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Preferential learning and memory resolve social dilemma

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ABSTRACT

Cooperation is widespread in society, thus how to explain this phenomenon has become one open question. According to empirical experience, preferential learning and memory seem to be two effective ways to this issue, which, however, still needs validation in scientific research. Motivate by this point, we consider one-step memory and preference learning (i.e. learning the strategy of subject performing best, which is tuned by a preferential parameter α) in prisoner's dilemma game. $\alpha = 0$ enables the model going back to control treatment where objects randomly selected. While for $\alpha > 0$, individuals prefer objects that perform better. Compared with control treatment, we find that increasing preferential parameter α can promote cooperative behavior monotonously. In particular, the larger the value of α, the stronger and more compact clusters they can form. Finally, in order to investigate the robustness of this mechanism, we also study the evolution of cooperation in small-world network and random regular network.

1. Introduction

Cooperative behavior among unrelated individuals is abundant in nature and society, ranging from microorganism groups to human society. Explaining its emergency has attracted great interest in interdisciplinary research fields including biology, physics and sociology [1–4]. Evolutionary game theory provides a powerful approach to solve this problem. The prisoner's dilemma game (PDG), which is one of the most popular models of this theory, has attracted much attention in both theoretical and experimental studies [5–10]. In a typical PDG, two players must simultaneously choose whether cooperate (C) or defect (D). They can receive the reward R if they both cooperate, and punishment P for mutual defect. However, if one choose defect while the other choose cooperate, it is able to obtain the temptation T while the co-player suffers the payoff S. The ranking of four payoffs satisfies $T>R>P>S$, from which it is obvious that no matter what choice the opponent takes, defector always outperforms cooperator. So, they will fall into the mutual defection state, which is the so-called social dilemma.

In order to resolve the above unfavorable situation, many mechanisms have been proposed over the past years [11–24]. Interestingly, Nowak [25] summarized all these scenarios to five mechanisms: kin selection, direct reciprocity, indirect reciprocity, network reciprocity and group selection. Among these achievements, network reciprocity has been widely studied by scholars from different fields and proved to be an effective way to promote the evolution of cooperation. After this seminal idea, more setups on complex network have been proposed, which can resist the invasion of defectors and promote the emergency of cooperation. Examples include the migration [22–24], punishment mechanism [25], expectation [26], coevolution mechanism [27–29] and environment factor [30,31], to name but a few. Recently, prisoner's dilemma game on interdependent network [32] also attract extensive investigate and explains many interesting phenomenon. Besides, preference learning, choosing object of better performance, has proven to be an effective way for maintaining cooperation [33].

In our society, except for mentioned mechanisms, we also rely on our memory, which may play a positive role in the evolution of cooperation [34]. However, individuals are restricted by limited information and memory, they always have clear memory for what just happened [35–41]. Inspired by these successful efforts, an interesting question appears: if we combine the one step memory and preference learning to explore the evolution of cooperation with the structure population, does this setup promote cooperation? Along this line, we use Monte Carlo simulation to answer this question and find that cooperative behavior can be promoted obviously. Especially, the stronger preferential learning, the higher the level of cooperation.

The rest of this paper is composed of three sections. In Section 2, we present our evolutionary game model, including the new definition of preferential learning. Section 3 describes numerical simulation results. Finally, we discuss the results and make a conclusion of the paper in Section 4.

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2. Model

In our work, we choose the weak PD game, in which the payoffs are defined as $T=b>1$(the temptation of defection), $R=1$(the reward of mutual cooperation), $P=S=0$. Thus we express the payoff matrix as:

$$M = \begin{pmatrix} 1 & 0 \\ b & 0 \end{pmatrix}. \tag{1}$$

As to interaction network, each player $x$occupies one node of $L*L$ square lattice with periodic boundary conditions, and each player is initially appointed to be either a cooperator or a defector on square lattices with equal probability, which can be described as

$$S_x = (1,0)^T, \ S_x = (0,1)^T. \tag{2}$$

The game is iterated forward in accordance with the Monte Carlo simulation procedure. First, player x plays the game with nearest neighbor y and obtained incomes P_x:

$$P_x = \sum_{y \in N_x} s_x^T M s_y, \tag{3}$$

where N_x represents the four neighbors of individual x. Then, player x will select an interaction object z with the following probability:

$$\pi_z = \frac{\exp(\alpha * P_z)}{\sum_z \exp(\alpha * P_z)}, \tag{4}$$

where α is a newly introduced preferential learning parameter. In particular, it is worth mentioned that P_z is composed of two parts: the payoff of neighbor y in current round, and the payoff of himself last round, i.e. $P_x(t-1)$, which represents one-step memory for his strategy and payoff. When $\alpha = 0$, it goes back to control treatment where an interaction object randomly selected from five individuals. When $\alpha > 0$, the focal player x prefers to learn the strategy who have a higher payoff. Lastly, player x adopts the strategy from object z with the probability W depending on the payoff difference:

$$W = \frac{1}{1 + \exp[(P_x - P_z)/K]}, \tag{6}$$

where K denotes the noise or its inverse, including irrationality and errors. Since the effect of noise K has been well studied in the previous papers [42,43], we use K to be 0.1. During a full Monte Carlo step all players will update their strategy. To worth raising, the key quantity the fraction of cooperation ρ_c was determined the last 5×10^3 steps of the full Monte Carlo simulations with 5×10^4 steps, and all the simulations are carried out on the lattice with $L = 100$.

3. Results

It is instructively to first examine how the frequency of cooperation change with the temptation b for different value of parameter α in Fig. 1. For $\alpha = 0$, the model returns back control treatment of spatial prisoner's dilemma game, and the cooperators died out quickly even b is small. However, as the increase of parameter α, the evolution of cooperation can be promoted more effectively. Especially, when $\alpha = 5$, cooperative behavior nearly dominant the whole population when the value of b is small, the defectors can only survive for larger b. So, when we consider the focal individual's last step state as one of its neighbors and preference learning, it is benefit for the evolution of cooperation. And the value of α plays a crucial role: the larger the value of α, the more obvious the facilitating effect. Moreover, it is worth noting that the threshold b_c, making extinction of cooperation, increase with α. In what follows, we will examine this claim more precisely.

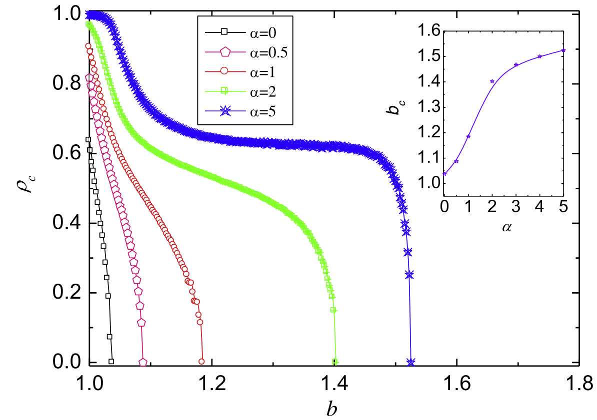

Fig. 1. The frequency of cooperators ρ_c as a function of the temptation parameter b with various selection parameter α. Compared with control treatment ($\alpha = 0$), with the increase of parameter α, cooperative behavior can be promoted effectively. The insets show the relationship between the threshold b_c, where cooperation dies out, and α. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

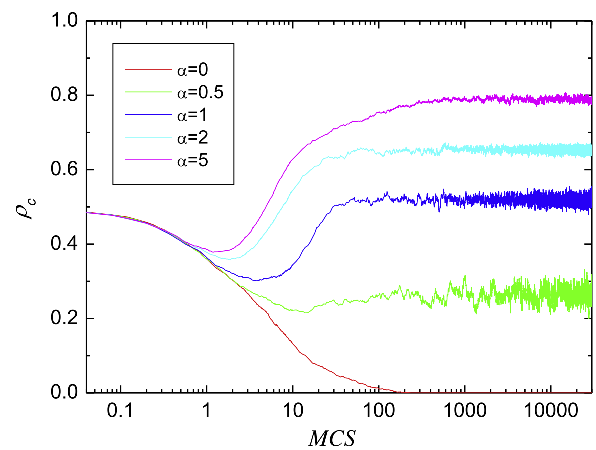

Fig. 2. Time evolution of the cooperative behavior on square lattices for $K = 0.1$, $b = 1.075$. From down to up, it represents the value of parameter $\alpha = 0$, 0.5, 1, 2, 5, respectively. For control treatment (red curve), cooperators go extinct quickly. While considering preference selection, the cooperative behavior increases gradually with the increasing of α. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

In order to explain the influence of parameter α, we explore the time evolution of cooperative behavior for different values of selection parameter with a given b and α in Fig. 2. It is obvious that cooperators die out when $\alpha = 0$ (red line). With the increase of parameter α, cooperators can survive from the invasion of defectors. The station state is mix C+D phase: when $\alpha \le 1$, defectors outperform cooperators and occupy the larger proportion of the whole population. However, when $\alpha > 1$, the cooperation level is higher than defectors'. Interestingly, except for the situation $\alpha = 0$, no matter what value of α, in the early stage of evolution, cooperative behavior decrease first and then increase to station state. Thus, this setup facilitates the evolution of cooperation. The larger the value of a, the higher level of cooperation.

Subsequently, to qualify the effect of α more precisely, we inspecting the spatial pattern formed by cooperators and defectors for different value of parameter α in Fig. 3. We simulate the evolution game fix $b = 1.075$, $K = 0.1$. When $\alpha = 0$ (Fig. 1(a)), the focal individual will randomly choose a neighbor to learn strategy from its nearest four neighbor and the last step state. Obviously, defectors dominant the whole square lattice even b is small. In Fig. 2(b), a small fraction of cooperators can survive by forming small clusters.