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Aspiration driven coevolution resolves social dilemmas in networks

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ABSTRACT

In realistic world, the role or influence of each individual is heterogeneous and usually varies according to surroundings. Inspired by this fact, here we study the emergence of cooperative behavior in weighted networks under the coevolution of game strategy and node weight, where the node weight is used to mimic the role or influence of subjects. In the prisoner's dilemma, if an individual's fitness exceeds the aspiration level, its weight becomes larger; otherwise weight decreases. While such an adjustment of weight is defined by the intensity parameter δ, it is interesting that there is an optimal range for δ guaranteeing the best evolution of cooperation. The facilitation of cooperative behavior mainly depends on the weight distribution of players, which is based on the formation of a cooperative cluster controlled by high-weight cooperators. These cooperators are able to prevail against defectors even when there is a large temptation to defect. Our research provides a viable route to resolve social dilemma and will inspire further applications.

1. Introduction

Cooperation, wherein unrelated selfish individuals help each other, is an elementary component of human society. Understanding the evolution of cooperation is one of the major challenges in both biology and social science, and significant progress has been made in this area [1–8]. Evolutionary game theory has become a useful tool and provided many insights into the reasons for the emergence and stability of cooperation among individuals [9–11]. In particular, a simple paradigmatic model, the prisoner's dilemma (PD) game, has received much attention in the last few decades [12–15]. In its basic version, two players simultaneously choose between cooperation (C) and defection (D). They receive a reward R (punishment P) if both cooperate (defect). If, however, one player cooperates while the other defects, the defector can acquire a temptation to defect $T=b$, and the cooperator receives the sucker's payoff (S). These payoffs are ordered as follows: $T>P>R>S$. Thus, defection optimizes an individual's payoff, although mutual cooperation yields the highest collective payoff [16].

To overcome this dilemma, several mechanisms have been proposed, including direct reciprocity, indirect reciprocity, kin selection, group selection, and spatial reciprocity [17]. Among them, network reciprocity, which was introduced by Nowak and May [18], is a very important dynamical rule that has inspired many additional studies; in their pioneering work, various types of spatial topology have been introduced in which players are arranged on a structured topology and can interact with only their direct neighbor. Consequently, topology has become a determinant factor of the success of

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cooperative behaviors, such as the BA scale-free network [19–21], ER random graph [22], small-world network [23–25] and multilayer coupling network [26,27]. In addition, other approaches have been considered that facilitate the evolution of cooperation, including aspiration [28-31], age structure [32,33], reputation [34–37], player features [38–41], memory [42,43], voluntary participation [44,45], social diversity [46,47] and information sharing [48].

In reality, strategies and environment, along with many other factors, affect the outcome of strategy evolution and evolve over time. Therefore, coevolutionary rules are a natural upgrade for evolutionary games. Coevolutionary rules can affect the fitness of players [49], network (or population) size [50,51], player teaching ability [52] (or reproduction ability) and mobility [53–55] (referring to Ref. [56] for a more comprehensive understanding of coevolutionary rules). However, the effect of player weight on cooperation in the game has been rarely considered [57], which seems inconsistent with the empirical case that each individual may exhibit heterogeneity in social status or social influence within a population. Moreover, the players' weight may adaptively change over time. In reality, players with more social influence are more adaptive than players with less social influence. Though the node weight has been proposed in Ref. [58], there is no uniform criterion with the change of weight for all the agents. Inspired by the unified standard of poor and rich families in the world, here we propose an aspiration-based coevolution of node weight by associating the weight of the node with the global aspiration. Through Monte Carlo simulation, we found that, even at the first time, all players have the same social influence, our coevolution setup makes the social influence of the player gradually become heterogeneous, which in turn promotes cooperation.

The rest of this paper is structured as follows. In Section 2, we describe our modified model with the node weighting mechanism. We present our main simulation results in Section 3. Finally, we summarize our conclusions in Section 4.

2. Methods

In this paper, we consider an evolutionary PD game. Each player is located on a regular square lattice of size $L\times L$ with four nearest neighbors under a periodic boundary condition. Based on the weak PD game with a normalized payoff matrix,

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

where $b\,(1<b<2)$ denotes the temptation to defect. As the payoff ranking is the same as in the classical PD game, the results are accordant. Here, each player (node) is assigned as either a cooperator ($s_x=C$) or a defector ($s_x=D$) with equal probability.

Within this study, we introduced a node weight that considers the social influence of the players in the model in the following way. At the beginning, we assigned the same social influence ($w_x=1$) to each individual, which will change adaptively according to interactions during subsequent steps. At each time step, each player x obtains his accumulative payoff p_x by playing with his four neighbors. We evaluate the fitness of player x according to the following expression:

$$F_x=w_x*p_x. \tag{2}$$

Next, node weight w_x is updated according to the aspiration-driven rule: the social influence (node weight) of the individual changes by comparing current payoff p_x with aspiration level A. If p_x is larger than aspiration level A, the node weight increases δ, which means the social influence increases, as described in Eq. (3).

$$\begin{cases} w_x=w_x+\delta, & p_x>A,\\ w_x=w_x, & p_x=A,\\ w_x=w_x-\delta, & p_x<A. \end{cases} \tag{3}$$

Specifically, in this paper, node weight falls within the interval $[1-\varepsilon,\ 1+\varepsilon\ ]$. Therefore, the model is equivalent to the traditional version when $\varepsilon=0$ or $\delta=0$, while $\varepsilon\neq0$ or $\delta\neq0$ incorporates heterogeneity. According to Ref. [57], w_x will stop evolving for all individuals when one w_x reaches its minimum or maximum value.

Hence, focal player x updates his strategy by randomly choosing neighbor y (with fitness F_Y) and adopting the strategy of player y with the following probability:

$$w=\frac{1}{1+\exp([(F_x-F_y)/K])}, \tag{4}$$

where K represents the amplitude of noise or its inverse $(1/K)$, which is called the intensity of selection. Without loss of generality, we set $K=0.1$ in this paper. During one full Monte Carlo time step (MCS), each player has a chance to update his strategy once on average.

The presented results of MC simulations were obtained typically for $L=200$ size, but larger system sizes were also considered (close to phase transition point) in order to avoid finite-size effects. To assure the system reaches a stationary state, we set transient time t to 30,000 and calculate the average frequency of the last 5000 MC time steps after full Monte Carlo simulation over all 50,000 steps. Moreover, the data were averaged over independent runs up to 10 times for each set of parameter values to assure suitable accuracy.