Research on the Dynamic Evolution Law of Knowledge Sharing Behavior Based on Expectation in Online Learning Community

Dan Xia, Huirong Ke, and Yuan Tian

***Abstract*—This paper analyzes the characteristics of knowledge sharing behavior in online learning communities, builds a prisoner's dilemma game model of learners' knowledge sharing behavior based on expectation, and conducts an evolutionary simulation experiment on this model. Through experimental simulation, this paper studies the effect of expectation-based learning motivation on knowledge sharing behavior, and reveals the evolution law of knowledge sharing behavior in the network under the influence of this factor. The research in this paper is of great theoretical significance for improving the willingness of users to share knowledge in online learning community.**

***Index Terms*—Knowledge sharing, evolutionary game, prisoner's dilemma, learning motivation.**

I. Introduction

With the advent of the era of knowledge economy, typical online learning communities, such as CSDN, Zhihu and Muchong forum, have developed vigorously, providing people with new ways of knowledge exchange with their high openness, diversity and interactivity. They have penetrated into all aspects of people's work and study. The development of online learning communities relies on the active communication and sharing of community users. The active level of user interaction and the quality of community knowledge determine the long-term development of online learning communities [1]. Generally speaking, the knowledge sharing level and enthusiasm of users in online learning communities not only affect the knowledge quality of the community, but also stimulate the sharing initiative of other users and attract more users. The production of high-quality content in the community largely requires members to contribute knowledge, that is, to share knowledge. From the perspective of knowledge transfer, knowledge sharing is the process in which the owner of knowledge shares his knowledge with others [2]. For users, knowledge sharing takes time and energy and may not be able to obtain effective returns, resulting in some users in the community are not willing to share knowledge, or hold a negative attitude. Up to now, scholars at home and abroad have conducted extensive and in-depth research on the theory of knowledge sharing behavior, influencing factors and internal mechanism.

Knowledge sharing behavior of rational individual in online learning community is subjective and social. Game theory (non-cooperative game) is a tool for modeling and predicting rational individual behavior, which has been widely used in research on individual cooperative incentive [3]. Evolutionary game theory is an effective theoretical framework now for the study of cooperative phenomena. After using game theory to study the evolution of cooperative behavior of network individuals in literature [4], spatial evolutionary game theory has become an effective tool to study the dynamics of node behavior in network [5]-[7]. Spatial evolutionary game theory mainly focuses on and studies the evolution process of individual's strategy adjustment to the current network environment changes, as well as the proportion of each strategy in the evolutionary steady-state network. In recent years, the theory of spatial evolutionary game based on bounded rationality has been introduced into the study of knowledge sharing behavior, which has attracted wide attention of scholars. More recently, Hou *et al*. [8] bulit an evolutionary game model on knowledge conversion and sharing among users, analyzed the game strategy selections of the community's users when the parameter settings of the process of socialization, externalization, combination and internalization changed. Wang *et al*. [9] constructed the evolutionary game model of social Q&A community knowledge sharing, and analyzed three kinds of knowledge sharing equilibrium states in social Q&A community under the different assumptions of evolutionary game. The different states of the knowledge quality and quantity of social Q&A communities and the knowledge sharing strategies of community users were affected by the game model parameters such as users' sharing willingness and ability, user acceptances and community incentive, perceived cost of knowledge sharing through the simulation. Cai G and Kock N [10] studied the e-collaboration from a game-theoretical perspective by focusing on the strategic interaction between players. Wakeland W and Jolly R studied the information sharing in organizations, especially the impact of sharing freely versus not sharing by using game theory and agent based simulation. Moreover, to discuss the evolutionary path and its formation mechanism of knowledge sharing in scientific collaboration network, Tu [11] built the spatial evolutionary game model, and ran the complex network simulations in different network structures and colonies of different competitive coefficient. All the above studies have established the evolutionary game model of knowledge sharing mechanism, and carried out dynamic game analysis, and obtained more scientific and objective conclusions. However, there is still no specific research on the internal mechanism of knowledge sharing in

Manuscript received May 15, 2019; revised July 13, 2019.
The authors are with Central China Normal University, China (e-mail: 116350703@qq.com).

doi: 10.18178/ijiet.2019.9.10.1297

online learning community.

In this paper we analyses the problem of low willingness to share knowledge among individuals in online learning community, builds a prisoner's dilemma game model of learner's knowledge sharing behavior, and studies the impact of expectations on learners' knowledge sharing behavior by using spatial evolutionary game theory, with a view to creating a good learning atmosphere for online learning community and building a healthy learning community full of vitality.

II. Research on Evolutionary Game of Knowledge Sharing in Online Learning Community

Evolutionary game theory provides a powerful framework for studying the evolution of knowledge sharing behavior in online learning communities. Network evolutionary game uses network structure to simulate the mutual contact between individuals and study the close relationship between game model and strategy evolution rules, it has received wide attention in recent years [12]. The model presented in this section uses grid network to explore the evolution of cooperation in prisoner's dilemma of knowledge sharing under the condition of different strategy choices. Based on the above analysis of the characteristics of learners' knowledge sharing behavior in online learning communities, this section stipulates the strategic choice rules that individuals tend to choose when facing with the maximization of their own interests, and on the basis of this rule, the influencing factors of learning motivation based on expectation are introduced.

A. Game Model

The game model on complex networks usually consists of three parts: the individual involved in the game, the individual strategy and the profit. The prisoner's dilemma model is a classical model in game theory, which is suitable for studying two-player-two-strategy game and can better describe the cooperative dilemma of individual knowledge sharing game in online learning community [13]. In this paper, we consider the prisoner's dilemma game on the two-dimensional square lattice network. The individuals are distributed on the square lattice network, where the nodes represent the individuals and the connection indicates the game relationship between two individuals. The grid network set in this study has periodic boundary conditions, that is, all nodes have a degree of 4, and each individual plays a game with four neighbors connected to it. Individuals participating in the knowledge sharing transaction(game) are rational individual users in the community. They are divided into knowledge providers and knowledge acquirers [14]. Individual optional strategies are sharing strategy(C: can be represented by vector $s=[1,0]^T$) and non-sharing strategy (D: can be represented by vector $s=[0,1]^T$). At the initial moment, each individual chooses the strategy with equal probability.

When an individual plays a knowledge-sharing game with a neighbor node, the benefits are distributed according to the following rules: If both individuals adopt the sharing strategy, they will gain the benefit R respectively, while the two individuals who adopt the non-sharing strategy will each get the punishment benefit P. If one shares and the other does not, the non-sharer will get a higher benefit T from the sharer, while the sharer will get a lower benefit S. Based on the knowledge sharing transaction relationship among individuals in the network, a knowledge sharing transaction process between two individuals is modeled as a two-person prisoner's dilemma game model. The individual game payoff matrix A is shown in the Table I below:

TABLE I: Payoff Matrix of Knowledge Sharing Game

		Individual 2	
		Sharing	Non-sharing
Individual 1	Sharing	*R R*	*S T*
	Non-sharing	*T S*	*P P*

The above four parameters satisfy $T>R>P>S$. From the analysis of the equilibrium strategy of a round of game, it can be seen that no matter what strategy the opponent chooses, the benefit of the individual choosing the non-sharing strategy is the best, that is, the non-sharing strategy is the equilibrium strategy of the game, and the individual is trapped in the prisoner's dilemma. In this paper, the weak prisoner's dilemma game is adopted [4], that is, $R=1$, $S=P=0$, $T=b>1$, and b is the only adjustable parameter--called "the temptation of betray," that is, learners acquire knowledge shared by other learners without sharing knowledge, b is an unearned earnings. When $b>1$, system betrayal is dominant. For each round of the game, the total payoff of each individual is set as the sum of the benefits of the game with all its neighbors.

B. Strategy Update Rule

In most cases, in order to maximize their current benefits, individuals' strategies will constantly change with the changes of the complex network environment. The individual's strategy choice is related to the payoff of the surrounding individuals, the more the individual's payoff is, the more the individual's strategy tends to be learned. The process of individual strategy renewal is actually a behavior of imitation and learning. In this paper, the classical Fermi dynamics is used as the strategy evolution rule. Individuals randomly select one of their neighbors to imitate their previous strategy with a certain probability. The learning probability is as follows:

$$W(s_j \to s_i) = 1/(1+\exp[(P_i - P_j)/k])$$

Among which, P_i represents the payoff of individual i, s_i represents the strategy of i in current round, the parameter k describes the noise factor of the environment, and depicts the irrational degree of individual. While $k \to 0$,it means that the individual has complete rationality, and it only learns the strategy of neighbor whose payoff is higher than its own. With the increase of k, the degree of individual rationality decreases, and the possibility of learning the strategies of low-income neighbors increases. Based on the existing research, this paper takes $k=0.1$ [15].

Previous studies have proved that personal motivation plays a key role in the willingness and behavior of knowledge sharing. In order to maximize payoff, individual generates learning motivation, that is, expectation is the key factor affecting individual motivation. Assuming that the individual's learning motivation is related to his or her expectation of payoff, if the actual payoff is greater than the expected, the individual's learning motivation will be weakened, and conversely it will be enhanced. In order to promote the occurrence of knowledge sharing behavior in online learning communities, this paper proposes the influencing factors of expectation-based learning motivation and studies the influence of expectation-based learning motivation on knowledge sharing behavior. After introducing this influencing factor, an individual selects a neighbor in the process of knowledge sharing transaction, and then with a certain probability, an individual chooses whether to make strategy adjustment according to the profit difference between the two and his own learning motivation [16]. The strategy update rules are as follows:

$$W(s_j \to s_i) = \omega_{i,t} / (1+\exp[(P_i - P_j)/k])$$

Among which, $\omega_{i,t}$ denotes the learning motivation of individual i at t times. Learning motivation $\omega_{i,t}$ can be calculated by the following formula:

$$\omega_{i,t} = \begin{cases} 1 & P_i < E \times k_i \\ \exp(-(P_i - E \times k_i)) & otherwise \end{cases}$$

Among which, k_i=4 denotes the degree of individual i ,while E represents individuals' expected returns from each pair of game, it is obviously $0 \le E \le b$.

III. Simulation and Result Analysis

A. Simulation Settings

In order to reveal the dynamic behavior microscopically, a computer simulation program is used to track the dynamic evolution process. The simulation in this paper is carried out on a two-dimensional grid network of $N = 100 \times 100$ size. Using Monte Carlo simulation method to study the evolution of knowledge sharing behavior of nodes (nodes: individual learners in online learning community) in the network [17]. The simulation consists of a series of discrete Monte Carlo time steps. Each Monte Carlo time step consists of two parts:1) Nodes play with their neighbors and calculate the payoff; 2) Nodes update strategy with a certain probability according to Fermi rule. Nodes seek for higher payoffs by constantly adjusting strategy, and the frequency of cooperation under steady state is obtained after 2000 Monte Carlo step iteration. In evolutionary game, evolutionary steady state refers to that the proportion of each strategy in the network fluctuates very little with time, and the frequency of cooperation is an important indicator to measure cooperation behavior, that is, the proportion of cooperation nodes.

B. Equilibrium Analysis of Nodes' Strategy Evolution

In order to study the evolution process of nodes' strategy over time in the network and whether it can finally enter the evolutionary steady state, Fig. 1 shows that when *E*=0, that is, without introducing expectation, the value of *T* is 1.0, 1, 05, 1.10 and 1.15 respectively, the evolution process of the proportion of cooperative nodes over time in the network. By analyzing the trend of the curve, it can be seen that no matter at what T value, the network cooperation frequency will initially have a sharp decline process, and then gradually tend to be stable and fluctuating, indicating that the nodes that choose non-sharing strategy are in the majority and the betrayal behavior is dominant in the initial state of network evolution. From the evolution process of the nodes' strategy, it can be found that the nodes' strategy in the network has entered into evolutionary steady state after more than 1000 times step of evolution. In evolutionary steady state, the proportion of cooperative nodes are approximately 75% (*E*=0, *T*=1.0), 45% (*E*=0, *T*=1.05), 15% (*E*=0, *T*=1.10), and 0% (*E*=0, *T*=1.15) respectively. It can be seen that the larger the temptation T value of betrayal is, the more unfavorable it is to the emergence of cooperative behavior, and the more difficult it is to maintain cooperative behavior between nodes. This conclusion can also be derived from the analysis of the game payoff matrix A.

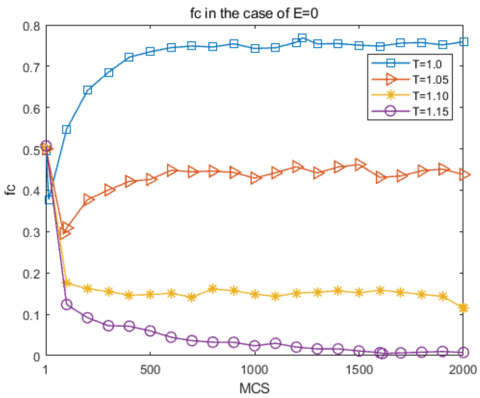

Fig. 1. Evolution of the frequency of cooperation over time under different *T* values.

The evolution of the strategy on the two-dimensional lattice presents a very rich dynamics characteristic [18]. In order to understand the evolution process of the network game more intuitively, under the condition of *E*=0, that is, without introducing the factors of learning motivation based on expectation, the experiment extracts and preserves the strategy set of all nodes in the network corresponding to the time step of 2000th Monte Carlo at each *T* value. The evolution of spatiotemporal chaotic patterns of node strategy are studied under different T values when the system reaches evolutionary steady state. Fig. 2 shows the spatiotemporal distribution pattern of node strategy in the corresponding 2000th step network when *T*=1.0, 1.05, 1.10, 1.15 numbered as a), b), c) and d). The yellow color represents the sharing strategy, while purple represents the non-sharing strategy. It can be seen from the observation that as the value of *T* increases, the proportion of yellow area becomes smaller and smaller, that is, the proportion of nodes choosing sharing strategy becomes lower and lower in steady state, indicating that the evolution result of strategy under steady state is closely related to T value.

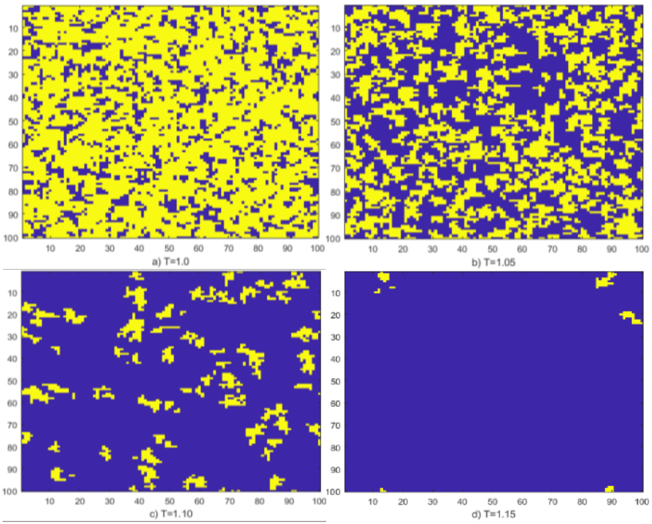

Fig.2. Spatiotemporal distribution pattern of strategy in steady state corresponding to different *T* values.

C. Effectiveness Analysis of Learning Motivation Influencing Factors Based on Expectation

To study the effect of expectation-based learning motivation on cooperation frequency in prisoner's dilemma game, Fig.3 shows the evolution of the proportion of cooperative nodes in the network over time when *T*=1.10 and the value of expectation *E* is 0.0, 0.3, 0.5 and 0.8 respectively. It can be found that an excessive *E* (*E* = 0.8) does not promote cooperation well. In this case, the network cooperation frequency tends to zero in steady state. While the appropriate expectation *E* can effectively promote the cooperative behavior between nodes in the network (the proportion of cooperative nodes is significantly increased). Therefore, it indicates that there may be an optimal expectation E to ensure the highest cooperation frequency. It is not difficult to analyze by observing the trend of the curve in Fig. 3 that the optimal expectation E value in this comparative study is 0.3.

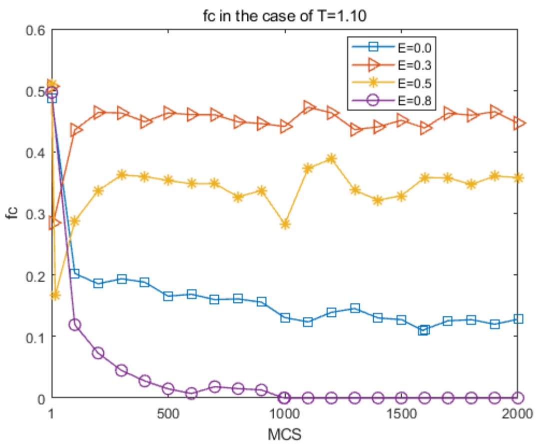

Fig. 3. Evolution of the frequency of cooperation over time under different *E* values.

The patterns below are based on *T*=1.10, introducing the factors of learning motivation based on expectation, the experiment extracts and preserves the strategy set of all nodes in the network corresponding to the time step of 2000th Monte Carlo at each *E* value. The evolution of spatiotemporal chaotic patterns of node strategy are studied under different E values when the system reaches evolutionary steady state. Fig. 4 shows the spatiotemporal distribution pattern of node strategy in the corresponding 2000th step network when *E*=0.0, 0.3, 0.5, 0.8 numbered as a), b), c) and d). The simulation conditions in Fig. 4a) are the same as those in Fig. 2c), both of which are distribution pattern of node strategy without introducing expectation and *T*=1.10. Compare Fig. 4 b), c) and d) with a) respectively, it can be found that the yellow area accounts for the largest proportion when *E*=0.3 in Fig. 4b). The pattern reflects that the evolutionary result of strategy is influenced by the value of expectation E in steady state. Adjusting learning motivation with appropriate expectation can significantly promote the emergence of cooperation.

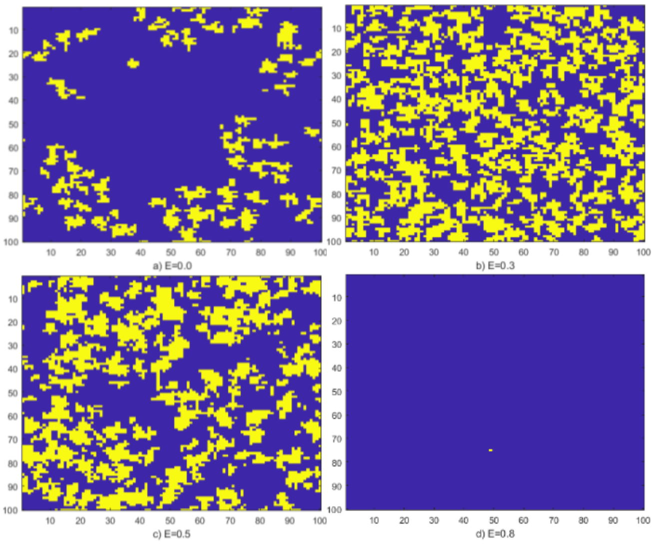

Fig. 4. Spatiotemporal distribution pattern of strategy in steady state corresponding to different *E* values.

IV. CONCLUSION AND PROSPECT

The existing research on knowledge sharing mostly adopts the method of combining theoretical and empirical research methods, and the research is mostly macro-static, lack of microscopic and dynamic. In this paper, the evolutionary game theory is used to study the knowledge sharing behavior in online learning community. Cut from the perspective of the key factors affecting knowledge sharing, this paper proposes the influencing factors of learning motivation based on expectation. Taking the network cooperation frequency in steady state as the measurement standard, the process and result of expectation on knowledge sharing behavior are analyzed. The research in this paper has certain theoretical and practical significance for promoting the development of online learning community academic exchanges towards a benign trend.

However, there are still many shortcomings in this study, which need to be further improved in the following study. The deficiencies in this study and future research directions are summarized as follows:

1) This paper studies the knowledge sharing behavior based on regular two-dimensional grid network. Since the node degree distribution of real social networks is not uniform, the validity of the expectation-based learning

motivation introduced in this paper also needs to be verified in networks with different topology structure (such as scale-free networks, ER random networks);

2) In most real online learning communities, individual knowledge sharing behavior tends to affect a wider range of groups, presenting the characteristics of group interaction. The Prisoner's Dilemma game model studied in this paper is based on peer-to-peer interaction, and can try to introduce the public goods game model to further the study.
3) In addition to considering the structural characteristics of real networks and game models, future research will focus more on how to optimize strategy updating rules, introduce different strategy updating rules to remedy the shortcomings of traditional Fermi dynamics, and propose incentive or punishment mechanisms to effectively promote cooperative behavior.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Dan Xia: Provided macro guidance, and concuted the research; Huirong Ke (Correspondent Author): Completed the experiment simulation, analyzed the experimental result, and wrote the paper; Yuan Tian: Participated in discussion. All authors had approved the final version.

Acknowledgment

This work is supported by the Fundamental Research Funds for the Central China Normal Universities (CCNU19QN019).

References

[1] J. Wang, "Research on influencing factors of user viscosity of academic community in the perspective of knowledge sharing," 2015.
[2] S. Y. Sun, "Research on user knowledge exchange behavior in virtual academic community," 2018.
[3] W. C. Yang, J. K. Wang, and G. H. Cui, "Cooperation promotion mechanism of social networks based on nodes strategy learning behaviors," *Computer Engineering*, vol. 43, no.11, pp. 146-151, 2017.
[4] M. A. Nowak and R. M. May, "Evolutionary games and spatial chaos," *Nature*, vol. 359, no. 6398, pp. 826-829, 1992.
[5] G. Szabo and G. Fath, "Evolutionary games on graphs," *Physics Reports*, vol. 446, pp. 97-216, 2007.
[6] Z. Li, J. Gao *et al*., "Evolution of cooperation in lattice population with adaptive interaction intensity," *Physica A: Statistical Mechanics and its Applications*, vol. 392, no. 9, pp. 2046-2051, 2013.
[7] X. W. Wang, S. Nie, L. L. Jiang *et al*., "Cooperation in spatial evolutionary games with historical payoffs," *Physics Letters A*, vol. 380, no. 36, pp. 2819-2822, 2016.
[8] G. S. Hou, P. M. Wang *et al*., "Research on evolutionary game of the knowledge conversion and sharing of online health community users," *Information Science*, vol. 35, no. 7, pp.31-38, 2017.
[9] P. M. Wang, G. S. Hou, *et al.*, "Evolutionary game analysis of Knowledge sharing of users in social Q&A community based on knowledge quality & quantity," *Journal of Modern Information*, vol. 38, no. 4, pp. 42-49, 2018.
[10] G. Cai and N. Kock "An evolutionary game theoretic perspective on e-collaboration: The collaboration effort and media relativeness," *European Journal of Operational Research*, vol. 194, no. 3, pp. 821-833, 2009.
[11] J. Tu. "Research on the evolution of knowledge sharing in scientific collaboration network," *Information Studies: Theory & Application*, vol. 41, no. 2, pp. 39-45, 2018.
[12] Y. Li, "Research on mechanism design of network evolutionary game and its applications," 2014.
[13] Z. H. Rong, Z. X. Wu, W. X. Wang, *et al*., "Research on the networked cooperative dynamics of coevolutionary games," *Journal of University of Electronic Science and Technology of China*, vol. 42, no. 1, pp. 10-22, 2013.
[14] G. Li, Y. Q. Lu, "Analysis of "prisoner's dilemma" game in virtual community knowledge sharing: Based on complete information static and repeated game," *Library*, vol. 2, 2019.
[15] G. Szabo, C. Toke, "Evolutionary prisoner' dilemma game on a square lattice," *Physical Review. E*, vol. 58, no. 1, pp. 69-73, 1998.
[16] H. F. Zhang, "Individuals' different behaviors induce rich and colorful overall behaviors on complex network," 2011.
[17] M. Perc, J. J. Jordan, D. G. Rand *et al*., "Statistical physics of human cooperation," *Physics Reports*, vol. 687, no. 8, pp. 1-51, 2017.
[18] D. M. Shi, "Emergence of cooperation on the complex networks," 2017.

Dan Xia was born in Hubei, China in 1985. She is a teacher in School of Educational Information Technology, Central China Normal University, China. Her research interests include image processing, learning analysis, evolutionary game.

Huirong Ke was born in Anhui, China in 1994. She is a master degree candidate in School of Educational Information Technology, Central China Normal University, China, since 2017. Her major is digital media technology. Her research interests include complex network, evolutionary game.

Yuan Tian was born in Hubei, China in 1982. She is a teacher in School of Educational Information Technology, Central China Normal University, China. Her research interests include virtual reality, facial expression recognition, learning emotion.