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On exploring the genetic algorithm for modeling the evolution of cooperation in a population

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ABSTRACT

In this paper, we propose a genetic algorithm approximation for modeling a population which individuals compete with each other based on prisoner's dilemma game. Players act according to their genome, which gives them a strategy (phenotype); in our case, a probability for cooperation. The most successful players will produce more offspring and that depends directly of the strategy adopted. As individuals die, the newborns parents will be those fittest individuals in a certain spatial region. Four different fitness functions are tested to investigate the influence in the evolution of cooperation. Individuals live in a lattice modeled by probabilistic cellular automata and play the game with some of their neighborhoods. In spite of players homogeneously distributed over the space, a mean-field approximation is presented in terms of ordinary differential equations.

1. Introduction

The prisoner's dilemma game has been used for modeling many social interactions where exist competition for benefit [1–4]. The game consists in an hypothetic case where two criminals have been arrested after a crime and are in two separated chambers. The prisoners may both cooperate not delating each other. In this case, they receive the benefit of going to jail for a minimum sentence. If one of prisoners defects and delates the other, the defector is free, and the other get the highest sentence. If both defect, they get a penalty lower than such highest penalty. Many of life's situations have this structure: if you play one round, the best payoff is when you defect; however, in a iterated game, which players interact repeatedly, pure defection leads to a situation that selfishness is pernicious. Therefore, the cooperation begins to appear as a common solution for combating the population self-destruction [5].

Robert Axelrod organized a strategy tournament for iterated prisoner's dilemma game in 1980s. The winning strategy was *tit-for-tat*, where the player begins cooperating and from there, always imitate the last strategy used by its opponent, that is, cooperate when the opponent cooperate, and defect if the opponent defect [6]. Since a defector is punished, the cooperation arises. The reasons for success of tit-for-tat are four: such strategy is *nice*, since it cooperates in the first move; it is also *retaliatory*, because always retaliates a defection; it is *forgiving*, cooperates if the opponent switch to cooperation; and it is *non-envious*, it does not try to score more than opponent [2].

The prisoner's dilemma importance can be noted by the wide range of applications which the game is used: In [7], a relation between the growing commerce in Europe and wars decline is analyzed. Considering only one interaction between countries, it was better to attack a neighboring country to get benefits. However, in many interactions, nations realized that it was better not to destroy an opponent, but pay for what they produced. This was the beginning of commerce in Europe. In

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[8], the evolution of competitive interactions among viruses is stressed. Finally, Pothos et al. [9] shows a psychological experiment which tried to understand how the personality influences the cooperative behavior.

Although there is a great use of prisoner's dilemma in modeling biological and economical systems, there is also a contrary opinion to the approach that phenotypic traits replaces actions, fitness replaces utility and natural selection replaces rational behavior. Natural selection is not always represented by such rational behavior in game dynamic, yet they may denote developmental or learning processes [10].

An evolutionary game has interactions among players over time. The strategies of individuals tend to change according their benefits, that is, higher payoff strategies replace lower payoff strategies. Moreover, the players future actions are not influenced by other players intentionally [11]. The way how the strategies evolve over time may have different reasons: the lower payoff strategies individuals die first, and are replaced by individuals with higher payoff strategies; individuals with lower payoff strategies may copy by imitation the better strategies [12]. Usually, the values of game payoffs are constant, but periodic values also lead to equilibrium over time [13].

Based on the evolutionary prisoner's dilemma, the evolution of cooperation indicates how the cooperative agents evolve over time. Cooperation exists in many social environments [1,2], however, it is not trivial how the cooperation arises in certain conditions. Why should a player cooperate with other competitors? Why cooperation is so important in natural selection for social evolution, if the natural selection is related to competition? Some mathematical models indicate the cooperation importance for strategies success in populations either using game theory [4] or evolutionary game theory [1,14]. Nevertheless, in evolutionary games, individuals play according to programmed behavior, which is not necessarily an optimal behavior [15].

Evolution of cooperation has been studied based on different population approaches: complex networks models [16–18] using topological parameters [19,20]; networks with local interactions[21]; focusing on spatial individuals distribution [6,5,22]; populations with the invasion barrier, which protects the mixed strategy from being invaded by lower payoff strategies [23].

According to [3], "Understanding the genetic evolution of behavior requires the interaction between evolutionary game theory and population genetics". This is a motivation for mixing genetic algorithm and evolutionary game theory.

Genetic algorithm (GA) is a heuristic search which imitates the process of natural evolution due to the processes of *inheritance*, *mutation*, *selection*, and *crossover*. The solution search initial state has a candidate solutions population, whose fitness are evaluated. The more fit solutions are selected, then their genome is modified (recombined and randomly mutated) to generate the new population that, in the next iteration, will have the fitness evaluated until the intended fitness level has been reached [24–26].

The use of genetic algorithm and game theory is relatively unexplored, even with the reliable process of solution evolution in genetic algorithm [27]. Some models had been studied with use of stochastic games in simple 2×2 matrix games [28,29]. In the paper [30], the genetic algorithm itself is treated as a game, and the way how individuals adapt seeking the best fit in population are: social learning by imitation (see also [21]) or learning by communication. The model presented in next section mixes GA and evolutionary game theory using prisoner's dilemma game. The learning process will be based on the reproduction of individuals: newborns will have the more adapted parents in a certain neighborhood.

In the next section, the model of evolution of cooperation based in probabilistic cellular automata (PCA), ordinary differential equation (ODE) and genetic algorithm is presented. In Section 3, the simulation results are numerically investigated. In Section 4, the results are discussed.

2. The game with PCA, ODE and GA

2.1. The PCA and ODE approach

The population is modeled by probabilistic cellular automata in a $N = n \times n$ $(n = 200)$ square matrix with periodic boundary conditions (that is, the top edge of the matrix contacts the bottom edge and the left edge contacts the right edge; thus, a torus embedded in a three-dimensional space is formed from a two-dimensional plan in order to eliminate edge effects). When an individual (represented by a cell in the lattice) dies, a new one takes its place. Therefore, the total number of individuals $N = n^2$ remains constant. The strategies of all cells are simultaneously updated throughout a simulation.

The neighborhood is defined as a square matrix of side $2r + 1$ centered on such a cell. Each cell start connections with m other neighbors cells (two or more connections between the same two cells are allowed). The maximum radius where a connection can be made is r. The case $r = 1$ including all 8 surrounding cells is known as Moore neighborhood of unitary radius (e.g. [31]), and it is considered the layer 1. The case $r = 2$ includes all 8 surrounding cells from layer 1 and the 16 surrounding cells from layer 2.

Creation of connections between a cell and any cell pertaining to the layer i has a probability given by $q_i = 2(r + 1 - i)/(r(r + 1))$, where $i = 1, 2, \ldots, r$ [32]. Thereby, the probability of linking a cell to any of the 8 cells composing the layer $i = 1$ is 66.7%, and to any of the 16 cells composing the layer $i = 2$ is 33.3%. Such a random network is mainly locally connected [32] like graphs called "small-worlds" [33], because the clustering coefficient C is "high" $(C \gg m/N)$ and, since "long-range" interactions are allowed, the average shortest path length l is "small" (that is, $l \sim ln(N)/ln(m)$).