 1. In the next section, we will present our simulation results and analyze them.

III. Simulation Results and Analyses

In this section, we will conduct some simulations to validate the proposed model. We primarily focus on the impact of different threshold values T on cooperation frequency. Additionally, to ensure experimental accuracy, we also take experiments on different network sizes.

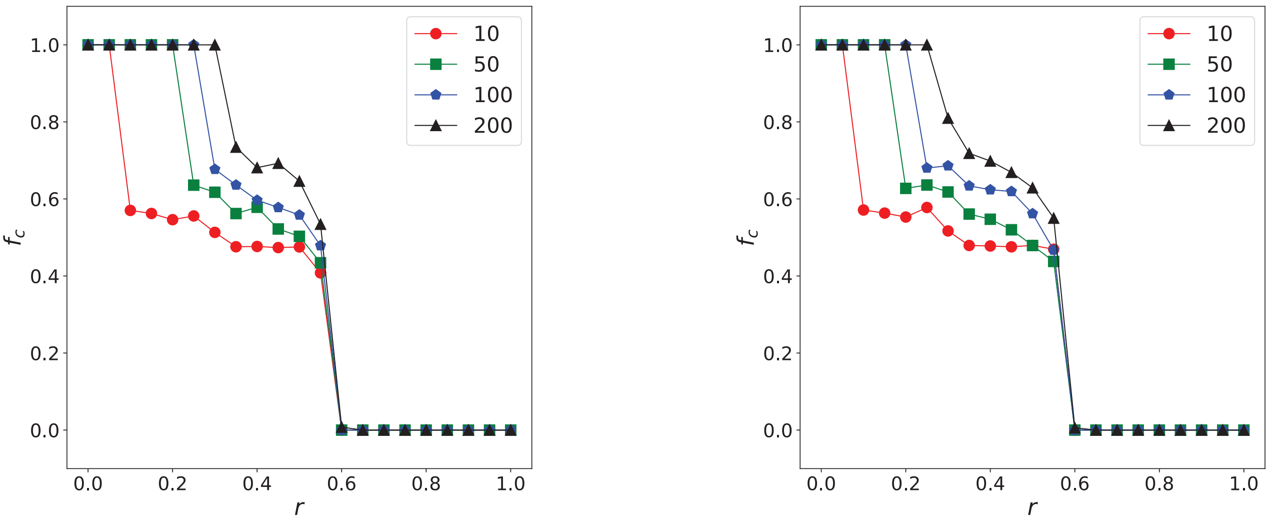
A. Methods

In the initial stage of each simulation, we set the side length of the square lattice network as $L = 50$ ($L \times L = 2500$ nodes). Each node is randomly assigned as a cooperator or a defector, with equal probability of 0.5. According to our simulation, the evolution process is stable after 3000 iterations. Therefore, we calculate the cooperation density by averaging each cooperation density from the $3000th$ step to the $4000th$ step in all following simulations. All simulation results are carried out on $Python$.

B. Effect of threshold T on cooperation frequency

The cooperation level usually intrigues and concerns people, and cooperation frequency f_c indicates the proportion of cooperators as a commonly used indicator of it. Thus, we explore the evolutionary relationship of f_c over time under different thresholds in our model. We set iterations=5000 to ensure that f_c remains stable after a long period of time. The results are shown in Fig. 2.

From Fig. 2, it can be observed that f_c reaches a steady state around 3000 steps, and the larger the threshold, the higher f_c in the steady state. At the same time, we can also find that all of the curves show the same trend and overlap together at the beginning, and f_c all increases and then decreases before reaching stability. This is because the behavior score N of all nodes does not reach the threshold in initial, the reputation will be completely forgotten regardless of cooperators defectors in the next round. The reputation of nodes is only determined by the reputation increment of this round. Even if neighbors have chosen to defect in previous rounds, they can obtain high reputation if they choose to cooperate in this round. There is also the higher probability of being selected for strategy updates. That's why f_c will increase rapidly at the beginning, and all curves overlap with



(a) $L = 30$

(b) $L = 50$

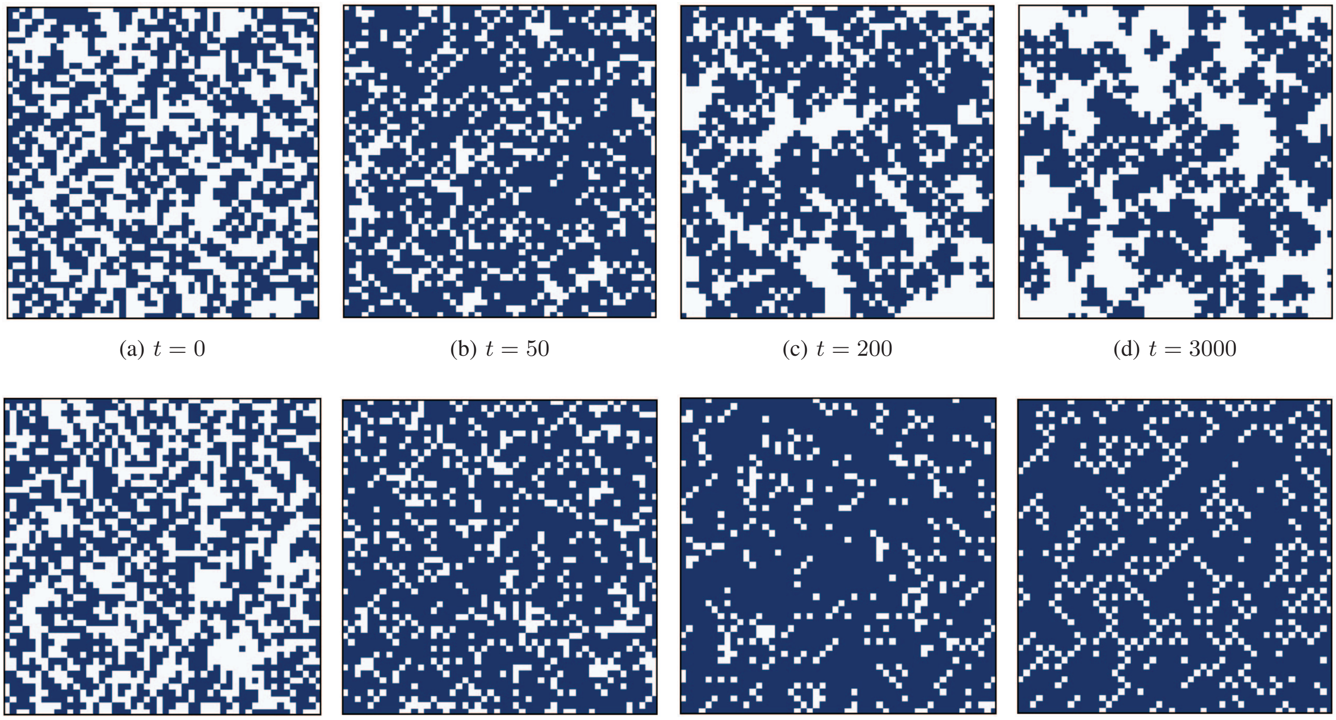
Fig. 3: **Curves of the cooperation frequency f_c against the game parameters.** This figure presents the cooperation frequency with the change of the game parameters for $T = 10$, $T = 50$, $T = 100$ and $T = 200$. Fig. 3a and Fig. 3b respectively show the results for $L = 30$ and $L = 50$. Each cooperation frequency point is obtained by averaging the last 1000 evolution steps in the 4000 total steps.

each other. However, those nodes that frequently choose to cooperate can easily reach the threshold. While nodes that often choose to defect need to cooperate more frequently to compensate for their previous mistakes if they want to keep reputation. Before reaching threshold, their reputation will still be forgotten even if they choose to cooperate. Therefore, there is a situation may be like, a neighbor cooperates many times and its behavior scores far exceeds T, its reputation will still be higher than other neighbors even if he chooses to defect during this round. When node select neighbors for strategy updates, he will choose to learn from that neighbor and ultimately choose defection, that also explains why all curves will decline after increasing. Furthermore, nodes take different amounts of time to reach different thresholds. Consequently, curves that represent different T will have different peaks. The larger the T, the later the peak appears, and the higher the peak value is.

To focus on the effect of T on the frequency of cooperation, we present the relationship between the cooperation frequency f_c and the cost-benefit ratio r in Fig. 3. To show the robustness of the experiment, we provided the experimental results for two different network scales, $L = 30$ and $L = 50$. We can find that the experimental results for the two different network scales are very similar, all of the curves first maintain a pure cooperation state for a period of time, then the f_c value drops rapidly as r increases, eventually reaching a pure defection state. Thus, we focus on analyzing the case where L=50. Fig. 3b shows that the pure cooperative state for $T = 10$ lasts only until $r = 0.1$, which is the lowest. It is to say that defectors start to appear when $r = 0.1$. For $T = 50$ and $T = 100$, the threshold of the existence of defectors is $r = 0.2$ and $r = 0.25$, respectively, both higher than $T = 10$. And for $T = 200$, there is the highest threshold for the existence of defectors which is 0.3. It provides the largest parameter space for the pure cooperative state. Additionally, their cooperation annihilation thresholds are all about 0.6 which means that the cooperation frequency f_c decreases to 0 when r increases to 0.6. Therefore, we can conclude that the collapse threshold of pure cooperation will increases if T increases. In other words, a higher T is more favorable for pure cooperative state, while the state of pure defection is not affected by it.

C. *Snapshots of effect of threshold T on cooperation frequency*

To further discuss the influence of the threshold value T on the cooperation frequency in the square lattice network, we provide the snapshots of cooperators and defectors in different timestamps. Fig. 4 illustrates snapshots of cooperators and defectors under different values of T. From Fig. 4, we can find that the cooperation frequency increases at first, and then decreases as the number of iterations increases, which is consistent with the results in Fig. 2. Cooperators gather together to counteract the invasion of defectors under different parameters. In Fig. 4a and Fig. 4e, they are both in the initial state at t=0, where cooperators and defectors are randomly distributed on the network. As shown in Fig. 4b and Fig. 4f, their cooperation frequency starts to increase, but their snapshots almost have no different at this time, because the time step is still not large enough, and the node's behavior



(a) $t = 0$ (b) $t = 50$ (c) $t = 200$ (d) $t = 3000$

(e) $t = 0$ (f) $t = 50$ (g) $t = 200$ (h) $t = 3000$

Fig. 4: **Snapshots for different parameter T.** This figure shows snapshots of the cooperation evolution in different T. Blue represents cooperator, and white represents defector. The square lattice size is set to 50×50. Initially, 50% of cooperators and defectors are randomly distributed on the network. The cost-to-benefit ratio $r = 0.3$. The parameters T are 10 and 200 from top to bottom and the time steps are $t = 0, 50, 200, 3000$ from left to right.

score has not reached the threshold T, so different thresholds have little effect on the cooperation frequency. Comparing the snapshots in Fig. 4c and Fig. 4g, the latter snapshot has a higher cooperation frequency than the former. And the cooperation frequency in Fig. 4c is less than that in Fig. 4b. That is because some nodes' behavior scores have exceeded T under $T = 10$ when $t = 200$, while nodes that often choose defection previously need to cooperate more times in order to reach T, and their reputation will be forgotten before that, making it difficult for their strategy to be learned when strategy updating, so the cooperation frequency starts to decrease. Besides, due to its higher T, the cooperation frequency in Fig. 4g is higher than in Fig. 4f. The nodes' behavior scores have not reached T at that time, hence its cooperation frequency continues to increase. From Fig. 4d and Fig. 4h, we can find that both of their cooperation frequency has decreased compared to $t = 200$, but the snapshot with the largest threshold in Fig. 4h has a quite higher number of cooperators than that in Fig. 4d. This is also consistent with our previous conclusion.

IV. Conclusion and Outlook

In this study, we investigated the influence of memory-based reputation on cooperation frequency. Primarily, we suppose the model where nodes' reputation will be forgotten. Only when the node's behavior score exceeds the given threshold T, will the node's reputation be carried over to the next round in proportion to its behavior score. Then, to further discuss the impact of T on the cooperation frequency, we plot different curves and conclude that the collapse threshold of the cooperative state increases as the T value increases, meaning that the larger the T value, the more favorable it is for pure cooperation, while the pure defection state is not affected by the T value.

In this work, we only take the impact of the threshold T on the cooperation frequency into consider, and the node's behavior score is quite simply set. More factors need to be considered in order to get the node's behavior score in real life. For example, we can add the evaluation of neighbors to score the nodes. And we directly set ξ to 1 in the reputation increment, while different values of ξ may also have an impact on the cooperation frequency. Additionally, different interaction and replacement networks can be further considered. Our model assumption can also be extended to higher-order interaction among individuals.

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