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Historical payoff promotes cooperation in the prisoner's dilemma game

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ABSTRACT

Understanding the evolution of cooperation among selfish individuals remains a large challenge. Network reciprocity has been proved to be an efficient way that can promote cooperation and has spawned many studies focused on network. Traditional evolutionary games on graph assumes players updating their strategies based on their current payoff, however, historical payoff may also play an indispensable role in agent's decision making processes. Another unavoidable fact in real word is that not all players can know exactly their historical payoff. Based on these considerations, in this paper, we introduce historical payoff and use a tunable parameter u to control the agent's fitness between her current payoff and historical payoff. When u equals to zero, it goes back to the traditional version; while positive u incorporates historical payoff. Besides, considering the limited knowledge of individuals, the structured population is divided into two types. Players of type A, whose proportion is v, calculate their fitness using historical and current payoff. And for players of type B, whose proportion is $1-v$, their fitness is merely determined by their current payoff due to the limited knowledge. Besides, the proportion of these types keeps unchanged during the simulations. Through numerous simulations, we find that historical payoff can promote cooperation. When the contribution of historical payoff to the fitness is larger, the facilitating effect becomes more striking. Moreover, the larger the proportion of players of type A, the more obvious this promoting effect seems.

1. Introduction

In realistic society, the worker will give up their reproductive opportunities in order to help the queen to reproduce, vampire bats sharing a meal of blood, fish inspecting predators in pairs [1]. Despite existing ubiquitous cooperative behaviors, understanding how and why the cooperation among selfish individuals emerges and sustains remains a big challenge [2]. Evolutionary game theory generates important framework into the evolution of cooperation, which attracts many works across a myriad of scientific disciplines [3–6]. In particular, prisoner's dilemma game (PDG), severed as a useful paradigm, captures the essential social dilemma between social welfare and individual comfort [7,8]. In its original form, mutual cooperation (defection) yields reward R (punishment P). If one player cooperates and the other defects, the former will receive the sucker's payoff S and the latter will get the temptation to defect T. The rank of these payoffs satisfies $T > R > P > S$ and $2R > T+S$, from which the selfish individuals are forced to choose defection, irrespective of the opponent's choice.

Over the past decades, a number of mechanisms or scenarios have been proposed to explain these puzzles [9–25]. Particularly, spatial structure, which is called network reciprocity, has been proved to be a very efficient mechanism that can promote cooperation and has spawned many scholars focusing on these issues [26]. This pioneering research was firstly suggested by Nowak and May [27], in which players were assigned on the vertex of networks and obtained their payoffs by interacting with their direct neighbors and then updated their strategies by payoff differences. Interestingly, it proved that spatial structure played an important role that cooperators can form compact clusters to survive. In line with this work, many works investigate this issue via spatial

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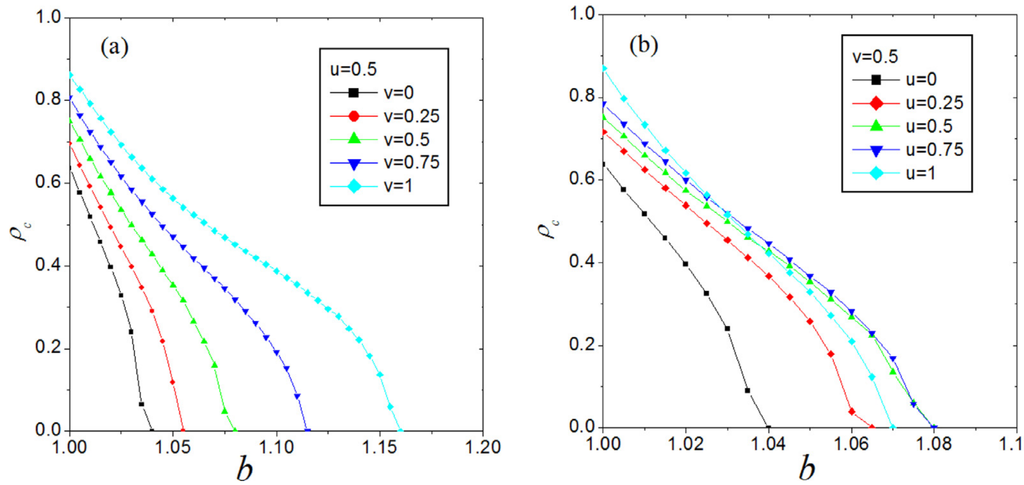

Fig. 1. (a) Fraction of cooperation ρ_c as a function of the temptation to defect b for different values of parameter v, we fix $u=0.5$. Comparing to the traditional game ($v=0$), we can see that when the proportion of the players of type A becomes larger, the cooperation could be extensively promoted. (b) The fraction of cooperation independence on the temptation to defect b when $v=0.5$ and u varied. It is obvious that the parameter u can promote the evolution of cooperation when b is relatively small. However, when the value of b exceeds 1.03, there exists an optimal u that make cooperators thrive best (when $u=0.75$).

structure or some other factors and reached fruitful achievement, for example, different network topologies such as small-world network [28], ER graph [29], BA scale-free network [30], multilayer network [31], voluntary participation [32], age structure [33], social diversity [34], preference selection [35], and punishment and reward [36–38]. Furthermore, co-evolution schemes [39,40], time scales in evolutionary dynamics [41,42], tit-for tat or win-stay-lose-shift strategies [42–44] have also been extensively investigated.

In traditional evolutionary games on network, the agent's strategy updating is determined by their current payoff [27]. However, historical payoff also plays an indispensable role in agent's decision making processes. For example, stock holders make choices based on stocks' historical information; in some companies, the decision makers often make choices relying on their experience. Based on these facts, in this paper, we integrate the agents' historical payoff in traditional PDG via a parameter u. In addition, considering the limited knowledge of individuals, we has classified the population into two types: Players of type A, whose proportion is v, calculating their fitness by historical and current payoff. While for players of type B, whose proportion is $1-v$, their fitness is only determined by their current payoff due to the limited knowledge. Besides, the proportions of the aforementioned two types of players are denoted by v (type A) and $(1-v)$ (type B) and remain unchanged during the simulations. The rest of this paper are organized as follows: we first describe our modified model of PDG; subsequently, the main simulation results are shown in Section 3; lastly, we summarize our conclusions in Section 4.

2. Model

Let's first consider the interaction network. We focus on games in structured populations where each player occupies the nodes of $L*L$ square lattice with periodic boundary conditions. Besides, each player can choose either cooperation or defection with equal probability which can be expressed as follows:

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

Related to the model, we choose the weak PD game, in which the payoffs are defined as $R=1$, $P=S=0$, and $T=b>1$. Thus the payoff matrix can be expressed by matrix M.

$$A = \begin{pmatrix} 1 & 0 \\ b & 0 \end{pmatrix}. \tag{2}$$

At each time step, player x plays the game with his nearest neighbors and obtains his income P_x:

$$p_x = \sum_{y\in\Omega_x} s_x^T A s_y. \tag{3}$$

where Ω_x represents the nearest neighbors of individual x. And the payoffs P_y of neighbors of player x can be obtained in the same way. Based on the aforementioned phenomenon existing in our life, we consider the agent's historical payoff when calculating player's fitness. In detail, two types of players (A and B) are distinguished and their division is performed with the probability v and 1-v and keep constant during the simulation. If player x belongs to A type, we integrate his historical payoff into the fitness calculation. Namely:

$$\begin{cases} F(x,\ t) = P(x,\ t) & t=1 \\ F(x,\ t) = u*P(x,\ t) + (1-u)*P(x,\ t-1) & t\geq 2 \end{cases}. \tag{4}$$

where u is used to control the contribution of historical payoff to the fitness calculation. $P(x,t)$ and $P(x,\ t-1)$ are the accumulated payoff of player x at time t and t-1, respectively. When $u=0$, traditional game is recovered, while positive u incorporates historical payoff. On the contrary, given that player x belongs to type B, F_x equals to his accumulated payoff at time t $P(x,t)$, which is to say there is no influence of historical payoff.

The game is iterated forward in accordance with the Monte Carlo (MC) simulation procedure. First, a random selected player x evaluates his fitness. Then he chooses at random one neighbor y, who also gets his fitness in the same way. Lastly, player x adopts the strategy from neighbor y with the probability W depending on the fitness differences:

$$W = \frac{1}{1+\exp[(F_x - f_y)/K]}. \tag{5}$$

where K denotes the noise or its inverse $(1/K)$ represent the so-called intensity of selection, including irrationality and errors. Since the effect of noise K has been well studied in the previous papers [45,46], we thus use K to be 0.1.

During one full Monte Carlo step (MCS) each player has a chance to adopt one of the neighboring strategies once on average. Results of Monte Carlo simulations presented below were obtained on 200×200 lattices, besides, we have also tested our results in larger sizes of the lattice and got the same results. Key quantity the fraction of cooperators ρ_c was determined within the