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The Evolutionary Game Study of Knowledge Transfer Behavior in Cooperative Crowdsourcing Community of Innovation

*Juan Xue[1,2], **Chang Q. Ding, ***Jing Yuan

*[1]Business School, Hohai University
China, West Focheng Rd, Nanjing, (xuej@njupt.edu.cn);
*[2]Library, Nanjing University of Posts and Telecommunications
China, No.9 Wenyuan Road Qixia, Nanjing, (xuej@njupt.edu.cn);
**Business School, Hohai University
China, West Focheng Rd, Nanjing, (731857580@qq.com)
***College of Foreign Studies, Guilin University of Electronic Technology
China, Guilin 541004 (354032340@qq.com)

Abstract

The development of crowdsourcing innovation mode depends on the stability and continuity of knowledge transfer behavior in crowdsourcing community. This paper examines the evolutionary process of knowledge transfer behavior among agents of the crowdsourcing community of cooperative innovation; and builds up an evolutionary game model to knowledge transfer behavior in the crowdsourcing community. We find that the cost of knowledge transfer, knowledge potential difference and knowledge collaboration effect significantly influence the requestors' choice of strategies in games, and the cost and benefit of knowledge transfer significantly influence the crowdsourcers' choice of strategies in games. Our study on the dynamic evolution of knowledge transfer behavior in the crowdsourcing community contributes to the theoretical development of literature and provides valuable recommendation for managers in decision-making.

Key words

Crowdsourcing, knowledge transfer, evolutionary game, network community, utility

function.

1. Introduction

Crowdsourcing is an open innovation business model with "user participation" as the core[1]. As it has become an increasingly common way to gather input from a virtual community for problem solving and product design, businesses have become concerned with how to build and sustain these virtual communities in the first place. The virtual community is the organizational and technological platform of crowdsourcing. The knowledge within crowdsourcing community compensate and complement interactively and dynamically, which determines that knowledge transfer is the key to the success of crowdsourcing. The premise of knowledge transfer is that the members of crowdsourcing community are willing to adopt cooperative behavior to contribute their tacit knowledge[2]. A Few studies have empirically examined what drives continued knowledge transfer behavior, but none have explored the evolution issues from the perspective of mathematical modeling in crowdsourcing community.

The knowledge transfer behavior among members in crowdsourcing community exemplifies the evolution of knowledge interactions over time. We employ evolutionary game approach to explore the dynamic evolution process of knowledge transfer among agents of the crowdsourcing community under the premise of bounded rationality. We aim to:

(1) Set up the utility function and payoff matrix of knowledge transfer of agents in crowdsourcing community;

(2) Model agent interactions in crowdsourcing community on the basis of evolution game theory, identify the equilibrium of the dynamic evolution and examine how model parameters shape the evolutionary equilibrium;

(3) Analyze how management strategies affect crowdsourcing community discussion forums. In short, we seek to provide a mechanism for crowdsourcing administrators to establish knowledge transfer strategies and implement manage.

This paper is organized as follows. Section 2 is a literature review. Section 3 proposes the utility function and payoff matrix of the members' knowledge transfer in the crowdsourcing community. Section 4 builds the evolutionary game model and examines how model parameters shape the evolutionary equilibrium. Finally, this paper comes to a conclusion and provides managers with valuable suggestions in decision-making.

2. Literature Review

2.1 Crowdsourcing

The term "crowdsourcing" was first coined in 2006 by Jeff Howe who defined it as "the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and general large) network of people in the form of an open call"[1]. Crowdsourcing is an online, distributed problem solving and production model that leverages the collective intelligence of virtual communities for specific purposes[3, 4].Because the virtual community-the crowd-is at the heart of any crowdsourcing application, how to recruit individuals to a crowdsourcing community and sustain their participation are the pressing questions for crowdsourcing practitioners[5]. In the vein of content (innovation activities and information contents) and nature (competition and cooperation), crowdsourcing is categorized into 4 models(see Figure 1)[6]. It should be noted that this research mainly focuses on the cooperative crowdsourcing of innovation model.

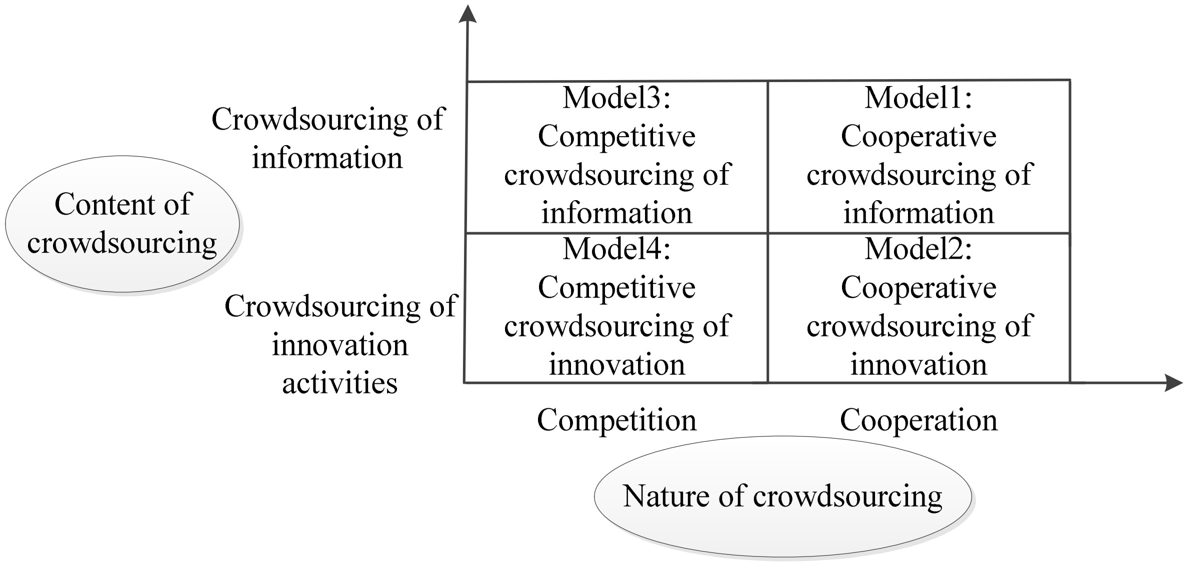

Figure 1. The classification of crowdsourcing

In contrast with traditional development, cooperative crowdsourcing of innovation has the following characteristics (see Table 1). First, the developers in crowdsourcing are individuals in the Internet. Normally, they have expertise in specific domain and skills to perform development task. Second, the development organizations in crowdsourcing are formed dynamically in term of the collaboration among requestors and crowdsourcers. They actually are virtual organizations consisting of various participants in the virtual communities and evolving during the crowdsourcing process. Third, the interactions between participants in crowdsourcing are performed either to from virtual development organizations or to exchange development details, while in traditional development, the interactions between developers are normally performed by face-to-face discussions[7].

Table 1. Comparison between cooperative crowdsourcing of innovation and traditional development

	Traditional Development	Cooperative crowdsourcing of innovation
Developer	From development organization	From Crowds in the Internet
Organization	Real organization	Virtual community
Interaction	Face-to-face	By Internet and Web2.0

2.2 Modeling knowledge transfer through game theory

Jiang et al. studies the evolutionary process of knowledge sharing among users of the social commerce and concludes that the evolutionary game rule and social network structure significantly influence the degree of cooperation and knowledge sharing among users[8]. Samieh and Wahba point out that the payoff for knowledge transfer among individuals can be described by multi-party game[9]. Bo studies the effect of the agents' adaptive expectation on dilemma game in complex networks from an agent-based approach, and shows that agent's adaptive expectation plays an important role in cooperation emergence on complex networks[10]. Wei et al. have study the knowledge-meta game behavior in the network dynamic state based on the complex network, and conclude that the more game partners choosing the strategy of "transfer", the more network link, and the quicker the balanced state realizes[11].

In this research, we employ evolutionary game theory to study the knowledge transfer strategies among agents crowdsourcing community, contribute to the behavioral evolution theory of knowledge transfer in the crowdsourcing community and offer decision support for management practice in crowdsourcing community.

3. The utility function and payoff matrix

There are two kinds of agents in crowdsourcing community, one is known as "requestor", the person represents the enterprise to release the development requirements, and the other is called as "crowdsourcer", the individual is interested in the development requirements and signs up to perform work [12].

3.1 The utility function of knowledge transfer

Knowledge transfer behavior of the agents is the external performance of motivation, and utility determines the knowledge transfer behavior[13]. According to knowledge transfer theory, knowledge transaction cost theory, as well as knowledge collaboration theory, we build the utility function of knowledge transfer of the two kinds of agents respectively, which are illustrated as follows:

$$u_i = u_i(K_i, \alpha_i k_j, \beta_i(K_i + \alpha_i k_j), c_i k_i, \lambda k_i) \quad (1)$$

$$u_j = u_j(K_j, \alpha_j k_i, \beta_j(K_j + \alpha_j k_i), \gamma_{ji} k_j{}^m k_i{}^n, c_j k_j, w k_i) \quad (2)$$

Here:

agent i represents crowdsourcer, agent j represents requestor.

u_i and u_j signifies the utility function of knowledge transfer of the agent i and agent j, separately.

K_i is agent i 's knowledge stocks, and K_j is agent j 's knowledge stocks.

k_i is agent i 's amount of knowledge transfer, and $k_i = s_i K_i$. Knowledge can be lost a bit while being transferred because of the agent's expression ability and the implicitness, complexity and systematicness of knowledge, and s_i is the knowledge transfer loss caused by agent i.

$\alpha_i k_j$ is the amount of knowledge acquired from agent j by agent i, and α_i is the knowledge absorption coefficient of agent i which is relevant to the knowledge absorptive capacity.

$\beta_i(K_i + \alpha_i k_j)$ is the knowledge internalisation effect increment of agent i. Internalisation is the process of embodying explicit knowledge into tacit knowledge[14]. Through internalisation, explicit knowledge acquired from agent j is converted into tacit knowledge by agent i, which should be based on agent i 's knowledge stocks--- K_i. β_i is the knowledge internalisation coefficient of agent i, which reflects the agent's capability of understanding, comprehension and application.

$c_i k_i, c_j k_j$ is the knowledge transfer cost of agent i and agent j separately.

λk_i is the knowledge transfer benefit of agent i.

$\gamma_{ji} k_j{}^m k_i^n$ stands for the knowledge collaboration effect. As collaboration is the essential elements in crowdsourcing process, all the cooperative crowdsourcing communities of innovation support more or less collaboration among their participates. γ_{ji} is collaboration coefficient, m, n is the elastic coefficient of knowledge transfer of agent j and agent i, respectively, $m,n > 0$, $m+n=1$.

ωk_i is the cost of knowledge absorption paid by the requestor to attract the broader engagement from the crowdsourcing community. The requestor should build the reward mechanism to provide the incentive for crowds in the community to participant the task including the financial incentives and some social rewards mechanisms[15].

3.2 The payoff matrix of knowledge transfer

The behavior of knowledge transfer in the crowdsourcing community can be expressed on the basis of interactive game relationship. Table 2 gives a symmetric game payoff matrix of knowledge transfer.

Table 2. Game payoff matrix

Agent j / Agent i	Transfer(T)	Don't Transfer (N)
Transfer(T)	H_i, H_j	T_i, R_j
Don't Transfer (N)	R_i, T_j	L_i, L_j

$$H_i = K_i + \alpha_i k_j + \beta_i (K_i + \alpha_i k_j) - c_i k_i + \lambda k_i \tag{3}$$

$$H_j = K_j + \alpha_j k_i + \beta_j (K_j + \alpha_j k_i) + \gamma_{ji} {k_j}^m {k_i}^n - c_j k_j - \omega k_i \tag{4}$$

$$T_i = K_i - c_i k_i \tag{5}$$

$$T_j = K_j - c_j k_j \tag{6}$$

$$R_i = K_i + \alpha_i k_j + \beta_i (K_i + \alpha_i k_j) \tag{7}$$

$$R_j = K_j + \alpha_j k_i + \beta_j (K_j + \alpha_j k_i) - \omega k_i \tag{8}$$

$$L_i = K_i \tag{9}$$

$$L_j = K_j \tag{10}$$

4. The evolutionary game model and analysis

4.1 The model

Assuming that the number of agents in the crowdsourcing community is N, including N_i crowdsourcers and N_j requestors in the whole game cycle. Let p_i be the percentage of crowdsourcers holding a "Transfer" behavior, and p_j be the percentage of requestors holding a "Transfer" behavior, then the percentage of which holding a "Don't Transfer" behavior is $(1-p_i)$ and $(1-p_j)$, respectively.

$$N(t) = N_i(t) + N_j(t) = n_{i,T}(t) + n_{i,N}(t) + n_{j,T}(t) + n_{j,N}(t) \tag{11}$$

$$p_i = \frac{n_{i,T}(t)}{N_i(t)}, p_j = \frac{n_{j,T}(t)}{N_j(t)} \tag{12}$$

Then, the expected benefit of the two kinds of agents from "Transfer" can be expressed as:

$$\Pi_{i,T}(t) = p_j H_i + (1-p_j)T_i \tag{13}$$

$$\Pi_{j,T}(t) = p_i H_j + (1-p_i)T_j \tag{14}$$

The expected benefit of the two kinds of agents from "Don't Transfer" can be expressed as:

$$\Pi_{i,N}(t) = p_j R_i + (1-p_j)L_i \tag{15}$$

$$\Pi_{j,N}(t) = p_i R_j + (1-p_i)L_j \tag{16}$$

The average benefit of the two kinds of agents is:

$$\begin{aligned}\overline{\Pi_i} &= p_i \Pi_{i,T}(t) + (1-p_i)\Pi_{i,N}(t) \\ &= p_i\{p_j[K_i + \alpha_i k_j + \beta_i(K_i + \alpha_i k_j) - c_i k_i + \lambda k_i] + (1-p_j)(K_i - c_i k_i + \lambda k_i)\} \\ &+(1-p_i)\{p_j[K_i + \alpha_i k_j + \beta_i(K_i + \alpha_i k_j)] + (1-p_j)K_i\}\end{aligned} \tag{17}$$

$$\begin{aligned}\overline{\Pi_j} &= p_j \Pi_{j,T}(t) + (1-p_j)\Pi_{j,N}(t) \\ &= p_j\{p_i[K_j + \alpha_j k_i + \beta_j(K_j + \alpha_j k_i) + \gamma_{ji} k_j{}^m k_i^n - c_j k_j - \omega k_i] + (1-p_i)(K_j - c_i k_i)\} \\ &+(1-p_j)\{p_i[K_j + \alpha_j k_i + \beta_j(K_j + \alpha_j k_i) - \omega k_i] + (1-p_i)K_j\}\end{aligned} \tag{18}$$

The dynamic replication equations of the two sides of the game are:

$$F(p_i) = \frac{dp_i}{dt} = p_i(\Pi_{i,Z}(t) - \overline{\Pi_i}) = p_i(1-p_i)(p_j \lambda k_i - c_i k_i) \tag{19}$$

$$G(p_j) = \frac{dp_j}{dt} = p_j(\Pi_{j,Z}(t) - \overline{\Pi_i}) = p_j(1-p_j)(p_i \gamma_{ji} k_j{}^m k_i^n - c_j k_j) \tag{20}$$

From equation (19), we can find three possible solutions to game equilibrium:

$$p_i = 0,1; p_j = \frac{c_i}{\lambda}, and(p_j{*} = \frac{c_i}{\lambda}) \quad (21)$$

Again, form equation (20), we can find three possible solutions to game equilibrium:

$$p_j = 0,1; p_i = \frac{c_j}{\gamma_{ji}}(\frac{k_j}{k_i})^n, and(p_i{*} = \frac{c_j}{\gamma_{ji}}(\frac{k_j}{k_i})^n) \quad (22)$$

From the dynamic replication equations $F(p_i)$,we can find when $p_j = \frac{c_i}{\lambda}$ and $p_i \in [0,1], F(p_i) \equiv 0$, which is equivalent to achieve the equilibrium in a game; When $p_j \neq \frac{c_i}{\lambda}$ and $p_i = 0$ or $p_i = 1$, which is equivalent to achieve the equilibrium in a game. In the same way, from the dynamic replication equations $G(p_j)$, we can find when $p_i = \frac{c_j k_j}{r_{ji} k_j{}^m k_i{}^n} = \frac{c_j}{r_{ji}}(\frac{k_j}{k_i})^n$ and $p_i \in [0,1], G(p_j) \equiv 0$, which is equivalent to achieve the equilibrium in a game; when $p_i \neq \frac{c_j}{r_{ji}}(\frac{k_j}{k_i})^n$ and $p_j = 0$ or $p_j = 1$, which is equivalent to achieve the equilibrium in a game.

4.2 Identifying evolutionary equilibrium through dynamic replication

The equilibrium state must have the anti-interference ability to the small disturbance based on the nature of evolutionary equilibrium strategy, and if some game participants deviate from the equilibrium strategy, the model will return to the equilibrium state[16]. According to the stability theory of differential equation, the derivative at stagnation point of dynamic replication equation must be less than 0, i.e.

$$F'(p_i) = \frac{dF(p_i)}{p_i} = (1-2p_i)(p_j \lambda k_i - c_i k_i) < 0 \quad (23)$$

$$G'(p_j) = \frac{dG(p_j)}{p_j} = (1-2p_j)(p_i \gamma_{ji} k_j{}^m k_i{}^n - c_j k_j) < 0 \quad (24)$$

From equation (23)-(24), we are able to determine the equilibrium of the game under different scenarios. We summarize them in the following Propositions1-2.

Propositions1. If the following scenario conditions are both met, the two kinds of agents' evolutionary equilibrium will reach “Transfer”.

(Scenario 1) $\begin{cases} F'(0) > 0 \\ F'(1) < 0 \end{cases}$, *i.e.* $p_j > \frac{c_i}{\lambda}$, (Scenario 2) $\begin{cases} G'(0) > 0 \\ G'(1) < 0 \end{cases}$, *i.e.* $p_i > \frac{c_j}{\gamma_{ji}}(\frac{k_j}{k_i})^n$

Propositions2. If the following scenario conditions are both met, the two kinds of agents' evolutionary equilibrium will reach "Don't Transfer".

(Scenario 3) $\begin{cases} F'(0) < 0 \\ F'(1) > 0 \end{cases}$, *i.e.* $p_j < \frac{c_i}{\lambda}$,

(Scenario 4) $\begin{cases} G'(0) < 0 \\ G'(1) > 0 \end{cases}$, *i.e.* $p_i < \frac{c_j}{\gamma_{ji}}(\frac{k_j}{k_i})^n$

We can obtain the dynamic phase diagram in Figure 2, in which the arrow indicates the direction of evolutionary equilibrium. There are two stability strategies in the phase diagram, i.e. the point of E_1 and E_4. When the initial transfer ratios of the two kinds of agents ($p_{i,0}, p_{j,0}$) are in the A region, i.e. $p_{i,0} > p_i^*, p_{j,0} > p_j^*$, the model can evolve to the point of E_4 over time, i.e. $p_i = p_j = 1$, and all agents adopt "transfer". When the initial transfer ratios of the two kinds of agents are in the C region, i.e. $p_{i,0} < p_i^*, p_{j,0} < p_j^*$, the model will evolve to the point of E_1 over time, i.e. $p_i = p_j = 0$, and all agents adopt "don't transfer". The point of O is the threshold to change the evolution characteristics of the model (also be known as saddle). When $p_{i,0}$ and $p_{j,0}$ is near O, the small changes in the initial stat will affect the final results of the model evolution, that is the sensitivity of the model to the initial state[17].

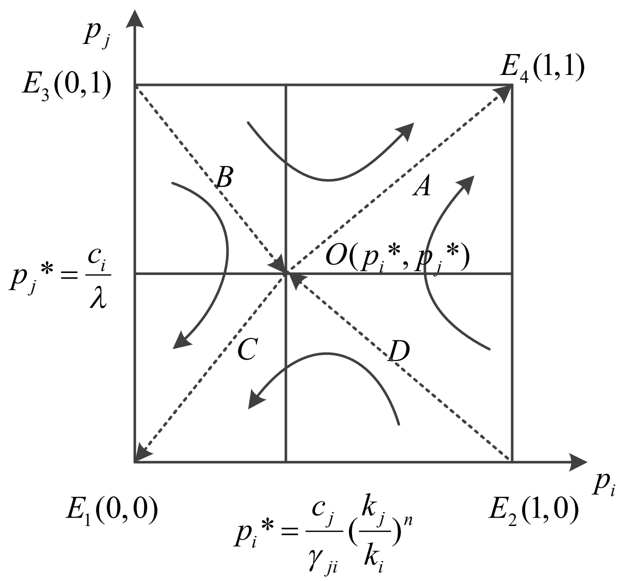

Figure 2. Dynamic phase diagram of evolutionary game

4.3 Result

It's necessary to make the initial transfer ratio ($p_{i,0}, p_{j,0}$) in area A as far as possible in order to make the evolutionary game equilibrium achieve "Transfer". As shown in Figure 2, it's obviously that p_i^* and p_j^* is smaller, the area of A is larger, and the area of C is smaller. So, in the process of the knowledge transfer evolutionary game, some parameters of the payoff matrix of the two sides would affect the trend of the convergence of the evolutionary process.

4.4 Discussion

From $p_j^* = \frac{c_i}{\lambda}$, we can know that when the knowledge transfer cost of agent i (the crowdsourcer) is much lower than the benefit, then p_j * is small. Consequently, the agent i prefers to select "Transfer". From $p_i^* = \frac{c_j}{\gamma_{ji}}(\frac{k_j}{k_i})^n$, we can find that when the knowledge transfer cost of agent j (the requestor) is small, the knowledge collaboration coefficient is larger and the knowledge transfer potential energy of the agent i is much higher than that of the agent j, then p_i^* is smaller. Consequently, the agent j tends to select "Transfer".

5. Conclusion

In this research, we study the evolutionary equilibrium of knowledge transfer among agents in crowdsourcing community via the dynamic replication method. We find different game scenarios have a significant influence on agents' choice of strategy. In the many factors affecting the decision-making of the agents, knowledge collaboration effect, knowledge transfer cost, and knowledge transfer potential is the main factor affecting the knowledge transfer behavior of requestor; the cost and benefit of knowledge transfer is the main factor affecting that of crowdsourcer.

To improve the duration and stability of knowledge transfer behavior in crowdsourcing community, four important managerial implications can be drawn by enterprise manager:

(1) Increasing the knowledge potential difference among the members. Enterprise should attract more people to enjoy the community, refine the community's knowledge structure, and enhance the complementarity and heterogeneity of members' knowledge;

(2) Reducing the cost of knowledge transfer. Enterprise should provide convenient and effective channels for interactions to promote exchanges among members and increase members' sense of belonging;

(3) Increasing the members' knowledge transfer benefit. Enterprise should apply some incentive strategies for the crowdsourcing when necessary, especially non-material incentives;

(4) Improving knowledge collaboration effect. The agents of enterprise need to promote the absorption, integration, and innovation of knowledge. They should be expert in communicating with members in crowdsourcing community, and maximize the knowledge collaboration effect.

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