Co-Evolution in an Competitive Market

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Abstract. In this paper, we provide the model of co-evolution in a society of economic agents. Economic agents are defined as autonomous software entities equipped with their own utility functions. Their utility functions governed by the market mechanism. We also provide the evolutional explanation on how the social competence that provides the motivation for the coordinated behavior can be emerged through the competitive interactions among economic agents. Especially we need to understand the following basic issues how get the architecture of an agent, as a component of a complex system, suited for evolution, how self-interested behaviors evolve to coordinated behaviors, and how the structure of each goal (utility) function can be modified for globally coordinated behaviors. We show that the concept of sympathy becomes a fundamental element for co-evolution.

Keywords:
emergence of optimal behaviors, market mechanism, economic agent, emotion

1 Introduction

In a large-scale complex adaptive system composed of those many rational agents, two types of strategic behaviors may occur: agents mutually interact and behave to achieve the common goal of the society, while at the same time, each agent also behaves to optimizes its own goal. For an individual rational agent, it behaves to improve its own utility function based on its local observation. This ability is based on principles of the individual rationality. By a social goal we mean a goal that is not achievable by any single agent alone but is achievable by a society of agents. The key element that distinguishes a social goal from an agent's individual goal is that they require cooperation. Then how will the evolution of individually rational behaviors proceed to coordinated behavior?

We describe the model of economic agent as the basis for social cooperation learnable through competitive interaction. We call the latter ability as competitive cooperation. Economic agents are driven by their own selfish motivations, and they are selfish in the sense that they only do what they want to do and what they think is in their own best interests, as determined by their own interests. The collective behavior of those agents is determined through the local interactions of their constituent parts. These interactions merit careful study in order to understand the macroscopic properties of collective behaviors . We especially ask the following questions: If agents make decisions on the basis imperfect information about other agents' goals or utility functions, and incorporate expectations on how its decision will affect other agents' utility functions, then how will the evolution of cooperation proceed? How will the structure of utility function of each agent should be self-modified for the co-evolution?

In this paper, we study the evolution of social cooperation without loosing the principle of competition in a society as a co-evolution. co-evolution is defined as the mechanism which utilizes adaptive decision-making of economic agents in a competitive market environment. Adaptive decision-making is facilinated by designing the agent to be somewhat modified selfish interest. In adaptive dicision-making mechanism, each economic agent modifies its own utility function by reflecting its sympathy level to the other members. With the principle of sympathy, It adapts its own decision to based on the current and previous performance. The goal of an agent is determined solely by how that agent affects other members of the society and how the decision of other agents affects its own utility function. Adaptive decision-making is facilitated by designing the agents to be somewhat modified selfish interest.

Co-evolution allows agents to achieve high-level social goals without the need for cooperative planning and communications. Then, over a time, a society of economic agents will be able to learn to cooperate together at an even higher-level of efficiency and adaptability. Under this co-evolution, cooperation emerges as a side-effect which lead them to learn the cooperative behaviors without sacrificing that the principle of competition among them.

2 A Model of Economic Agents

We consider a society of economic agents, $G = \{A_i : i = 1, 2, \ldots, n\}$. Economic agents are defined as autonomous software entities equipped with the adaptive capabilities. They have their own utility functions as the function of the market price which is governed with the market mechanism. We define the utility function of each agent $A_i \in G$ as

$$U_i(x_1, \ldots, x_i, \ldots, x_n) = x_i P_i\{x_i, x(i)\} \tag{1}$$

where $P_i\{x_i, x(i)\}$represents the price scheme associated to the activity of agent $A_i \in G$. And x_i represents the level of activity of agent $A_i \in G$, and $x(i) = (x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_n)$ represents the set of activities of all agents in G except agent A_i.

As a specific example, we consider the following social price scheme for each agent $A_i \in G$,

$$P_i = a_i - \sum_{j=1}^{n} b_{ij} x_j \tag{2}$$

where $a_i, b_{ij}, i, j = 1, 2, \ldots, n$,are some positive constant.

The competitive solution in which each agent maximizes its own utility function simultaneously is given as the solution of the following system of linear equations:

$$(B + B_1)x^\circ = a \tag{3}$$

where B is a $n \times n$ matrix with the (i, j)th element is, $b_{ij}, i, j = 1, 2, \ldots, n,\quad B_1$ is a diagonal matrix with the i-th diagonal element is b_{ii}, and a are the column vectors with the elements, $a_i, , i = 1, 2, \ldots, n$, respectively.

We define the socially optimal behavior as the set of the activities that optimize the summation of the utility functions of all agents defined as

$$S(x_1, \ldots, x_i, \ldots, x_n) = \sum_{i=1}^{n} U_i\{x_1, \ldots, x_i, \ldots, x_n\} \tag{4}$$

The socially optimal behaviors is then obtained as the set of the activities satisfying the following equations.

$$\partial S/\partial x_i = \partial U_i/\partial x_i + \sum_{j\neq i}^{n} \partial U_j/\partial x_i = 0, \quad i = 1,2,\ldots,n, \tag{5}$$

As an example of the quadratic utility functions with the linear social price scheme is given in (2), the social optimal solution is obtained as the solution of the following system of linear equations:

$$(B + B^T)x^* = a \tag{6}$$

where B^T is the transpose matrix of B.

We especially consider the case in which the interaction matrix B is symmetric with the diagonal elements are the same, i.e., $b_{ii} = d$ and the off-diagonal elements are, $b_{ij} = b, (0 < b < d), i,j = 1,2,\ldots,n$. The column vector a also has the same elements, i.e., $a_i = a, i = 1,2,\ldots,n,$.

The utility of each agent at competitive equilibrium is obtained as follows:

$$U_i^\circ(n) = a^2 d/\{2d + b(n-1)\}^2 \tag{7}$$

The utility as a society, which is defined as the summation of the utility of each agent is then given as

$$G^\circ(n) \equiv \sum_{i=1}^{n} U_i^\circ(n) = a^2 dn/\{2d + b(n-1)\}^2 \tag{8}$$

In the area with the number of agents is small, the summation of the utilities increase as the number of the agents increase, and it become to decrease if the number of agents increases, and it converges to zero as the number of agents in a society becomes so large. Such a turning point of the number of agents at which the value function change from the increasing function to the decreasing function is given at

$$2 \leq n \leq (2d/b) - 1 \tag{9}$$

The utility of each agent at socially optimal behavior is given as

$$U_i^*(n) = a^2/4\{d + b(n-1)\} \tag{10}$$

The utility as a society, which is defined as the summation of the utility of each agent is then given as

$$G^*(n) \equiv \sum_{i=1}^{n} U_i^*(n) = a^2 n/4\{d + b(n-1)\} \tag{11}$$

Here we are interested in how the adaptiveness of the whole organization may affect if the size of the organization increases, i.e, we will investigate the asymptotic value of the summation of the utility functions of each agent in the case that the number of agents increases. By taking the limits of those utility functions with the number of the economic agents, those values converge as follows:

$$\lim_{n\to\infty} G^\circ(n) = 0 \tag{12}$$

$$\lim_{n\to\infty} G^*(n) = a^2/4b \tag{13}$$

This implies the level and heterogeous (in this case b/d) of the interaction among agent, the increase of the agents do not give any effect on the collective behaviors.

Fig.1 shows the sums of the utilities as the function of the number of agents.

This implies that the utility under competitive behaviors converges to zero, and that of under socially optimal behaviors converge to same constant.

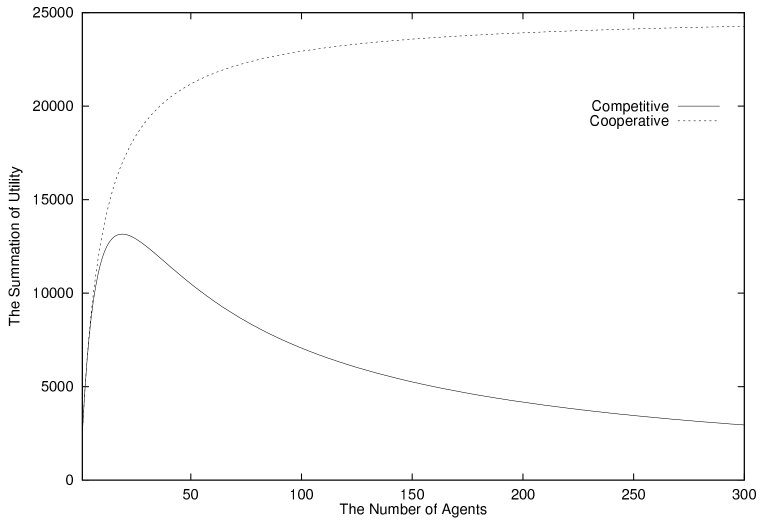


Fig. 1. The effect of the size of the society

3 Learning of Utility Function

In the previous section, we showed that the conditions of the individual optimality and the social optimality are different. This implies that if each economic seeks its own optimality the utility decreases as the number of agents in a society increases. Our question is then stated as follows, how will the evolution of cooperation proceed and how the emergence of cooperation can take place in a society.

We now consider the following modified utility function for each agent $A_i \in G$.

$$\overline{U_i}\{x_i, x(i)\} = U_i\{x_i, x(i)\} - \lambda_i\{x(i)\}x_i \tag{14}$$

If the condition is satisfied,

$$\mid \partial^2 U_i/\partial x_j x_k \mid < \mid \partial^2 U_i/\partial x_j x_i \mid \quad k \neq i \tag{15}$$

we have the following relation.

$$\lambda_i(x(i)) = -\sum_{j \neq i}^{n} (\partial^2 U_j/\partial x_j \partial x_i) x_j \tag{16}$$

As a specific example, we consider the decision-making of each economic agent with the utility function of the quadratic form in (1) The social price defined in (16) is given as follows:

The utility function of each agent defined in (14) consists of the two terms, the private utility function and the social utility function. By taking the derivative of the modified utility function of (14) by x_i, we obtain

$$\partial\overline{U_i}/\partial x_i = \partial U_i/\partial x_i - \lambda_i(x(i)) \tag{17}$$

we set $\lambda_i(x(i))$ in (17) as (18), the condition of the individual optimality under the modified utility functions is equivalent to the condition of the social optimality defined over the set of the original utility functions in (1).

$$\lambda_i(x(i)) = -\sum_{j\neq i}^{n}(\partial^2 U_j/\partial x_j \partial x_i)x_j = \sum_{j\neq i}^{n} b_{ji}x_j \tag{18}$$

We term $\lambda_i(x(i))$ as the level of the sympathy of the i-th economic agent. The sympathy level indicates the level of the influence of the decision of i-th agent to the utility functions of the other economic agents.

The condition of the individual optimality by considering the sympathy level is given as

$$M_i\{x_i, x(i)\} - \lambda_i\{x(i)\} = 0 \quad i = 1, 2, \ldots, n. \tag{19}$$

where we denote the derivative of the utility function as $M_i\{x_i, x(i)\}$.

The emergence of those social competence as intelligent can take place without any commitment among selfish agents. In a society, economic agents are driven by their own selfish motivations which lead them to learn the rules of decentralized decision-making or the coordinated behaviors. In Fig.2, we show the mechanism of the emergence of the social competence of each economic agent.

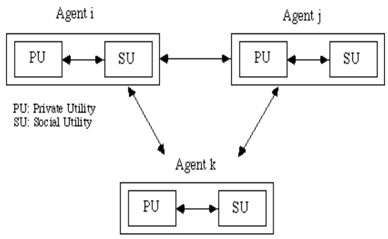


Fig. 2. The emergence of the social competence through the interactions

The process of building up intelligent behaviors and cooperative intentions may be called mutual or co-evolution [7][12]. Co-evolution from the social perspective is grounded in the actions of many agents' activities taken together, and it not a matter of individual choice. It is one's actions in relation to those of others (vice versa) that maintain its participation. Co-evolution is in this sense is the outcome of a web of activity emerged from the mutual interactions among agents. In the model of co-evolution, two types of learning may occur: the economic agent can learn to cooperate as a group, while at the same time, each agent can also learn its own by adjusting its activity level. Co-evolution would require the exchange of actions of the other agents.

The dynamic action selection process must be coordinated to achieve globally consistent and good actions. We define the co-evolution as the adjustment process of each agents' individually economic behavior. The co-evolution model describes how each agent, without knowing the others' utility functions, adjusts its activity level over time and reaches to an equilibrium situation.

Without complete knowledge of other agents, agent needs to infer the strategies, knowledge, plans of other agents. Economic agents can put forward their private knowledge for consideration by other agents based on its own local interactions, and agents would require the exchange of actions with other agents. Learning is then formulated as the web of activity emerged from the mutual interactions among economic agents. With the individual learning capability, each agent modifies its decision based on the current and previous performance in order to optimize its own utility function[1]. This adjustment process generates a partial action that governs the actions of the agents .The mutual adjustment process of behaviors is modeled as follows:

$$\begin{array}{lll} M_i\{x_i, x(i)\} > \lambda_i\{x(i)\} & then & x_i := x_i + \delta x_i \\ M_i\{x_i, x(i)\} < \lambda_i\{x(i)\} & then & x_i := x_i - \delta x_i \end{array} \tag{20}$$

At equilibrium , we have

$$M_i\{x_i^*, x^*(i)\} - \lambda_i\{x^*(i)\} = 0 \quad i = 1, 2, \ldots, n. \tag{21}$$

The use of directives by an agent to control another can be viewed as a form of incremental behavior adjustment[14]. The adjustment process without any sympathy by setting $\lambda_i = 0, i = 1, 2, \ldots, n.$, converges a competitive equilibrium.

The mutual adjustment process with the sympathy is modeled specifically as follows:

$$\begin{array}{l} \delta_i = x_i(t+1) - x_i(t) \\ = (\alpha_i/b_{ii})[M_i\{x_i(t), x(i,t)\} - \lambda_i\{x(i,t)\}] \end{array} \tag{22}$$

where $x(i,t) = (x_1(t), \ldots, x_{i-1}(t), x_i(t), x_{i+1}(t), \ldots, x_n(t))$. The mutual adjustment process is then given as follows:

$$x_i(t+1) = (\alpha_i/b_{ii})P_i(t) + (1-\alpha_i)x_i(t) - (\alpha_i/b_{ii})\lambda_i\{x(i,t)\} \tag{23}$$

We also describe the adjustment process of each agent's sympathy level as follows:

$$\lambda_i(t+1) = \beta_i[M_i\{x_i(t), x(i,t)\} - \lambda_i x(i,t)] + \lambda_i\{x(i,t)\} \tag{24}$$

With the definition the level sympathy in (21), we have the following process for learning:

$$\lambda_i(t+1) = \beta_i\{P_i(t) - b_{ii}x_i(t)\} + (1-\beta_i)\sum_{j\neq i}^{n} b_{ji}x_j(t) \tag{25}$$

The activity level of each agent should be determined solely by how its decision affects other members in the same society and how the decisions of other agents affect its own utility function. However, in the large society, it may difficult for each agent to consider the interactions with other agent. Therefore, we assume the following symmetric condition for mutual interactions.

$$b_{ji}/b_{ii} = k \quad (0 < k \leq 1), j = 1, 2, \ldots, n, j \neq i \tag{26}$$

The mutual adjustment process of behaviors based on goal-seeking with the sympathy is then modeled as follows:

$$\lambda_i(t+1) = \beta_i\{P_i(t) - b_{ii}x_i(t)\} + (1-\beta_i)b_{ii}k\sum_{j\neq i}^{n} x_j(t) \tag{27}$$

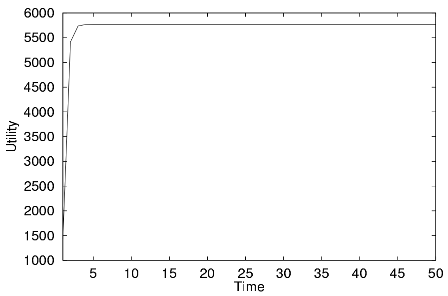
4 Some Simulation Results

The goal of the research is to understand the competitive interactions based on the self-interested motivations which produce purposive and optimal collective behavior. In this section, we address the question of how a society of the economic agents with different internal model can achieve complex collective behaviors as a whole. We especially address the following questions: How will the internal model of each economic agent affect the evolution of their collective behaviors, how will the collective behavior of in economic agents proceed by changing the combination patterns of different types of agents? In order to answer those questions, we did some simulation under the following condition.

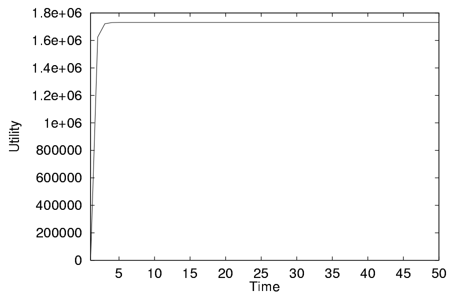
(simulate conditions)
(1) number of Agents:30
(2) social price scheme :$a_i = 300, b_{ii} = 1, b_{ij} = 0.1$
(3) initial action of each agent : 5

The following figures show the change of utility over the adaptive time.

(Case1) $\alpha_i = 0.1$(slow to adjust the market price) and $\beta_i = 0.1$(low learning speed)



(a) The utility of individual



(b) The utility of society

Fig. 3. The change of utility (with sympathy)

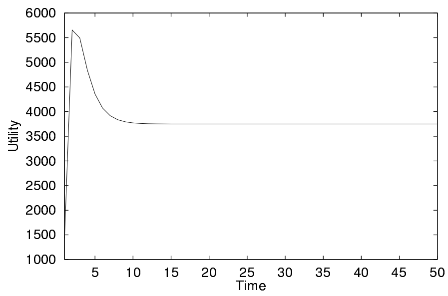
Fig.3 and Fig.4 shows the utility of an individual and the whole society. Fig.3 shows the utility under sympathy. Fig.4 shows that the utility without sympathy From this simulation, each individual can increase its utility with sympathy to other agent.

(Case2) $\alpha_i = 0.1$ (slow to adjust the market price) and $\beta_i = 0.9$ (high learning speed)

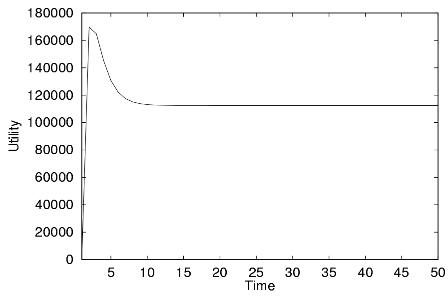
Fig.5 shows the case of the high speed of learning factor of sympathy, and in which the utility of each agent converges slowly.

5 Conclusion

The goal of the research is to understand the types of simples local interactions which produce complex and purposive group behaviors. We formulated and an-

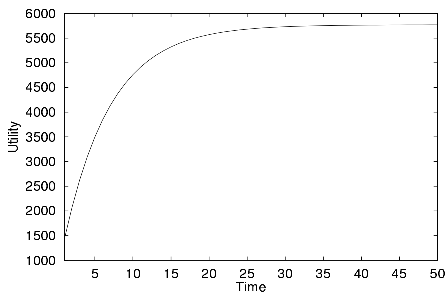


(a) The utility of individual

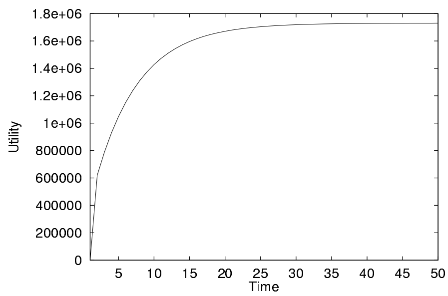


(b) The utility of society

Fig. 4. The change of utility (without sympathy)



(a) The utility of individual



(b) The utility of society

Fig. 5. The change of utility: slow convergence

alyzed the social learning process of independent economic agents. We showed that cooperative behaviors can be realized through purposive local interactions based on each individual goal-seeking. Each economic agents does not need to express its utility function, nor to have a priory knowledge of those of others. Economic agent adapts its action both to the actions of other agents.

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