Information-based matching explains the diversity of cooperation among different populations

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This paper introduces a bilateral matching mechanism to explain why different populations have different levels of cooperation. The traditional game theory assumes that individuals can acquire their neighbor’s information without cost after generating information. In fact, the environment and cognition of populations often limit the magnitude of information received by individuals. Our model divides information dynamics into two processes: generation and dissemination. After generating, information starts to disseminate in the population. Individuals match and interact with each other based on the information received and then confirm partnerships, which differs from traditional research’s unilateral partner selection process. Specifically, we find a function to simulate two constraints of information acquisition in different populations: information dissemination cost and cognition competence. These two kinds of constraints affect the choice of partnership and then the evolution of cooperation. The game evolved under the condition of information constraints. Through large-scale Monte Carlo simulations, we find that information dissemination and cognition underlie the evolution of cooperation. The lower cost of information dissemination and the more valid cognition of information, the higher level of cooperation. Moreover, deviations in cognition among individuals more sensitively determine the equilibrium cooperation density. As the deviations increase, cooperation density decreases significantly. This paper provides a new explanation for the diversity of cooperation among populations with different information dissemination costs and cognition competence.

I. INTRODUCTION

To cooperate or not to cooperate is a question. The world comprises different populations, some of which have established broad cooperation, i.e., the European Union and OECD. In contrast, others have experienced severe conflicts, i.e., the two World Wars and recent regional conflicts [1, 2]. According to Darwin’s evolutionary theory, selfish individuals do not choose to cooperate, even though cooperation benefits the whole [3]. 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 [4–11].

Network evolutionary games have been proved to be a powerful framework for investigating the evolution of cooperation [12–15]. The framework consists of three primary elements: (1) Network structure[16–18]. 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 [19–24]. According to certain rules, agents update their strategies during their evolution. Analyzing the three elements can help us find the key reasons for the emergence of cooperation. Nowak and May first applied the framework to investigate the evolutionary PD game. They regarded agents as network nodes, and agents were allowed 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 invasion of defectors [25]. This ground-breaking research has laid a new foundation for studying the evolution of cooperation [26].

Previous studies of evolutionary games assumed that agents interact separately with each of their neighbors. Later research found that cooperation emerges when agents are allowed to play selectively with their particular neighbors [27–30]. Szabó studied the influence of voluntary participation and random partnership on cooperation and found that partner selection has different influences under different network structures [31]. Chu’s research allowed agents to adaptively change the weight of their connections to their neighbors and found that this mechanism could boost cooperation [32, 33]. Santos also found that the self-organizing of agents’ strategies and social relationships are crucial in promoting cooperation [34]. Wang’s model assumed that agents choose partners based on the feedback effects of a particular parameter, and they found that cooperation can be achieved when the parameter is positive [35]. The model proposed by Shi assumed that agents choose their neighbors based on non-linear benefits, and they found that the mechanism can lead to a high level of cooperation [36]. Chen 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 there is a tolerance limit that can maximize the level of cooperation [37]. In the subsequent research, Chen considered the impact of reputation and behavioral diversity, in which they randomly assigned reputation values to agents and allowed them to
change the value adaptively. This heterogeneous reputation can also effectively promote cooperation [38]. Fu also reached a similar conclusion in their research on reputation-based selection mechanisms [39]. The model by Wu assumed that agents have heterogeneous social relationships, and each agent can participate in different amounts of public goods games, which significantly improves the level of cooperation [40]. Hauert proposed a voluntary participation mechanism in which the 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 [41]. The common conclusion of these studies is that heterogeneous partner selection is an essential factor affecting the evolution of cooperation.

The current partner selection is a unilateral mechanism. Namely, the agent’s selection does not need the consent of their neighbors, such as Wang’s single parameter feedback effect, Chen’s prestige tolerance mechanism, Fu’s reputation-based selection, and Hauert’s voluntary participation [42]. However, partner selection is more likely to be a bilateral matching process, which should depend on the interaction between individuals rather than exogenous variables [43–46]. Marriage, for instance, is a typical bilateral matching process in which cooperation can only be reached with the consent of both parties. In addition, existing research has not characterized the population environments in evolutionary games [47]. Realistically, cooperation may evolve differently with the change in population environments. Therefore, the interaction of partner selection and population environments needs to be further investigated.

In this paper, we propose a cognition-based bilateral matching game model in which agents select partners through a matching process based on information dissemination and cognition. Then agents play the PD game and update strategies. The model also examines the process of information dissemination in different populations and the influence of information cognition on the evolution of cooperation. We hope to determine the internal mechanism of the emergence of cooperation and the underlying reasons why the cooperation level differs between different populations.

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. Research framework

We first present the framework of the model, and the detailed modeling process will be given later. The model consists of four parts: network generation, matching process, game interaction, and strategy updating. (1) Network generation: A square lattice is generated at the initial stage. Nodes of the network represent agents in the game, and the edges connect agents and their neighbors. (2) Matching process: Each agent generates the expectation of its neighbor’s strategy selection according to the information received. Achieving matching means that both agents believe that one of their neighbor’s strategies will bring them more benefits than other strategies. (3) Game interaction: Agents achieving matching play the PD game and gain payoffs, while others quit the game and gain nothing. (4) Strategy update: Agents update strategies used in the next game round according to payoffs.

As the foundation of this paper, we regard bilateral matching as an information exchange process, the efficiency of which varies under different population environments. In the process, any two connected agents exchange information and then decide whether to match up with each other according to the information received. The cost of information dissemination and cognition competence can affect the efficiency of the exchange process. That is to say, the process of information dissemination affects cognition and matching, which in turn affects game interaction and strategy updating [48–52]. Before moving on, let us talk about information first.

B. Assumptions about information

We make the following assumptions about information: (i) Information refers to strategies selected by agents in each game round. Only after the dissemination of information can it be received by agents. Unlike traditional research, we divide information dynamics into two processes: generation and dissemination. Previous studies believe agents can obtain information without loss and cost [53]. However, there is no such thing as a free lunch, nor is information. This paper holds that information dissemination represents the process from information generation to reception. The process affects the accuracy and completeness of the information received. For example, we can easily obtain agents’ credit information in a society with complete credit systems. In contrast, it is not easy to do the same thing in a society without credit systems. (ii) Agents can only obtain information from their neighbors, and the magnitude of information received is related to the cost of information dissemination and cognition competence, which characterize the environment of different populations together. The cost of information dissemination measures the transparency and fluidity of information in a population. The greater the cost, the more difficult it is for agents to obtain relevant information. Clearly, in a society connected to the Internet, the cost is relatively small, and people can easily obtain the information they want. At the same time, the situation is the opposite in the era of paper letters. Information cognition measures how an agent can accurately obtain relevant information at a given cost of dissemination. We
assume that cognition is related to the payoff of an individual in the game.

(iii) Agents form the expectation of their neighbor’s future strategy selection according to the information received. Information is crucial to decision-making and the idea-generating [38, 54]. Within the framework of evolutionary games, agents update their strategies according to information such as strategy choice or payoffs. For example, if an agent knows that his neighbors have all chosen to cooperate in history, the agent will expect the neighbor to continue cooperating in the future. This setting is similar to reputation-based selection, which has been proven to be an effective mechanism for promoting cooperation [36–38, 52].

Under this assumption, let us start investigating the influence of information dissemination and cognition on the evolution of cooperation. Different populations have different dissemination costs, which depend on the transparency and fluidity of information. Meanwhile, different individuals in the population also have different information cognition competence. Individuals with different backgrounds often have significant differences in their cognition competence and in the ability to acquire and process information. These factors will comprehensively affect the information obtained by the individual, thus affecting the expectation of the neighbor’s future strategy choice and then affecting the game process. The results of studies in this setting may differ from traditional results [55].

C. Matching process

The model assumes that each agent generates the expectation of their neighbor’s strategy selection in the next round of the game based on the information received. Two connected agents will play the game when both agents believe that one of their neighbor’s strategies will bring them more benefits than other strategies.

FIG. 1. (Color online). Schematic diagram of the matching process

The matching process is shown in Fig. 1. A cooperater is represented by the blue and defectors by the red. The dotted line with blue arrows indicates that information is being disseminated between the two sides of the game, which underlies the matching process. If they match each other, they play the game, represented by the solid black line; otherwise, they quit the game, which is represented by the dashed black line.

Specifically, consider any two connected nodes $i$ and $j$. Let the strategy choice of any agent $i$ in time $t$ be expressed as

$$ s_i(t) = \begin{cases} 1 & \text{Cooperator} \\ 0 & \text{Defector} \end{cases} $$

Information generation process: The information generated by agent $j$ in period $t$ is the proportion of strategy of cooperation in history, and the magnitude of information is

$$ x_j(t) = \frac{\sum_{t=1}^{t} u_i(t)}{t} $$

Information dissemination process: Information will be disseminated within a specific population, based on which agent $i$ predict the probability that its neighbor $j$ choose to cooperate. That is

$$ b_{ij}(t) = x_j(t) \left( \frac{\sin \alpha U_i(t)}{e^{\beta U_i(t)}} + 1 \right) \quad (v_i, v_j) \in E $$

where $x_j(t)$ refers to the magnitude of information generated by agent $j$. The expression in brackets measures the cost of information dissemination in a specific population and the cognition competence of the agents. $b_{ij}(t)$ represents the expected probability formed by agent $i$ that agent $j$ chooses to cooperate based on the information in period $t$. The higher the cost of dissemination, the more difficult for agents to obtain information from their neighbors and thus make accurate predictions about their neighbors’ future strategy choices. The information cognition competence is related to the agents’ payoffs in the game. Payoffs come from choice, and choice is made based on information. Therefore, we assume that cognition competence is correlated with payoffs. $U_i(t)$ is the payoff of agent $i$ in period $t$. $\alpha$ and $\beta$ are the adjusting parameters.

In the PD game, cooperation yields more than defection in any case. Thus, a match can only be achieved if both parties expect the other to choose cooperation. The dissemination process affects the evolution of cooperation by influencing the expectations of both parties and then the matching process. Specifically, the dissemination affects the matching process in two aspects: (1) different agents may have different expected probabilities based on the same information. Namely, different agents within a population have different cognition abilities. (2) The expected probability formed by the same agent based on the same information may differ among populations. These two differences mainly come from the difference in dissemination cost and cognition competence. By adjusting parameters $\alpha$ and $\beta$, we can simulate the two differences among populations. In addition, since $b_{ij}(t)$ is a probability, $b_{ij}(t) \in [0, 1]$. For the part where $b_{ij}(t) < 0$, let $b_{ij}(t) = 0$; for $b_{ij}(t) > 1$, let $b_{ij}(t) = 1$.

If the evolution of the game can achieve an equilibrium, we call such an equilibrium a matching equilibrium. Namely, given the neighbor’s choice, the agent
chooses the strategy that is most beneficial to the neighbor. Such a balance can be achieved because if agents do not choose the most beneficial strategy for each other, it is difficult for them to achieve the matching, and they will gain nothing because the game will not be carried out. In contrast, the Nash equilibrium in traditional game theory emphasizes that an agent will make the most practical choice for himself given the strategy of the other, which leads to conflict between individuals and collectives [25].

D. Game interaction

This paper assumes that agents play the prisoner’s dilemma game with each other on a square lattice of $N = L \times L$ with periodic boundary conditions, and any agent has four neighbors (von Neumann). 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 $M$ is as follows

$$
C \begin{pmatrix} C & D \\ D & R & S \\ T & P \end{pmatrix}
$$

(4)

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 neighbor cooperates, and earns $S$ when the agent cooperates while its neighbor 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 vector $s$

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

(5)

In each game round, agent $i$ interacts with matched neighbors and gains payoffs

$$
U_i(s) = \sum_{v_j \in N_i} s M s^T
$$

(6)

where $s$ is the strategy vector, $M$ is the payoff matrix, and $m$ represents the matched neighbor of agent $i$. In the classic model by Nowak [25], each agent interacts with every one of their neighbors separately without considering of information dissemination and matching process. If we replace $N_m$ in our model with (neighbors of agent $i$), our model will degrade to Nowak’s classic model.

E. Strategy updating

In evolutionary game dynamics, agents update their strategies by learning. This paper adopts the Fermi rule as the strategy updating mechanism [56]. Namely, agent $i$ randomly selects a neighbor $j$ to compare their payoffs. The more the payoff of the selected neighbor exceeds that of agent $i$, the more likely the neighbor’s strategy will be adopted. The probability that agent $i$ adopts its neighbor’s strategy is

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

(7)

where indicates that the strategy of agent $j$ is transferred to agent $i$. $k$ describes irrational behavior in strategy updating [20]. 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 $k = 0.1$.

III. SIMULATION RESULTS

In this part, we conduct Monte Carlo calculation experiments. The scale of the population is set as $N = 100 \times 100$. In the initial stage, collaborators and defectors are distributed on the network with the same probability (0.5). The system tends to be in dynamic equilibrium after long-term evolution, and we focus on the steady-state cooperator density $\rho_c$. According to Nowak’s suggestion, the parameters of the payoff matrix are set as $R = 1, T = b, P = 0, S = 0$, and the temptation to defect $b$ varies from 1 to 2. By adjusting the parameters, we can simulate the cost of information dissemination and cognition in different populations. With the increase of $\alpha$, the expected probability of different agents based on the same information will change significantly as the payoff changes slightly. The higher $\beta$, the more accurately an individual can receive relevant information. The equilibrium cooperator density averages 50 experimental results under the same parameter setting.

Since different populations have different information dissemination costs and cognition competence, the expected probabilities formed by different agents will be different, which imposes a different effect on the matching process and game interaction. In each scenario, the proportion of cooperation increased significantly with the reduction of information dissemination cost and the improvement of cognition and was higher than that in traditional studies. In addition, cognition diversity among agents poses a more significant effect on cooperation in scenarios of lower dissemination cost and less valid cognition.

Specifically, in the upper panel of Fig. 2, the green line, the red line, and the blue line respectively indicate that the difference of expected probabilities among agents increases gradually as the cognition diversity increases. For, in the case of the green line of panel (a), the expected probability among agents falls at $[0.5, 0.91]$, while in the case of the blue line, the expected probability varies from 0 to 1. Panel (b) and (c) express similar
FIG. 2. (Color online). In the upper panel, different colored lines represent the cost of information dissemination and individuals’ information cognition in different environments. All individuals are distributed on the horizontal axis, \( U \) is the game payoffs of individuals, and the vertical axis represents the expected probability formed by individuals according to the information received (0.5). Figure (a) shows the situation with high information dissemination cost and low level of cognition competence, in which case many individuals cannot accurately recognize the relevant information. The blue line (e.g., \( Q = 3 \)) shows that the expected probabilities formed by different individuals based on the same information differentiate significantly among individuals. The red and green lines (e.g., \( Q = 2 \) and \( Q = 1 \)) show that the difference is decreasing. Figures (b) and (c) show that with the reduction of information dissemination costs and the improvement of cognition competence, individuals can recognize relevant information more accurately. The difference in expected probability gradually decreases. The lower panel represents the equilibrium cooperation density corresponding to different scenarios. The black curve (i.e., benchmark) represents the traditional results without considering the matching process.

meanings, but these two cases represent lower dissemination costs and more accurate cognition. The counterpart of the three colored lines above represents the equilibrium cooperation density in the lower panel. It can be seen that with the decrease of expected probability deviation in cases (a), (b), and (c), the equilibrium cooperation density gradually increases. In either case, the density was significantly higher than that of traditional results represented in the black line.

On the other hand, panel (c) shows that the reduction of information dissemination cost and the improvement of cognition competence enable individuals to perceive information more accurately, and the cognition deviation among different individuals gets small. The equilibrium cooperation density also increases to a higher level. Panel (a) and (b) represent the high cost of information dissemination and low level of cognition competence. In this case, the cognition deviation between individuals significantly impacts cooperation. As the cognition deviation gradually increased (green line scenario to blue line scenario), the equilibrium cooperation density decreased significantly.

To find the mechanism of evolution at the micro-level. We give a snapshot of the evolutionary process in which the defection strategy occupies the entire space, as shown in Fig. 3. It can be seen that in the case of significant cognition deviation, the evolutionary process shows a non-monotonic phenomenon. At \( t = 5 \), the system tends to be in full cooperation but soon turns towards total defection. Again, evolution shifts to full cooperation at \( t = 15 \); however, defection takes over at \( t = 25 \) and eventually takes over the entire space.

It can be seen from the snapshots that the information conducive to cooperation cannot be accurately identified due to the significant cognition deviation among individuals. Thus, those long-term partners do not get the corresponding incentive. They fail to match more neighbors of cooperators, which makes the cooperation strategy not get the corresponding high benefits and thus limits the spread of the cooperation strategy. This situation can be effectively avoided in a society with low information dissemination costs and a high level of cognition compe-
FIG. 3. (Color online). An instant snapshot of game evolution. Red nodes represent cooperator, and blue nodes represent defector. In the initial stage, all individuals were assigned the cooperation and defection with the same probability (0.5). The evolution process shows cooperation and defection alternate respectively, and finally, defection strategies occupy the whole game space.

In this case, a long-term partner will match more neighbors and reap higher game payoffs, in which the cooperative strategy can be more widely spread.

We also examine the evolution results under other parameters, i.e., \( \rho_0 \) and \( T \). As shown in Fig. 4, this model significantly promotes cooperation compared with traditional models. When the initial cooperation density \( \rho_0 \) exceeds 0.5, the system can achieve high cooperation, and \( T \) has little influence on cooperation. In the traditional model, cooperation can be achieved only when the initial cooperation density \( \rho_0 \) exceeds 0.7, and the proportion of cooperation decreases significantly with the increase of temptation \( T \). The reason is that, under the setting of this model, the more times individuals choose to defect, the fewer partner they can match. This result has nothing to do with the temptation, so it is challenging for the defector to obtain a higher payoff, and the defection is difficult to spread at any level of temptation. In traditional models, higher temptation brings higher payoff, making defection easy to spread. Briefly, information influences the evolution of cooperation through the matching process.

IV. CONCLUSION AND DISCUSSION

In this paper, by considering the bilateral matching process, we hope to find out the reason that underlies the emergence of cooperation. It can be seen from the simulation results that information dissemination and cognition competence have an important influence on the evolution of cooperation. With the reduction of information dissemination cost and the improvement of cognition competence, the equilibrium cooperation ratio has been significantly improved. Moreover, the cognition deviation among individuals is more sensitively negatively correlated to equilibrium cooperation density. With the increase of the deviation, the cooperation density decreases significantly.

It is found that the cost of information dissemination and cognition competence are two crucial factors affecting the evolution of cooperation. We can see that cooperation is better maintained in an environment with a low cost of information dissemination and a high level of cognition competence. At this point, cognition deviation does not significantly affect cooperation. However, in a society with a high cost of information dissemination and a low level of cognition competence, cognition deviation has an essential impact on the evolution of cooperation. The result indicates that the differences in cognition and opinions among people may reduce the level of cooperation when the mobility and transparency of information are still insufficient.

Compared with the concept of Nash equilibrium in traditional theories [25, 37, 55], the matching equilibrium proposed in this paper can better balance the conflicts be-
FIG. 4. (Color online). Results of game evolution under different model parameters. Panel (a) is the result of this model, while panel (b) is in traditional settings. The horizontal axis shows different initial cooperation densities $\rho_0$. The vertical axis shows different defection temptations $T$.

tween individuals and collectives. In the matching equilibrium, selfish individuals consider the interests of the other party and choose the most profitable strategy for the other party; otherwise, individuals can hardly match corresponding neighbors. This choice makes individuals avoid falling into a situation with no game partners, thus alleviating the conflict between individuals and collectives. It can be predicted that this matching equilibrium concept can help alleviate the social conflict, such as the tragedy of the Commons.

The findings of this paper are consistent with the reputation-based selection mechanism proposed by Chen and Fu et al. [21, 38]. In their research, when individuals choose cooperative strategies, their reputations will increase accordingly, and they will get more game opportunities and payoffs so that cooperative strategies can be spread [25, 32, 35]. The assumption about information in this paper is similar to reputation. When individuals cooperate, they can get more matched neighbors and thus get more game payoffs. However, previous studies have not considered the mechanism of the influence of that reputation. In this paper, we find that the process of information dissemination and cognition competence can affect the evolution of cooperation.

Nevertheless, the research of this paper still needs to step further [57]. Our modeling of information dissemination and cognition is still a preliminary attempt, and whether the modeling of information can well conform to reality still needs further verification. We consider only one dimension of information, i.e., strategic choices of the agent in history. If the information includes the strategies of neighbors or even global agents, the results may be different. In addition, the game model and network structure model adopted in this paper are relatively simple, and the robustness of the conclusions still needs to be further verified.

In short, this paper incorporates the pre-game matching process into the traditional research framework and divides the information dynamic process into information generation and information dissemination. This paper provides a new idea for studying the evolution mechanism of spatial games.

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