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RESEARCH ARTICLE

Asymmetric Information Dissemination in Double-Layer Networks Helps Explain the Emergence of Cooperation

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ABSTRACT This paper proposes a double-layer network game model based on asymmetric information, hoping to explore the impact of asymmetric information dissemination on the evolution of cooperation. The model assumes that agents in heterogeneous states play the Prisoner's Dilemma game in the network's physical layer, and heterogeneous information disseminates asymmetrically in the virtual layer of the network. Through mean-field theory analysis and Monte Carlo experiments, we found that the dissemination of asymmetric information significantly impacts cooperation. The positive information generated by the defector can promote cooperation in the short term but will hinder cooperation in the long term. Positive information generated by cooperators can promote cooperation in the long run. The system's final state depends on the relative intensity of the two kinds of information dissemination. Asymmetric information dissemination can promote cooperation because heterogeneous information has distinct dissemination intensities, which makes the number of active agents around the agents different. The positive information generated by cooperators can attract more active agents in the long run, thus obtaining more payoffs, making the agents in the system tend to cooperate. The positive information generated by defectors produces more silent neighbours in the long run, thus reducing the overall payoffs, which makes the agents in the system tend to defect. This paper provides a new explanation for the emergence of cooperation, which helps expand the existing research field.

INDEX TERMS Evolutionary computation, cooperative systems, complexity theory, social engineering.

I. INTRODUCTION

To cooperate or not to cooperate is a question. According to Darwin's evolutionary theory, selfish individuals do not choose to cooperate, even though cooperation benefits the whole [1]. However, cooperation is still widespread. For what reason do different populations have different levels of cooperation? Are there mechanisms to promote cooperation and avoid conflict? These fascinating questions continue to attract many researchers to dive in [2], [3], [4], [5], [6], [7], [8], [9], and [10].

Network evolutionary games have been proved to be a powerful framework for investigating the evolution of cooperation [11], [12], [13], [14]. The framework consists of three primary elements: (1) Network structure [15], [16], [17]. The relationships among agents are abstracted into networks, i.e., square lattice, small-world network, and scale-free network. (2) Game model. The Prisoner's Dilemma (PD) Game and Public Goods Game are commonly used models. (3) Strategy updating [18], [19], [20], [21], [22], [23]. According to specific rules, agents update their strategies during their evolution. Nowak and May first applied the framework to investigate the evolutionary PD game. They regarded agents as network nodes, allowing agents to learn the strategies of neighbors with high payoffs. The traditional PD game concludes that every selfish agent chooses to defect. However, Nowak's research shows that the cooperators will cluster to resist the

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invasion of defectors [24]. This ground-breaking research has laid a new foundation for studying the evolution of cooperation [25].

Traditional models have made significant progress in achieving cooperation by introducing exogenous mechanisms, but less attention is paid to the research on the driving force of information on human behaviour. Analyzing the three elements can help us find the critical reasons for the emergence of cooperation. Abramson, et al. compared the impact of dynamic network structures on cooperation and found that cooperation is closely related to network structure [26]. Zimmermann, et al. proposed the concept of coevolution of networks and strategy, which can effectively enhance cooperation [17]. Szolnoki and Perc showed that sharing information about strategy choice between players residing on two different networks reinforces the evolution of cooperation. They also observed the spontaneous emergence of correlated behaviour between the two networks, which further deters defection [27]. Li built a double-layer social network and found that the speed of information transmission in the double-layer network was significantly faster than that in the traditional network. Later, Zhu studied the spread of knowledge through a two-layer network and found that this network structure can significantly accelerate the spread of knowledge [28]. Such models could also be used in the study field of moral behavior.

In addition to network structure, many mechanisms conducive to the emergence of cooperation were proposed. These mechanisms influence strategy selection through strategy learning processes and game partner selection [29], [30], [31]. Chen et al. assumed that each agent has a prestige tolerance range, and only the neighbors in this range can interact with the agent. It was found that a tolerance limit can maximize the level of cooperation [32]. Fu et al. also reached a similar conclusion in their research on reputation-based selection mechanisms. The model assumes that individuals can switch partners according to reputation information, effectively promoting cooperation [33]. Hauert proposed a voluntary participation mechanism in which isolators quit the game and only get a small fixed income. Compared with the compulsory participation model, voluntary participation maintains cooperation at a high level [34]. Qin et al. found that the diversity of neighbors can significantly improve the level of social cooperation [35].

The above research found that heterogeneous partner selection and network structure are important factors affecting the evolution of cooperation. However, most of these studies often introduce exogenous mechanisms to promote cooperation and pay less attention to how information drives people's behaviour under different mechanisms. This paper argues that the evolution process may be driven by information, and different ways of information dissemination may lead to different behaviour patterns, thus producing different game results [36], [37], [38], [39], [40], [41], [42], [43]. Information is an important variable that affects individual behaviour. Research by Wang, et al. showed that cognitive bias caused by information processing constraints could significantly improve the level of cooperation [44]. Caplin and Dean proved that the environment would influence agents' cognition of information [45]. These studies together indicate that how information dissemination affects the evolution of cooperation is a matter of concern. Therefore, it is necessary to introduce the information dissemination process into the study of evolutionary cooperation.

This paper proposes a double-layer network game model based on asymmetric information to consider the reason for cooperation emergence from the perspective of information dissemination. The model constructs an isomorphic double-layer network, where information is disseminated in the virtual network and game interaction is conducted in the physical network. The information in the virtual layer will affect partner selection of the game in the physical layer. The game results in the physical layer will, in turn, influence the information dissemination in the virtual layer. At the same time, the model also divides information into positive and negative information and assumes that different information has different dissemination intensities. Under this setting, we explore the influence of asymmetric information dissemination on cooperative evolution. The rest of this paper is arranged as follows. The second section gives the model details. The third section gives the simulation results under different parameters. The conclusion and discussion will be given in section IV.

II. MODEL

A. NETWORK GAME MODEL

Evolutionary game is usually carried out in a network with a specific structure, in which agents are abstracted as nodes of the network and relationships among agents are abstracted as edges of the network. Agents only interact with their connecting neighbors, and information will spread along the edges. Game interaction can affect the information dissemination process, and information dissemination will have a feedback effect on game interaction. Network evolutionary games can be used to describe the interactions between agents in the real world.

Let us first define the population structure and evolutionary dynamics. The proposed network includes a physical layer $L1$ and a virtual layer $L2$, both connected point to point and with periodic boundaries. The network is $V\ on\ Neumann$ type. That is, any agent has four neighbours. Game interaction occurs in the physical layer, and information disseminates in the virtual layer. The game results of the physical layer affect the information dissemination in the virtual layer, and high payoffs bring high information dissemination intensity. In turn, the information dissemination in the virtual layer will produce a feedback effect on the game interaction in the physical layer. The higher the information intensity, the more active neighbours around the agent.

Furthermore, complex systems in the real world are considered to be composed of different networks. This paper uses a double-layer network to simulate this complex

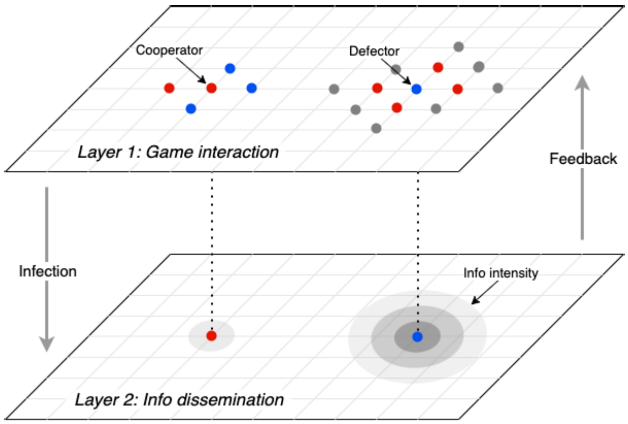

FIGURE 1. (Color online) The diagram shows the interaction between asymmetric information dissemination and cooperative evolution. All agents interact in a double-layer network. Different types of edges connect the physical layer and the virtual layer. Agents conduct game interaction in the physical layer, and information disseminates in the virtual layer. The game results will affect the information dissemination in the virtual layer, and the information dissemination will produce feedback effects that affect the game interaction. When surrounded by defectors (blue nodes), cooperators (red nodes) gain little payoffs, resulting in weak information intensity in the virtual layer; When faced with cooperators, defectors gain large payoffs and great information intensity, producing a feedback effect that can attract more game opportunities.

structure. Two different types of edges connect the physical layer and the virtual layer. One type of edge represents the game interaction between agents, and the other represents the dissemination chain of heterogeneous information between agents. The nodes in the double-layer network are identical, but the edges in the network are different. Therefore, the double-layer network is an interactive coupled network with the same node but different edges. By separating the game process from the information dissemination process, we simulate the game evolution in a double-layer interactive network.

In each game round, agents only play a prisoner's dilemma game with their first-order neighbours and gain payoffs. The PD game is often used to determine what mechanisms lead to cooperation because it reveals the conflict between individuals and collectives. Its payoff matrix A is as follows:

$$A = \begin{pmatrix} R & S \\ T & P \end{pmatrix} \tag{1}$$

where R, S, T, and P are payoff parameters. Any agent earns R when both choose to cooperate, earns P when they defect each other, earns T when the agent defects while its neighbour cooperates, and earns S when the agent cooperates while its neighbour defects. Since $T > R > P > S$, every selfish agent will choose to defect according to the traditional analysis, but the evolution may be different under this paper's setting. Cooperation and defection are respectively represented by the two-dimensional **s**

$$s = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \text{ and } \begin{pmatrix} 0 \\ 1 \end{pmatrix} \tag{2}$$

In order to consider the dissemination of asymmetric information, we divided information into positive information and negative information, and agents can only receive local information from first-order neighbours. Agents in the physical layer decide whether to play games according to the information received from the virtual layer. The agents receiving positive information may become active in playing games; Agents receiving negative information may become silent and do not play games.

The payoffs of agent i in period t are the sum of the payoffs from active neighbours the agent i play with, showing as follows

$$U_i(s) = \sum_{j \in N_i} sAs^T \tag{3}$$

where **s** is the strategy vector, N_i represents active neighbours of agent i. A is the payoff matrix.

The intensity of Positive information refers to the proportion of each agent's payoff in the total payoffs of game groups. The intensity of positive information that agent i disseminates to neighbour j is as follows

$$P_{ij}^p(t) = \frac{U_i(t)}{U_i(t) + \sum_{j \in N_i} U_j(t)} \tag{4}$$

where $U_i(t)$ and $U_j(t)$ are the payoffs of agent i and agent j in period t, N_i is the set of active neighbours of individual i. $P_{ij}^p(t)$ measures the probability that agent j receives positive information from neighbour i. Agent i disseminates positive information to its neighbour j, and the neighbour j receiving the positive information may become active and then participate in the game.

Neighbours who do not receive positive information may become silent and not participate in the game. Agents with higher payoffs in populations tend to have a more significant influence [43]. Such high payoffs may come from both cooperators and defectors. In other words, assuming that payoffs drive the behaviour, both cooperators and defectors can spread positive information. The intensity of information depends on the proportion of the payoffs in the group. This positive information reflects that payoffs drive the agent's behaviour.

Agent i also receive negative information from the virtual layer. Negative information is defined as the proportion of defectors among neighbours

$$P_i^n(t) = \frac{\sum_{j \in N_i} s_j(t)}{d_i} \tag{5}$$

where N_i is the set of neighbours of agent j, and d_i is the number of neighbours of agent i. After receiving negative information, agent i may change into a silent state, and the silent agent does not participate in the game. $P_i^n(t)$ measures the probability that agent i receives negative information, that is, the strategic environment that agent i faces. In the prisoner's dilemma game, a rational agent chooses not to participate because of the low or even negative returns brought by the defection of the neighbour. If any individual expects their neighbours to defect, then his rational choice is not to game. Therefore, negative information describes agents' responses to the environment.

After game interaction, the individual starts to update the strategy by learning. This paper adopts the Fermi rule as the strategy updating mechanism [24]. Namely, agent i randomly selects a neighbour j to compare their payoffs. The more the payoff of the selected neighbour exceeds that of agent i, the more likely the neighbour's strategy will be adopted. The probability that agent i adopts its neighbour's strategy is

$$P_{i\leftarrow j} = \frac{1}{1+e^{-(U_j-U_i)/k}} \tag{6}$$

where $P_{i\leftarrow j}$ indicates that the strategy of agent j is transferred to agent i. k describes irrational behavior in strategy updating. For $k = 0$, agents will adopt the strategy of neighbors with higher payoff with certainty. For $k > 0$, it means that agents may choose a neighbor's strategy with a lower payoff. To be consistent with most studies, let $k = 0.1$.

B. MEAN-FIELD THEORETICAL ANALYSIS

In order to analyze the complex dynamic systems, the mean-field approximation from statistical physics is often used.

In a sufficiently large network, the set of agents participating in the game can be considered as a continuous space. Each individual has only two strategy choices: cooperation or defection, so the number of each choice can be regarded as a density in the continuous space. Assume that the density of cooperative strategy in the network at any time is ρ $(0 \le \rho \le 1)$, and the density of defection is $(1-\rho)$.

$$\dot{N_C} = -\widehat{P^n}N_C + \left\{1-(1-\widehat{P^p_C})^{[(\hat{d}-1)\rho+1]}(1-\widehat{P^p_D})^{(\hat{d}-1)(1-\rho)}\right\} \times (d_C - N_C) \tag{7}$$

$$\dot{N_D} = -\widehat{P^n}N_D + \left\{1-(1-\widehat{P^p_C})^{[(\hat{d}-1)\rho]}(1-\widehat{P^p_D})^{(\hat{d}-1)(1-\rho)+1}\right\} \times (d_D - N_D) \tag{8}$$

Under the above settings, we can conduct a mean-field theoretical analysis of the model. First, we need to calculate the agents' average payoff from every game round. As the payoffs not only determine the intensity of information dissemination, they also affects the process of strategy updating. Therefore, we need to know how much average payoff a typical cooperator and defector will get in each game round.

The average payoffs of cooperative agents and defective agents are $\widehat{U_C}$,$\widehat{U_D}$

$$\widehat{U_C} = \rho N_C R + (1-\rho)N_C S \tag{9}$$

$$\widehat{U_D} = \rho N_D T + (1-\rho)N_D P \tag{10}$$

where $\widehat{U_C}$ is the average payoff of the cooperative agent, and the first part of the formula represents the expected payoff when cooperative agents game with cooperative neighbours; The second part shows the expected payoff when cooperative agents encounter defective neighbours. $\widehat{U_D}$ indicates the same meaning. N_C and N_D are the number of active neighbours around cooperative and defective agents, respectively.

The probability that cooperative agents and defective agents disseminate positive information is $\widehat{P^p_C}$ and $\widehat{P^p_C}$.

$$\widehat{P^p_C} = \frac{\widehat{U_C}}{\widehat{U_C}+\rho N_C\widehat{U_C}+(1-\rho)N_C\widehat{U_D}} \tag{11}$$

$$\widehat{P^p_D} = \frac{\widehat{U_D}}{\widehat{U_D}+\rho N_D\widehat{U_C}+(1-\rho)N_D\widehat{U_D}} \tag{12}$$

where $\widehat{P^p_C}$, $\widehat{P^p_D}$ respectively represent the proportion of the average payoff of a cooperative agent and a defective agent in the total payoffs of the game population. Any individual can disseminate positive information to neighbours, making the neighbours active with the probability.

The probability that any agent receives negative information and becomes silent is

$$\widehat{P^n} = 1-\rho \tag{13}$$

The probability of each agent turning to silent state is only related to the defective neighbours. Therefore, the average probability that agents turn to silent state is $1-\rho$.

According to Sandholm, et al. the change of cooperation density can be described by the differential equation of replication dynamics [46]. When the average payoff of cooperators is greater than the average payoff of all agents, agents in the system tend to cooperate. On the contrary, if cooperators' average payoff is less than all agents' payoff, agents tend to defect.

$$\dot{\rho} = \rho(\widehat{U_C}-\overline{U}) = \rho(1-\rho)(\widehat{U_C}-\widehat{U_D}) \tag{14}$$

where $\overline{U} = \rho\widehat{U_C}+(1-\rho)\widehat{U_D}$

According to the model settings, $\widehat{U_C}$ and $\widehat{U_D}$ are functions of ρ, N_C and N_D. In order to describe the dynamic evolutionary process of the system, we also need to obtain the dynamic equations of N_C and N_D. Equation 7 describes the dynamic evolution process of N_C

In equation 7, the first term is the cooperative agent's reduced number of active neighbours, which is equal to the probability of the agent turning to silent state multiplied by the number of active neighbours. The second term is the increased number of active neighbours of the cooperative agent, which is equal to the probability of the agent turning to active state multiplied by the number of silent neighbours. When an agent switches from silent state to active state, it may be affected by the positive information from one or more neighbours.

Therefore, we calculate the number of active states increase by the item in square brackets. The item inside the square brackets indicates the probability that a neighbour of the cooperative agent does not change into active state under any situation. The entire square bracket denotes the probability that a neighbour of the cooperative agent changes from silent state to active state. $d_C - N_C$ is the number of silent neighbours of the cooperative agent. Equation 8 describes the dynamic evolution process of N_D. $\hat{d}$ is the average degree of the agents in the network, d_C is the average degree of cooperative agents, and d_D is the average degree of defective agents.

Take Equation 13 into Equation 7, 8 and let

$$M(\rho) = 1-(1-\widehat{P_C^p})^{[(\hat{d}-1)\rho+1]}(1-\widehat{P_D^p})^{(\hat{d}-1)(1-\rho)} \quad (15)$$

$$N(\rho) = 1-(1-\widehat{P_C^p})^{[(\hat{d}-1)\rho]}(1-\widehat{P_D^p})^{(\hat{d}-1)(1-\rho)+1} \quad (16)$$

We can get the following proposition. Three dynamic variables determine the state of the evolutionary system: equilibrium cooperation density, the number of neighbors of cooperators, and the number of neighbors of defectors. We need an equation set to describe the dynamic process of the three variables.

Proposition: According to the mean-field analysis, the cooperation density of a double-layer network game based on asymmetric information is determined by the following dynamic equations

$$\begin{cases} \dot{\rho} &= \rho(1-\rho)\left[\rho N_C R + (1-\rho)N_C S\right] \\ & \quad - \rho(1-\rho)\left[\rho N_D T + (1-\rho)N_D P\right] \\ \dot{N_C} &= \left[\rho - 1 - M(\rho)\right]N_C + M(\rho)d_C \\ \dot{N_D} &= \left[\rho - 1 - N(\rho)\right]N_D + N(\rho)d_D \end{cases} \quad (17)$$

where $\dot{\rho}$ describes the changing process of the equilibrium cooperation density. $\dot{N_C}$ and $\dot{N_D}$ describe the change process of the number of active neighbours around cooperators and defectors, respectively.

This paper introduced asymmetric information dissemination, divided the information into positive and negative information, and distinguished agents into active state and silent state, which makes different information have a different impact on nodes, so that N_C and N_D became different. The model proposed in this chapter will degenerate into the classic model by Nowak et al. without consideration of information dissemination [11], [15]. When there is no difference in the agents' state, the number of neighbours of each agent becomes equal and constant. That is, $N_C = N_D = \hat{d}$, $\hat{d}$ is the degree of the node. At this time, N_C and N_D become constants, then the system is determined by the dynamic equation 14, and the only stable solution of the system is fully defection. Therefore, the core idea of this paper is that the game has an impact on the information dissemination on the virtual layer, and the information dissemination produces a feedback on the game on the physical layer, which makes the number of neighbours of agents different, leading to evolution results distinct with traditional research.

According to equation 17, we can obtain the theoretical solution of the system by numerical calculation. As can be seen on panel (a) in Fig. 2, the system converges to a stable point and maintains considerable cooperation in most scenarios. From panel (b), we can see that the number of neighbours around all agents declines at the initial point. This is because the temptation of defection increases the probability that cooperators receive negative information, decreasing the number of active agents around

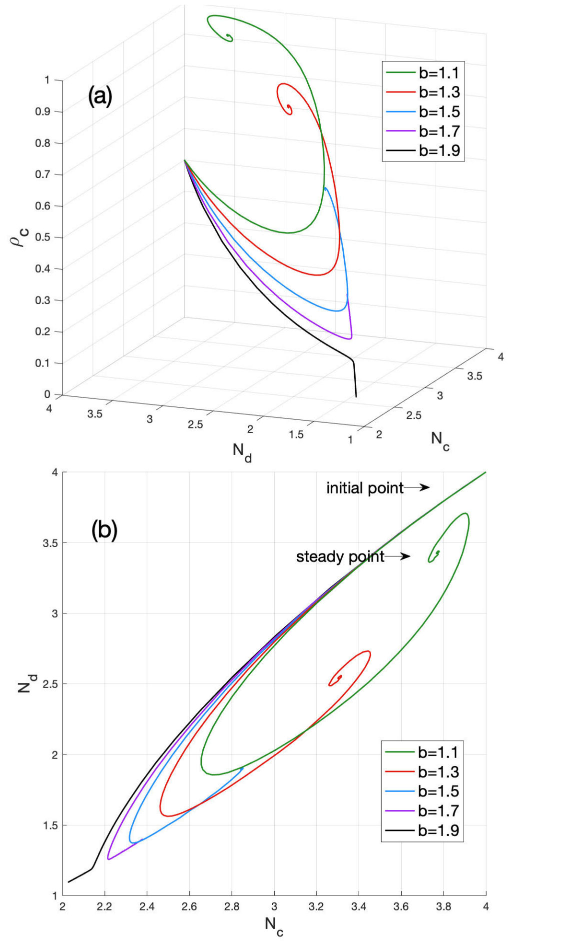

FIGURE 2. (Color online) The graph depicts the theoretical analysis results of the evolution process. The theoretical analysis results show that the number of neighbors around cooperators and defectors will constantly change during the evolution process. In the initial stage, the density of equilibrium cooperation decreases continuously due to the influence of defection temptation. When the number of cooperators' neighbors exceeds the number of defectors' neighbors, the system will undergo a phase transition. Finally, the system will stabilize at a high level of cooperation. Panel (a) shows the change of equilibrium cooperation density with time under different temptations to defect. The system has maintained a considerable level of cooperation in most scenarios. Panel (b) depicts the initial point and stable point of the evolution. The number of neighbours around cooperators and defectors decreased first and then increased. Cooperators finally occupied most of the space. The parameters are set to: $T = b$,$R = 1$, $P = 0$, $S = 0$.

them. However, the number of agents around defectors decreases less quickly than that of cooperators.

As the number of active agents decreases, the system eventually undergoes a phase transition. When the number of active agents around cooperators exceeds that of defectors, the system gradually shows a cooperative trend until it reaches a stable state. This is because, although defection brings high payoffs in the short term, it will reduce the number of active neighbours in the long term. Cooperation will form a positive feedback effect, enabling more active agents to gather around the cooperators, leading to an eventually cooperative system.

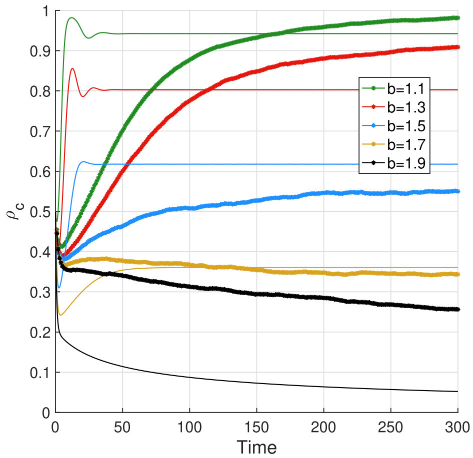

FIGURE 3. (Color online) The picture presents the change in cooperation density with time. The equilibrium cooperation density gradually increases with the decrease of defection temptation, and the system maintains a high level of cooperation in most cases. At the same time, the theoretical prediction results are highly consistent with the simulation results. The lines with asterisks represent the experiment results. The lines without asterisk indicate the results from theoretical analysis. As time passes, the system remains at a considerable level of cooperation, and the cooperation density decreases with the temptation to defect.

III. SIMULATION RESULTS

Through theoretical analysis, we guess that the difference between N_C and N_D may lead to an equilibrium cooperative solution after long-term evolution rather than the case where the defection occupied the whole space as predicted in the classical model. Through mean-field analysis, we built a system of dynamic differential equations for the evolution of network games. In order to verify the results of the theoretical analysis, we conducted Monte Carlo calculation experiments in this part. Monte Carlo simulation is often used to simulate the evolution process of the game. It helps approximate the actual results of the game through repeated sample experiments. We conduct simulation experiments through Matlab, and the experimental code is provided in the supplementary materials. The scale of the experiment was set as $N = 100 \times 100$ people. In the initial stage, cooperative strategies were assigned to each agent with the same probability (0.5), and each agent was set in active state with the same probability (0.5). After a long evolution, the system tends to be in dynamic equilibrium. We focus on the cooperator density ρ_c in a steady state. According to Nowak's suggestion, the game's payoff matrix parameters were set as $R = 1, T = b, P = 0$ and $S = 0$. The temptation to defect (b) varies from 1 to 2, and $k = 0.1$. The equilibrium cooperator density averages 30 experimental results under the same parameter setting.

A. THE IMPACT OF INFORMATION DISSEMINATION

Fig. 3 shows the evolution of cooperation density over time under asymmetric information dissemination. As seen in Fig. 3, the system can maintain considerable cooperation under most cases of defection temptations. Furthermore, the cooperation density increases with the decrease of the defection temptation. The agents in traditional models, however, tends to defect in most cases. At the same time, the experimental results are gradually close to the results under theoretical analysis (represented by lines without asterisk) with time. This indicates that the theoretical analysis of the model is consistent with the experimental results.

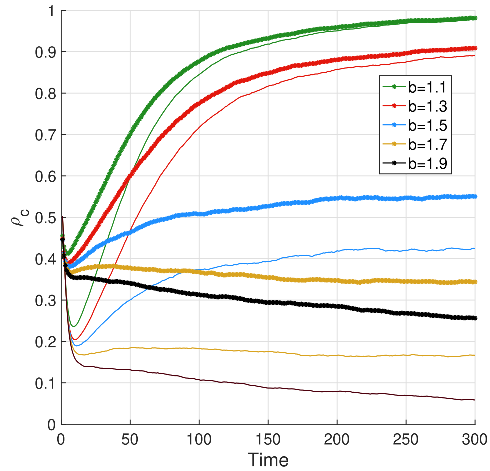

FIGURE 4. (Color online) The picture shows the change in active agents' density over time. The equilibrium cooperation density is highly related to the active agent density, and the higher the cooperation density is, the higher the correlation is. The result shows that the positive information generated by cooperators is conducive to spreading cooperation, while the positive information generated by defectors will hinder cooperation. This is because the cooperative strategy will activate more agents in the long run, while the defection will activate agents in the short run. However, it will endogenously cause more silent agents in the long run. The lines with asterisks represent the equilibrium cooperation density over time. The lines without asterisk indicate the active agents' density with time. As time goes on, the density of cooperation and the density of active agents maintain a considerable correlation in most cases.

In order to analyze the impact of asymmetric information dissemination on cooperation, we examined the changes in information dissemination over time. The lines with asterisks in Fig. 4 show the change in the density of agents in active state with time. The density of agents in active states is highly correlated with cooperation density. Moreover, this correlation is more significant in the case of high-level cooperation. This indicates that the positive information generated by defectors has a high dissemination intensity in the short term.

However, the negative information will hinder such dissemination, so it fails to support the aggregation of agents in active state in the long run, because many agents were trapped in the suroundings of defectors. It is not easy to achieve high-level cooperation. On the other hand, the intensity of positive information generated by cooperators is weaker than that of defectors in the short term, but the positive information generated can form a positive feedback effect, in the long run, activating more and more agents. In other words, cooperation strategies can gather more active agents in the long run.

B. SNAPSHOT OF GAME INTERACTION

The snapshot can reflect the course of game evolution over time in real time, and it can help us understand the details of

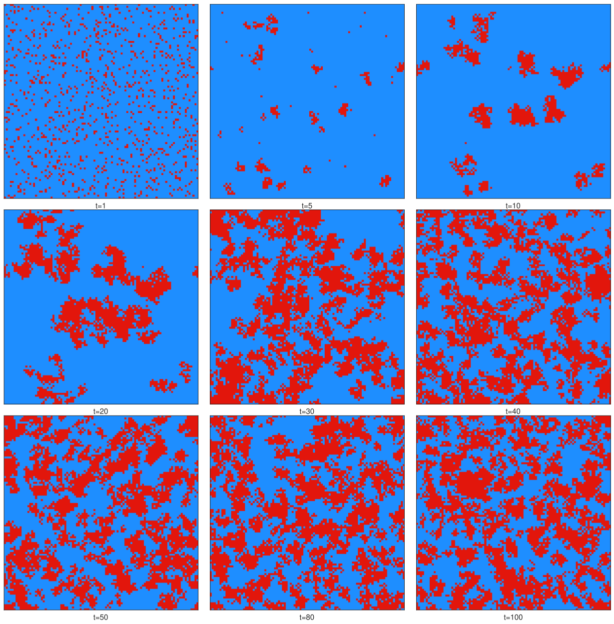

FIGURE 5. **(Color online) The instant snapshot presents the evolutionary process of the agents' state. Asymmetric information dissemination affects the density of agents in active states. The positive information generated by defectors will activate agents in the short term but will endogenously hinder the increase of active agents in the long term. The positive information generated by cooperators will produce positive feedback, thus promoting active agents. The active agents eventually occupy most of the space with the increase of cooperation density. Red nodes represent agents in active state, and blue nodes represent agents in silent state. In the initial stage, all individuals were assigned active state with the same probability (0.1), and a few active nodes start to gather. After clustering, agents in active state eventually occupied most of the space.**

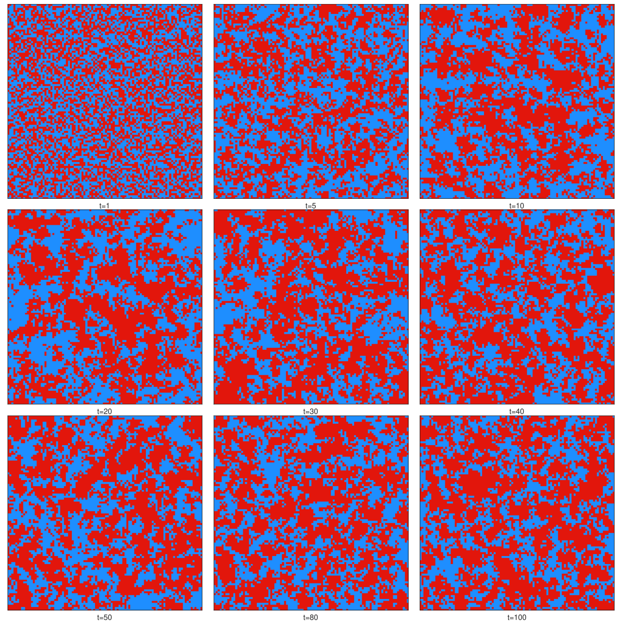

FIGURE 6. **(Color online) The instant snapshot shows the evolutionary process of cooperation. Due to the influence of the defection temptation, the agents tend to defect at the initial stage. With the spread of asymmetric information, the defection will be endogenously hindered, cooperative strategies will produce a positive feedback effect, and the system will eventually tend to almost complete cooperation. Red nodes represent cooperators, and blue nodes represent defectors. In the initial stage, all individuals were assigned cooperator and defector with the same probability (0.5). After the cooperators and defectors form clusters, the cooperation strategy spreads outward.**

system changes, thus helping to find the micro-level reasons for the game evolution. Therefore, we give snapshots of game interaction and information dissemination.

It can be seen from Fig. 5 that active individuals gathered at $t = 10$ due to the dissemination of information. Since then, cooperative agents began to achieve more payoffs, making positive information spread like ripples after $t = 20$. Negative information will hinder this process when agents choose to defect. The probability that the neighbours receive negative information increases, leading to more silent agents, thus endogenously preventing the further spread of the defective strategy. Meanwhile, the spread of positive information brought about by cooperator is conducive to realizing comprehensive cooperation. Next, we analyzed the impact of information dissemination by comparing the changes in agents' states with the changes in corresponding strategies. It can be seen that asymmetric information dissemination has a crucial impact on cooperative evolution.

Fig. 6 shows the snapshot of the game evolution corresponding to Fig. 5. Red nodes represent the cooperative strategy, and blue nodes represent the defective strategy. When $t = 10$, the system tended to defection, and cooperative agents could only resist the intrusion of defection through clustering. However, with the dissemination of positive information, many cooperators clustered in the region where positive information was disseminated, and cooperation further strengthened the dissemination of positive information. They activated more and more agents, thus forming positive feedback and promoting cooperation. After $t = 20$, it can be seen from Fig. 5 and Fig. 6 that the positive information has been widely disseminated, and the corresponding cooperation strategy has also occupied most of the space.

Furthermore, we found that in the initial stage of the game, cooperation and defection compete fiercely with each other, and accordingly, the intensity of information dissemination is the highest at this time; Later, cooperation occupies most of the space. Meanwhile, the speed of information dissemination was rapidly declining. This is because defection in the initial stage makes a distinct difference in the payoffs of each player. Defection or cooperation payoffs can produce a strong information dissemination effect. However, when the cooperation dominates, the payoff gap among agents decreases, making it challenging to generate powerful information dissemination, and the information dissemination tends to be stable. With the stability of information dissemination, the equilibrium cooperation density gradually tends to be stable.

IV. CONCLUSION

This paper proposed a double-layer network model to discover the impact of asymmetric information dissemination on the evolution of cooperation. The model assumed that game interaction takes place in the physical layer of the network and information dissemination takes place in the virtual layer of the network. We divided the information into positive and negative information, and agents were sorted into silent and active states. The game interaction on the physical layer will affect the information dissemination on the virtual layer, and the information dissemination will have a feedback effect on the game interaction.

Through theoretical analysis and simulation experiments, we found that the dissemination of asymmetric information impacts cooperation. Specifically, the dissemination of positive information is highly related to the equilibrium cooperation density. The positive information generated by the defector can promote cooperation in the short term but will hinder cooperation in the long term; Positive information generated by cooperators can promote cooperation in the long run. The system's final state depends on the relative intensity of the two kinds of information dissemination.

Information has been proved to be a fundamental variable of cooperative evolution [33], [36], [47]. Asymmetric information dissemination can promote cooperation because heterogeneous information has distinct dissemination intensities, which makes the number of active agents around the agents different. The positive information generated by cooperators can attract more active agents in the long run, thus obtaining more payoffs, making the agents in the system tend to cooperate. The positive information generated by defectors produces more silent neighbours in the long run, thus reducing the overall payoffs, which makes the system tend to defect. The traditional research did not fully consider the differences between different information dissemination and the changes in agents' states caused by the dissemination. Therefore, processing information by the traditional model can be regarded as a particular case of this paper. This research idea may expand the current studying fields.

Nonetheless, the research on the impact of information dissemination is still preliminary. The information was only processed discretely, and only positive and negative information was distinguished. If the information is continuously processed, the experiment's results may differ. We also did not consider network size effects. Different network sizes may influence the conclusions of this paper. Additionally, we only considered the agents' states with being active and silent. Only the cases related to payoffs were considered for processing information dissemination. Compared with the complex information dissemination process, these settings are still preliminary attempts in reality. In addition, the game model and network structure adopted in this paper are relatively simple, and the robustness of the conclusions still needs to be further verified.

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