Social Evolution in Imperfect World

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Abstract

Agent based simulation is a powerful tool for the research of complex systems such as human society. The important key word of this kind of research is "bounded rationality" of the agents. From the standpoint, we adopt following two hypotheses as the basis of our analysis: (1) each agent interacts only with his neighbors, and (2) each agent behaves by mimicking its neighbors. How the society gropes its way towards equilibrium in this imperfect world? The purpose of this research is to investigate the role of mimicry in social evolution. In this paper, we examined the growth of conventions in the society where individuals rely on hearsay to determine their action. Specific conditions as to which conventions are most likely to emerge from an amorphous state are clarified with computer simulations.

1 Introduction

The social evolution is the complex process made by interactions between individuals in the society. Game theory is commonly used when analyzing social evolution and there are two styles: one is the standard game theory and the other is the evolutionary game theory. The interpretation of the standard game theory is that the game is played exactly once between fully rational individuals. Evolutionary game theory, instead, assumes that the game is repeated many times by evolvable individuals chosen from large populations randomly. Much literature exists that investigates connections between the long run aggregate behavior and concepts of equilibrium solutions of the games [1].

The evolutionary game theory with bounded rationality [3] and local interaction must be used to construct an appropriate model for analysis of social evolution in real world, because the ability and the activity of each individual in society are not sufficient. So, the following two concepts form the basis of our analysis: (1) each agent interacts only with his neighbors, (2) each agent myopically behaves by imitating the behavior of his neighbors. We formalize these ideas in a model with a finite population of agents in which agents are repeatedly matched within a period to play a game.

One key concept for the analysis of the evolutionary game is the evolutionary stable strategy [2]. The predominant strategy is said to be evolutionary stable if there exists a barrier which prevents other strategies from invading. It is known that aggregate behavior converges to a Nash equilibrium that also satisfies the condition of the evolutionary stability [2]. The evolutionary stability can explain whether a strategy is robust to evolutionary pressures, but can not explain how a population arrives at such a strategy.

Another key concept for analysis of the evolutionary game is the replicator dynamics. This is a simultaneous differential equations of the number of agents who adopt some strategy. The description is an accurate, but we can only describe the strictly limited situation such as random matching with homogeneous agents.

In general, an evolutionary process has two basic elements: a mutation and a selection. The evolutionary process based on a biological mutation mechanism is very slow. However, social evolution may be fast because there exists a mechanism of mimicry, the transmission process of superior strategies from one head to another by imitation.

The criterion of evolutionary equilibrium highlights the role of mutations. The replicator dynamics, on the other hand, highlight the role of selection. Agent based simulation is a new methodology for studying an evolutionary games in the large that highlights the concepts of both mutation and selection. The purpose of this paper is to clarify the role of mimicry in social evolution.

2 The Model of Social Evolution

2.1 Local Matching

In order to describe the interactions among agents, we adopt local matching model. In this model, agents interact much more with their neighbors than with those who are far away [4]. They adapt other agents' successful strategies as guides for their own choices. Hence, their success depends in large part on how well they do in their interactions with their neighbors. Neighbors can serve another function: A neighbor can provide a role model. If the neighbor is doing well, the behavior of the neighbor can be imitated. In this way, successful strategies can spread throughout a population from neighbor to neighbor [5]. The position of each agent remains fixed in his locations, but their strategies can spread.

2.2 Learning Strategies

We assume that agents are less sophisticated and that they do not know how to calculate best replies. Agents are not so rational or knowledgeable as to correctly guess or anticipate the other agent's strategies.

An important aspect of social evolution is the learning strategy adapted by each individual. In the previous literature, agents are viewed as being genetically coded with a strategy and selection pressure favors agents that are fitter, i.e., whose strategy yields a higher payoff against the population. We consider two types of learning strategies: complete mimicry and partial mimicry. The latter is implemented as crossover in a genetic algorithm's words, we then call it crossover strategy. Each agent interacts with the agents on all eight adjacent squares and imitates the strategy of any better performing one. In each generation, each agent attains a success score measured by its average performance with its eight neighbors. Then if an agent has one or more neighbors who are more successful, the agent copy the strategy of the most successful neighbors in complete mimicry model and crossover his strategy with the strategy of the most successful neighbor in partial mimicry model.

2.3 Interactions Formulated as Games

Possible combinations of interactions can be formulated games as shown in Table 1. We classify those interactions into several types based on the payoff structures that describe interactions, and they are given the following special names in game theory. Later, we explain about a description of parameters (a, b, k) in detail; (1) The dilemma game (Table 1(a)), (2) The coordination game (Table 1(b)), (3) The mixed-motivation game (Table 1(c)).

Table 1: Local interactions formulated as games

(a) Dilemma game ($\beta \geq 1$, $\alpha \leq 0$)

	The other's strategy	
Own strategy	S_1 (Cooperate)	S_2 (Defect)
S_1 (Cooperate)	1 1	β α
S_2 (Defect)	α β	0 0

(b) Coordination game ($0 < k \leq 1$)

	The other's strategy	
Own strategy	S_1 (Cooperate)	S_2 (Defect)
S_1 (Cooperate)	k k	0 0
S_2 (Defect)	0 0	1 1

(c) Mixed-motivation game ($0 < k \leq 1$)

	The other's strategy	
Own strategy	S_1 (Cooperate)	S_2 (Defect)
S_1 (Cooperate)	0 0	k 1
S_2 (Defect)	1 k	0 0

3 The Implementation

3.1 Agents

Each agent's decision rules are represented as binary strings. A binary string of each agent consists of 22 positions (Table 2). Each position p_j, $j \in [1, 22]$, is represented as follows. The first and second position encodes the action that the agent takes at iteration $t = 1$ and $t = 2$. A position p_j, $j \in [3, 6]$, encodes the history of mutual hands (cooperate or defect) that the agent took at iteration $t-1$ and $t-2$ with his neighbor (opponent). A position p_j, $j \in [7, 22]$, encodes the rule of action that agent i takes at iteration $t > 2$, corresponding to the history (p_j, $j \in [3, 6]$). We consider agents' actions as follows: C = 0 and D = 1, and line up the actions of him and his opponent at $t - 2$ and $t - 1$. First position of rule (p_7) represent the action for (0000) = (CCCC), and second position (p_8) represent for (0001), ..., and the last position represent for (1111).

Table 2: Example of genes of agent i (TFT)

	$t=1,2$		memory				strategy decision part (0 = C, 1 = D)															
p_j	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
i	0	0					0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1

3.2 Algorithm

The complete mimicry and partial mimicry algorithms are implemented like [8]. Details are as follows:

(Step1) An agent i, $i \in [1 \dots N]$, interacts with his neighbors at all eight adjacent squares, and the game is repeated for T iterations.

(Step2) An agent i chooses his action. His initial action, at $t=1$ and $t=2$, is determined by decoding bits in the position p_1 and p_2. For $t>2$, $t \in [1 \dots T]$, an agent i chooses his action at t by using the information about his memories (position p_j, $j \in [3,6]$) and strategy decision part (position p_j, $j \in [7,22]$).

(Step3) The payoffs during T iterations of the games are accumulated.

(Step4) After T iterations, an agent i compares his payoff with his neighbors

(Step5) An agent i updates his binary strings using the genetic operator: [for complete mimicry] copy from, [for partial mimicry] crossover with, the neighbor who acquires the highest payoff for partial mimicry and mutation.

(Step6) if generation is *lastgen* then exit, else goto Steps 1.

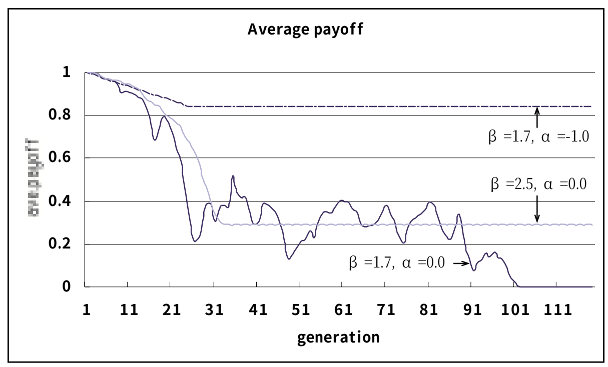
4 Simulation Results

Simulations are done in three types of games with both mimicry strategy and partial mimicry strategy (= crossover strategy). Agents are set in an area of 20×20 ($N = 400$ agents), with wrap-around. Parameters are as follows: $lastgen = 500$, $T = 10$, $mutate = 0.001$.

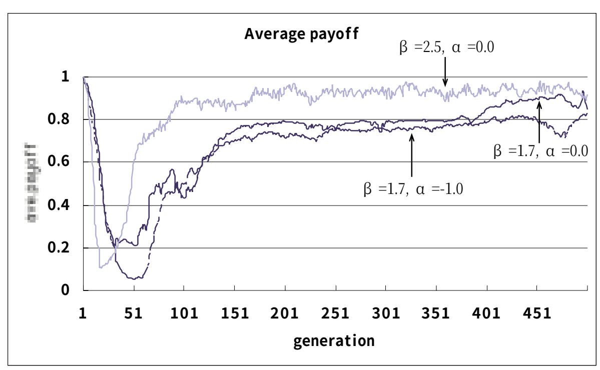
4.1 Social Dilemma Game

One agent located in a center who adopts All_D strategy and his strategy gives an influence to his neighboring agents. Fig. 1(a) represents the average payoff of each agent in mimicry case. As a result of this simulation, the population rapidly evolves but it is very unstable and the stability of social evolution depends on the parameters α and β.

On the other hand, The payoff of each agent with the partial mimicry case (= crossover strategy) are shown Fig. 1(b). For any combination of parameters (β, α), each agent can acquire higher payoff. We can also conclude that the social evolution with the crossover strategy is very stable. The evolutionary process with the crossover strategy doesn't depend on a combination of parameters (β, α). However, many generations are required to reach this desirable state compared with the former model.



(a)



(b)

Figure 1: Average payoff in Dilemma Game: (a) mimicry strategy, (b) crossover strategy

4.2 Social Coordination Game

In this game, we set up random strategy as the initial state of all agents in order to investigate whether an agent that has various strategies in the initial state cooperates mutually or not. The parameter $k = 1.0$ in Table 1(b). The result of simulation is shown in Fig. 2. In both cases of mimicry and crossover strategies, each agent is able to acquire a high payoff.

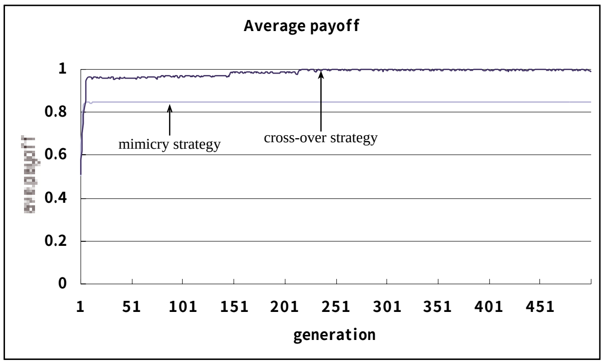


Figure 2: Average payoff in Coordination Game

4.3 Social Mixed-motivation Game

In this game, significant differences were observed between the mimicry strategy and the crossover strategy. Fig. 3 shows the case in which $k = 1.0$ in Table 1(c). we also investigate another k value. As a result, in the evolution with the mimicry strategy, there are many agents who persist with either strategy S_1 or S_2, and then, they can not acquire the payoff at high level. On the other hand, the evolution with the crossover strategy, whatever value we set for parameter k, each agent can acquire a higher payoff. Consequently, in the mixed-motivation game, we can say that evolution with the crossover strategy leads to a more efficient society than with the mimicry strategy.

5 Conclusion

The role of mimicry on social evolution is investigated by analysis of the interactions in a finite population of agents in which agents are repeatedly matched with their neighbors to play games. The hypotheses employed here is the limited ability of agents to receive, decide, and act upon information they get in

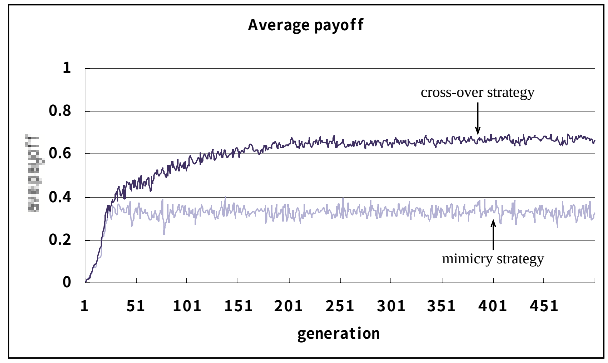


Figure 3: Average payoff in social mixed-motivation game

the course of interactions. We analyzed social learning and showed how the society as a whole learns even when the individuals composing it do not. Especially, we examined how conventions evolve in a society from an amorphous state where there is no established custom and individuals rely on hearsay to determine what to do. With simulations, we find specific conditions as to which conventions are most likely to emerge.

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