Co-evolution in Social Interactions

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Abstract- An interesting problem which has been widely investigated is under what circumstances will a society of rational agents realize some particular stable situations, and whether they satisfy the condition of social efficiency? This will crucially depend on how they interact and what information they have when they interact. For instance, when strategic interactions are modeled as coordination games, it is known the evolutionary process selects the risk-dominant equilibrium which is not necessarily efficient. We consider the networks of agents, in which each agent faces several types of the strategic decision problems. We investigate the dynamics of collective decision when each agent adapts the strategy of interaction to its neighbors. We are interested in to show how the society gropes its way towards an equilibrium situation. We show that the society selects the most efficient equilibrium among multiple equilibria when the agents composing it do learn from each other as collective learning, and they co-evolve their strategies over time. We also investigate the mechanism that leads the society to an equilibrium of social efficiency.

1 Introduction

The concept and techniques of game theory have been used extensively in dealing with strategic decision-making situations. However, game theory has been unsuccessful in explaining on how agents know which equilibrium can be realized if a game has multiple equally plausible equilibria [Fudenberg et al. 98]. Introspective or deductive theories that attempt to explain the problem of equilibrium selection impose very strong informational assumptions on the decision-making process [Hansaryi et al. 88]. In most game theoretic models, agents are assumed to have perfect knowledge of the consequences of their decision.

As a consequence, attention has shifted to evolutionary explanations motivated by the evolutionary game theory [Hofbauer et al. 98][Smith 82]. Evolutionary game theory assumes that the game is repeated by trial and error. The evolutionary selection process operates over time on the population, and more fit agents or strategies can be selected by natural selection [Hammerstein et al. 94]. That is, selection pressure favors agents which are fitter, i.e., whose strategy yields a higher payoff against the average of the population. Two features of the evolutionary approach also distinguish it from the introspective approach of the game theory. First, agents are not assumed to be so rational or knowledgeable as to correctly guess or anticipate the other agents' strategies. Second, an explicit dynamic process is specified describing how agents adjust their strategies over time as they learn from their experiences.

This paper is about social games. We especially consider the networks of games in which each agent is repeatedly matched with its neighbors to play the two-person games such as coordination games and hawk-dove games. We investigate how the society gropes for its way towards equilibrium in an imperfect world where agents interact locally. They do not perform optimization calculations, instead observe the current performance of their neighbors, and learn from the most successful one. The search for evolutionary foundations of game-theoretic solution concepts leads from the notion of an evolutionarily stable strategy to alternative notions of evolutionary stability to dynamic models of evolutionary processes. The commonly used technique of modeling the evolutionary process as a system of a deterministic difference or differential equations may tell us little about equilibrium concepts other than that strict Nash equilibria are good. We attempt to probe deeper into these issues by modeling the choices made by the agents with the own internal models. The term evolutionary dynamics often refers to systems that exhibit a time evolution in which the character of the dynamics may change due to internal mechanisms. We focus on evolutionary dynamics that may change in time according to each agent's local rule of interaction. We then model the microscopic evolutionary dynamics induced by both agents' conscious decision and adaptive decision .

There is no presumption that the self-interested behavior of agents should usually lead to collectively satisfactory results. How well each agent does for it in adapting to its social environment is not the same thing as how satisfactory a social environment they collectively create for themselves. We explore the mechanism so that emergent collective behavior can be manipulated in order to achieve desirable situations. We discuss the role of collective learning by considering the problem of equilibrium selection. We use the term emergent to denote stable macroscopic patterns arising from the local rules for interaction. We investigate the mechanism in which collective learning produces some kind of coherent and systematic emergent behavior of social efficiency.

2 Networks of Strategic Decisions

An agent's behavior is called "purposive behavior", if it is based on the notion of having preference, pursuing a goal, and maximizing an interest. The goal or interest of an agent often relates directly to other agents who are also pursuing their own interest. An agent's outcome, whichever way it makes the choice, also depends on the number of agents who choose one way or the others. We call this type of behavior "contingent behavior", which also depends on what others are doing. In the simplest form of our model, agents are born with internal models and local rules of interaction, and they behave to maximize their utility or interest. Their behavior is both purposive and contingent in the sense that their rational decision also depends on how the others behave.

This paper also considers the dynamics of collective decision when agents adapt their decision to the others'. We especially consider the networks of games as shown in Figure 1, in which each node represents an agent and each link represents social interaction between two agents. We model the strategic decisions of agents as follows: Each agent faces the binary decision with externalities. An externality occurs if one cares about others' decisions, and they also affect each agent's strategic decision. Depending on the structure of the binary decision, we model social interaction between two agents as a coordination game or a hawk-dove game.

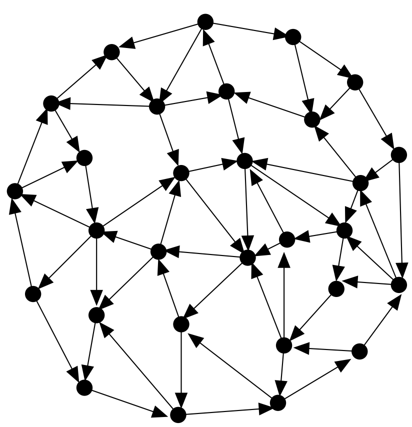


Figure 1: Conceptual view of networks of local interactions of agents and social games

These situations, in which an agent decision depends on the decisions of the others, are the ones that usually do not permit any simple summation or extrapolation to the aggregates [Iwanaga et al. 00]. To make that connection we usually have to look at the system of interactions between agents and the collectivity. Much literature on collective behavior has reacted against the older notion that irrationality is the key to explanation [Granovetter 78] [Smith 82]. They agree that collective behavior often results from rational, and calculated action. The greatest promise lies in analysis of situations where agents behave in ways contingent on one another, and these situations are central in theoretical analysis of linking micro to macro levels of collective decision. We especially address the following question: How do the micro-worlds of agents generate the global macroscopic orders of optimality? We aim at discovering fundamental local or micro mechanisms that are sufficient to generate the macroscopic orders of social efficiency. This type of self-organization is often referred as collective orders emerged from the bottom up [Holland 95].

3 Social Games and Equilibrium Selection

There are many situations where interacting agents can benefit from coordinating their actions. Examples where coordination is important include trade alliance, the choice of compatible technologies or conventions such as the choice of a software or language [Axelrod 97]. These situations can be modeled as coordination games, in which agents are expected to select the strategy that the majority does. However coordination games have multiple equilibria with the possibility of coordinating on different strategies, which is known as the problem of miss-coordination. The traditional game theory is silent on how agents know which equilibrium should be realized if a game has multiple equally plausible equilibria, where these can be Pareto ranked. The game theory has been also unsuccessful in explaining how each agent should learn in order to improve an equilibrium situation [Fudenberg et al. 98].

As a specific example of a coordination game, we formulate the endogenous choice problems of partners. Each link in Figure 1, represents social interaction formulated as the following coordination game: Agents periodically have the discretion to add or sever links to their neighbors. All possible outcomes between two agents are given as the payoff matrix in Table 1. If both agents add the links, they receive the payoff α. The parameter β represents the loss of the one-sided addition to the network. If the partner severs the network, the network cannot be connected, hence the effort for adding to the networks becomes to be meaningless. Social interaction model is characterized by the fact that each agent can completely control with whom they interact. With such endogenous interaction patterns, the question is whether the society may select an efficient equilibrium, in which each agent is linked as shown in Figure 1, starting from any initial configuration of the networks.

The coordination game with the payoff matrix in Table 1 has two equilibria with the pairs of the pure strategies $(S_1,\ S_1)$, $(S_2,\ S_2)$, and one equilibrium of

Table 1: The payoff matrix of a coordination game ($\alpha, \beta > 0$)

	The other's strategy	
Own's strategy	S_1 (add)	S_2 (sever)
S_1 (add)	α α	0 $-\beta$
S_2 (sever)	$-\beta$ 0	0 0

the mixed strategy. The most preferable equilibrium, defined as Pareto-dominance, is (S_1, S_1), which dominates the other equilibria. There is another equilibrium concept, the risk-dominance. If α - $\beta < 0$, the equilibrium (S_2, S_2) risk-dominates (S_1, S_1). If the value $\theta = \beta \ / \ (\alpha + \beta)$, defined as the threshold, is greater than 0.5, the Pareto-dominant equilibrium (S_1, S_1) also risk dominates (S_2, S_2). However, if θ is less than 0.5, the equilibrium (S_2, S_2) risk dominates (S_1, S_1). The optimal situation of the society is realized if all agents choose the Pareto-optimal strategy S_1. How do rational agents make their decision when Pareto-dominant and risk-dominant strategies are different? Absent an explanation of how agents coordinate their expectations on the multiple equilibrium, some agents expect the equilibrium (S_1, S_1) and the others expect (S_2, S_2), and then they often face the problem of miss-coordination.

An evolutional approach tries to explain how an equilibrium emerges based on trial-and-error learning. Successful strategies are adopted with higher probability than unsuccessful ones. In general, an evolutionary process combines two basic elements, a mutation mechanism that provides variety and a selection mechanism that favors some varieties over others. The criterion of evolutionary equilibrium highlights the role of mutation. The replicator dynamics, on the other hand, highlight the role of selection, which is modeled as follows: Each agent is assumed to choose one of the possible pure strategy. The population state, in which each component of the state represents the population share of agents who adapt each possible pure strategies. The replicators are here the pure strategies, and these can be imitated from parents to child. As the population state changes, so do the payoffs to the pure strategies and also their fitness [Weibull 96].

Even if we consider the social coordination games in an evolutionary setting, the situation remains the same. The risk-dominant equilibrium is selected from among the set of Nash equilibria, even if it is inefficient. The basin of attraction of the risk-dominant equilibrium is larger than that of the Pareto-dominant equilibrium. In addition, if agents sometimes make mistakes, the society occasionally switches from one equilibrium to another. As the likelihood of mistakes goes to zero, it is known that the risk-dominant equilibrium becomes to be stochastically stable [Kandori et al. 93].

We consider another type of social interaction such that each link in Figure 1 is modeled as a hawk-dove game with the payoff matrix in Table 2. The hawk-dove game is often used to explain the conflict among agents. We suppose there are two possible behavioral types, one escalates the conflict until injury or sticks to display and retreats if the opponent escalates. These two types of behavior are described as "hawk" and "dove". The prize corresponds to a gain in fitness V, while an injury reduces fitness by C. If a hawk meets a hawk, they fight until one is seriously injured. The fitness of the winner increased by V, that of the loser reduced by C, so that the average increase in fitness is $(V - C)/2$, which is negative if the cost of the injury is assumed to exceed the prize of the fight. If a dove meets a dove, they engage in threatening display, but flee when confronted with real danger, and therefore, its expected fineness is given by $V/2$. If a hawk meets a dove, the dove runs away and the hawk wins the contested resource of value of V.

Table 2: The payoff matrix of a hawk-dove game ($0 < V < C$)

	The other's strategy	
Own's strategy	S_1 (Hawk)	S_2 (Dove)
S_1 (Hawk)	$(V - C)/2$ $(V - C)/2$	0 V
S_2 (Dove)	V 0	$V/2$ $V/2$

There is the unique Nash equilibrium in mixed strategies, i.e., both agents use the strategy S_1 ('hawk') with probability V/C and the strategy S_2 ('dove') with the probability $1 - (V/C)$ [Smith 82]. At equilibrium of the mixed strategy, the expected fineness is given as $(V/2)\{1 - (V/C)\}$, which results in inefficient equilibrium. The Pareto-optimal equilibria (S_1, S_2) and (S_2, S_1), or more precisely, the state in which all agents play S_1 (hawk), or the state in which all agents play S_2 (dove), are both asymptotically unstable with respect to the evolutionary dynamics. In a population of almost all hawks, the dove strategy of avoiding conflict does better than the hawk strategy. Then doves increase their proportion of the population. Similarly in a population of almost all doves, however, the hawk strategy does better than the dove strategy. Then hawks increase their proportion of the population, and only the mixed equilibrium remains. In this way, the evolutionary dynamics drives the population to that equilibrium [Weibull 96].

4 Spatioal Evolutionary Dynamics with Collective Learning

In order to formulate the social interactions in large, we may have two fundamental models, random matching and local matching [Cohedent 98]. The approach of random (or uniform) matching is modeled as follows: At each time period, every agent is assumed to match (interact) with one agent drawn at random from a society. An important assumption of random matching is that they receive knowledge of the current strategy distribution. Agents can calculate their best strategy based on information about what other agents have done in the past. What happens when an agent does not have all of this information?

In this section, we describe spatioal evolutional dynamics with the following two hypotheses:

1. Each agent interacts with his neighbors (local interaction).

2. After interaction, they improve their rules of interaction with crossover (collective learning).

The first hypothesis reflects limited ability on the agent's part to receive, decide, and act upon information they get in the course of interaction. The second interpretation is that agents may not perform optimization calculation, instead they observe the current performance of their neighbors, and learn from the most successful one.

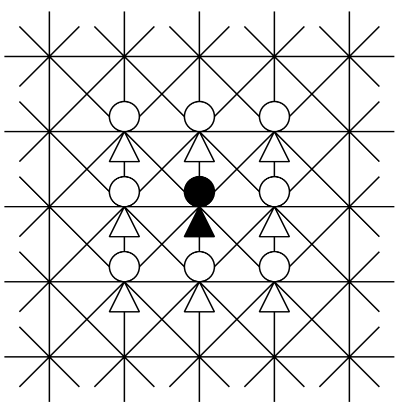


Figure 2: A model of spatioal evolutionary dynamics

We especially consider the structure of territories in which the entire territory is divided up so that each agent interacts with eight neighbors as shown in Figure 2 [Lindgren 97] [Nowak et al. 95]. Each agent interacts with the agents on all eight adjacent squares and imitates the strategy of any better performing one. They adapt the most successful strategy as guides for their own decision (individual learning). Hence their success depends in large part on how well they learn from their neighbors. If the neighbor is doing well, its strategy can be imitated by all others (collective learning). Each agent is modeled to be matched several times with the same partner, and the strategies for the same partner is coded as the list. A part of the list is replaced with that of the most successful agent as shown in Figure 3 (crossover) [Uno et al. 99 (a)] [Uno et al. 99 (b)]. Neighbors can serve another function as well. If the neighbor is doing well, the behavior of the neighbor can be imitated, and successful strategies can spread throughout a population from neighbor to neighbor. The consequences of their behaviors may take some time to have an effect on agents with whom they are not directly linked.

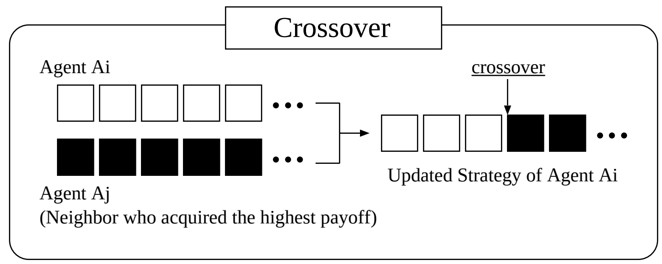


Figure 3: Illustration of crossover as individual learning

5 Simulation Results

Although the static equilibrium notion is worth examining, perhaps more interesting is the dynamic evolution. In many applications it is also of interest to know which strategies survive in the long run. We arrange agents for an area of 50×50 ($N = 2,500$ agents) as the lattice model in Figure 2 with no gap, and four corners and end of an area connect it with an opposite side. At each time period, each agent plays the coordination game in Table 1 with his 8 neighbors as social games or the hawk-dove game in Table 2 as social hawk-dove games.

5.1 Social Coordination Games

We investigate the role of collective learning in social games. We demonstrate various evolutionary phenomena by studying the behavior in the following two completely different models: The means-field model in which all agents with all (or equivalently the random matching model in which each agent interacts with a randomly chosen partner), and the local interaction on the lattice model.

In Figure 4, we show the simulation results by changing the parameters α, β in Table 1. The x-axis represents the threshold value $\theta = \beta/(\alpha+\beta)$. The y-axis represents the ratio of the Pareto-optimal strategies (S_1) in the society at equilibrium. The dot line in Figure 4 represents the result of the evolutionary approach. If $\theta < 0.5$, the Pareto-optimal strategy S_1 also risk-dominate S_2, therefore all agents finally chooses S_1. However if $\theta > 0.5$, all agents finally choose the risk-dominant strategy S_2 with

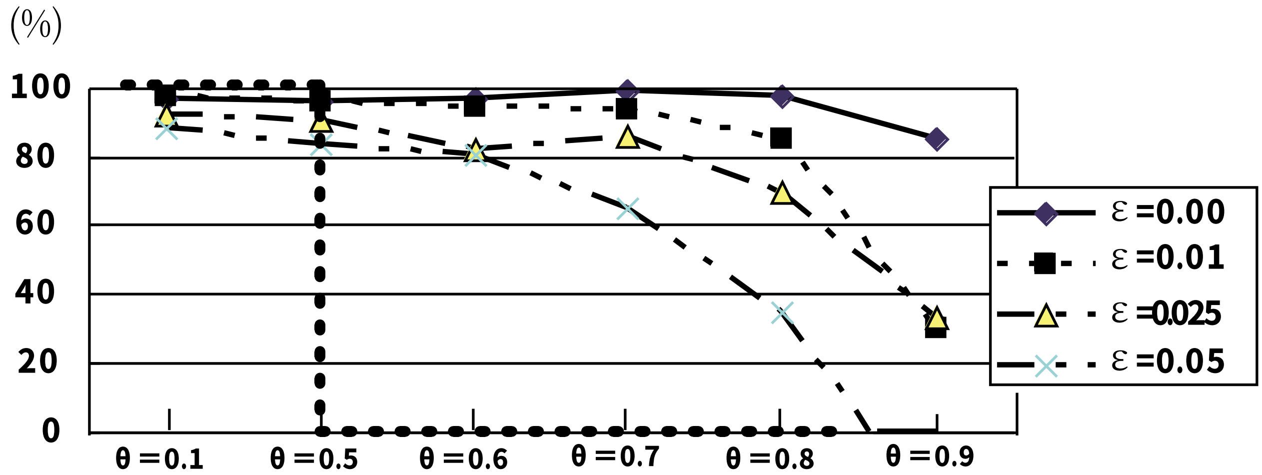
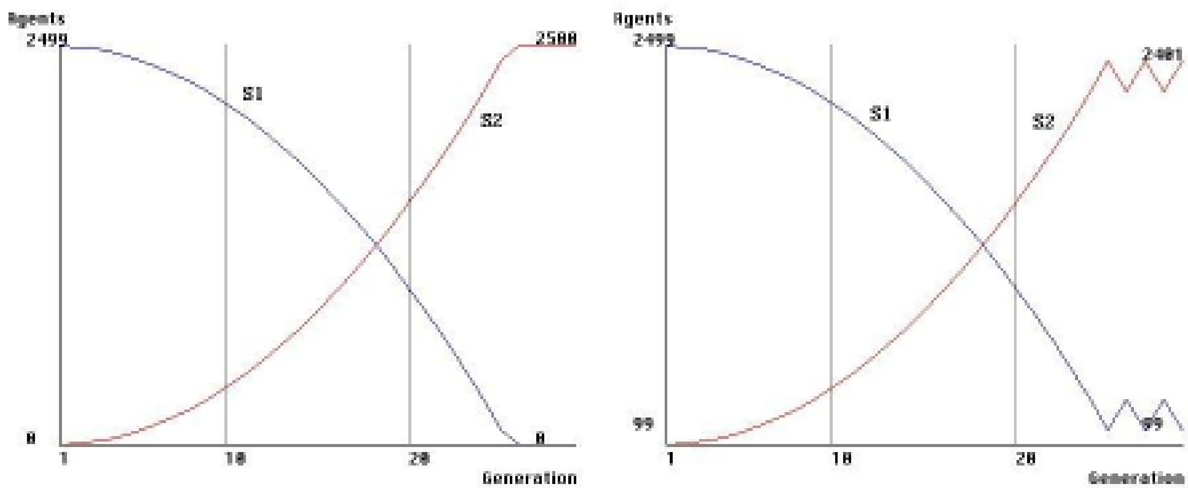


Figure 4: The ratio of the Pareto-dominant strategy (S_1) at equilibrium



(a) $(V, C) = (2, 10)$

(b) $(V, C) = (2, 4)$

Figure 5: The numbers of agents who choose S_1 and S_2.

the means-field model. With the lattice model with collective learning, if the threshold value θ is less than 0.8, then almost every agent finally choose S_1. However, if the threshold θ is greater than 0.8, more agents become to choose the risk-dominant strategy S_2.

We also considered the effect of mistakes for equilibrium selection. We assume that agents sometimes make mistakes in the implementation of their strategies. That is, with some probability ϵ, the agents do not use the current strategy determined by their rules of interaction, but the other one. We use different noise levels of $\epsilon = 0.01$, $\epsilon = 0.025$, and $\epsilon = 0.05$. With the high rate of mistake ($\epsilon = 0.05$), the risk-dominant-strategy S_2 becomes to dominate if the threshold value θ is large ($\theta > 0.8$). However, with the low level of mistakes, the Pareto-dominate strategy S_1 still dominates the society.

The differences between the mean-field model and the lattice model with collective learning are evident in all these cases. We found that the collective learning process leads the society of rational agents to the Pareto dominant equilibrium situation in most cases. In this context, even if mistakes or errors when they choose their strategy are introduced, we found social coordination games with collective learning always converges to the Pareto dominant equilibrium.

5.2 Social Hawk-Dove Games

We simulated social hawk-dove games by changing the parameters V and C in Table 2. In Figure 5, we show the simulation results with the cases (a) $(V, C) = (2, 10)$ and (b) $(V, C) = (2, 4)$. The initial condition is set as follows: Only one agent at the center is set to choose S_2 ('dove') and the rest of the agents choose S_1 ('hawk'). In these figures, the x-axis represents the update times of the strategies, and the y-axis represents the number of agents who chose S_1 and S_2 at each generation. The simulation results shown in Figure 4 indicate that the number of agents of the strategy S_2 (dove) increased gradually, and finally almost all agents chose S_2 (dove). That is, they gradually learn to hate to fight with others, which is also a socially efficient situation.

An important aspect of collective intelligence is the learning strategy adapted by each agent. An interesting problem which has been widely investigated is under what circumstances will agents, converge to some particular equilibrium? We endowed our agents with some simple way of collective learning and describe the evolutionary dynamics that magnifies tendencies toward more better situation. By incorporating a consideration of how agents interact into models, we not only make them more realistic but we also enrich the types of aggregate behavior that can emerge. The introduction of spatial dimensions, so that agents only interact with those in their neighborhood also affect the dynamics of the system in various ways. The possibility of spatiotemporal structures allows the socially optimality where the model with random matching may result in inefficiency.

6 Conclusion

This paper discussed strategic models in which agents interact locally with their neighbors and learn from the most successful one. We compared the global model with global interaction in which all agents can interact with each other and the lattice model with local interaction in which agents can only interact with their immediate neighbors. As an example, we showed how social networks evolve to a socially optimal situation where everybody is fully connected starting from randomly disconnected situation. We also discussed the role of collective learning in social games. The hypotheses we employed here reflect limited ability of agents. The learning strategy employed here is crossover, and they mimic to the most successful neighbor. The methodology of collective learning is very slow to evolve, but it is essential especially in imperfect worlds. We investigated how the society selects the most efficient equilibrium among multiple equilibria when the agents composing it do learn each other, and showed that collective learning is essential for realizing social efficiency.

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