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Protection and improvement of indirect identity cognition on the spatial evolution of cooperation☆

Yichao Yao, Bin Pi, Ziyan Zeng, Minyu Feng *

College of Artificial Intelligence, Southwest University, Chongqing, 400715, China

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ABSTRACT

In the public goods game on the network, individuals might believe that their neighbors' neighbors have more similar situations to their own than their direct neighbors since they play games with the same individuals. Based on this assumption, we make individuals learn strategies from second-order neighbors and consider the neighborhood profits of other individuals with a certain probability as the basis for selecting their own neighbors, to propagate strategies and adapt the network structure while considering the self-identification of individuals. To study the effects of examining neighborhood profits on cooperation and network topology, we conduct simulations using different levels of examination intensity. A rich evolutionary landscape is observed led by different parameter combinations. When the individual's consideration intensity of neighborhood profit is low, cooperation will increase with higher intensity. However, cooperation will be inhibited if an individual considers neighborhood profit moderately. Furthermore, if the individual's consideration of neighborhood profit is strong, the complexity of the network structure will emerge spontaneously, and the protection of cooperation will occur. In addition, we have observed the separation of degree distribution among individuals in different strategies in the evolution. The results imply the inner principle of the protection mechanism for cooperation existing in reality, and the coupling between the formation of network complexity and the promotion of cooperation.

1. Introduction

Cooperation is the foundation of social development and prosperity. Although various forms of conflict and contradiction exist in human evolution, cooperation has never lost its vital position in promoting the society prospered, and civilization developed [1,2]. Cooperative behaviors can be found in a wide range of areas, from interactions between nations to the social lives of individuals, and even to interactions between cells. However, in individual actions, the best interests of individuals and the best interests of the collective are often inconsistent, bringing disadvantages to those who give and trust [3]. Therefore, cooperative behavior is often not the best way for individuals to improve their competitiveness in the fierce competition of nature. The existence of generous cooperators is inconsistent with the basic premise of natural selection [4]. In a special issue of science published in 2005, the evolution of cooperation was among the top 25 of 125 important scientific questions to be addressed [5], and the research on the evolution of cooperative behavior

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* Corresponding author.
E-mail address: myfeng@swu.edu.cn (M. Feng).

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is of fundamental importance in many fields such as life science and social science. In the research on the evolution of cooperation, the evolutionary game on the network provides an effective research framework for cooperation [6,7]. Meanwhile, with the rapid development of complex network [8,9], many networked game models have been proposed and combined with classical evolutionary game theory, which is widely used to study the cooperative evolution based on the hypothesis of the group or pair interaction [10]. Among them, the prisoner's dilemma game(PDG) and snowdrift game(SG) have been studied extensively [11], the multigame and the public goods game(PGG) on the complex network has been studied extensively also [12,13]. In recent years, the second-order reputation evaluation and the networked decision-making dynamics have been well studied [14,15], and Gao et al. studied the combined influence of reputation and multi-species of strategies [16]. Besides, group size and noise index have been shown to have a wide impact on the public goods game on the network [17,18].

A universal principle for the emergence and maintenance of cooperation in social dilemmas is that the existence and form of social structure may greatly affect the interaction between social individuals, thus creating an environment in which the cooperators can be maintained [19]. After Nowak and May's study of the PDG on square lattice networks [20], cooperative behavior on complex networks has been widely studied, and the evolution characteristics of various game models on scale-free networks, regular networks, and small-world networks have been well-analyzed [11,21,22]. In addition, the existence of numerous special mechanisms in the real world has also been proved to have an impact on the promotion and maintenance of cooperation [23,24], which is representative of the heterogeneity of an individual's neighbor strategy and the individual's strategy in different environments [25,26]. For example, Su et al. investigated the evolution of cooperation based on the edge dynamics rather than the traditional nodal dynamics in networked systems [27] and developed a general framework of interactive diversity [28], Jia et al. introduced dubbed link players into the network and it forms social insulation between cooperative and defecting clusters [29]. However, in reality, not only the individual's game strategy change over time but also the environment. Individuals may have the ability to change the environment according to his/her own will, so as to directly or indirectly change the topological nature of the interaction structure between individuals, which is reflected as the co-evolution of network structure and individual strategy in the evolutionary game on the network. As a natural upgrade of static game theory on the network, co-evolution rules add network changes to the evolution process, which creates more possibilities for the evolutionary game on the network [30,31]. The adaptability of spatial structure has brought more space for individuals to choose their behaviors. Initially, Zimmermann et al. defined the vulnerability of the edges by the revenue they can generate and thus observed that network plasticity under certain rules can significantly promote cooperation [32]. Subsequently, Pacheco et al. designed more exquisite co-evolution models and studied the impact of time-scale separation of network structure and individual evolution on cooperation [30,33]. The importance of this time-scale separation was further demonstrated by Rand et al. through human volunteer experiments [34]. Research on the adaptive network has also achieved rich results in recent years. For example, the impact of population growth and social relationship inheritance on cooperation in adaptive networks has been widely studied also [35], revealing the internal mechanism and influencing factors of social cooperation from a broader perspective [36,37]. Nowak et al. found the positive effect of reputation on cooperation in 2008 [38], while Ackay et al. observed the collapse and rescue of cooperation in the coupling process of network structure and evolutionary game [39]. In addition, network adaptation rules not only affect group cooperation but also provide some enlightening for the formation of network structure in real society [40,41]. Li et al. modeled scale-free networks through evolutionary games on adaptive networks [42], while Hiroki et al. obtained spontaneous emergence of network complexity from the adaptive evolution of networks [43].

However, in most of the research above, the individual's strategy update and network adaptation behavior are mostly based on the attributes possessed by their immediate neighbors or the attributes of the links possessed by the individual [30,43], which assume that the individual should take some personal information of its opponents as the basis of its actions in the evolution. But in reality, individuals also rely on other kinds of information as a basis for behavior changes, for example, people are often self-driven based on their own historical experiences in the absence of other information available [44,45]. Recent studies have shown that in real life, people do not always make decisions based on the behavior and strategy of their most immediate game opponent [46–48]. For example, when people meet someone on a blind date, they consider not only the character of that person, but also their social circle or interest circle, we might consider the behavior and strategies of employees in our department to better deal with the same boss, ask for better treatment, and we might decide whether to take a course based on the grades of our fellow students. From the example above, we can find that people's choice of strategy and the environment may not consider their direct game objects like a blind date, their boss, and their teacher, but will consider those who play games with the same people and are not necessarily to game with them directly, such as the colleagues or classmates and so on, those are the neighbor's neighbors. Taking into account the level of information globalization and individual information acquisition capability today, we can hypothesize a highly informationized population, in which the individuals have the capability to acquire information about other specific groups and individuals to update their own strategies and adapt the network [49], similar to other evolutionary game researches with global information [50]. Previous studies have driven individuals on the network to comprehensively consider the benefits of multiple neighbors within a certain radius when changing their strategies, and proved that the strategy learning considering distant individuals and multiple neighbors could promote cooperation than the case that only considering the benefits of one direct neighbor [51]. Moreover, previous studies have proved that evolutionary games on adaptive networks can spontaneously emerge in network complexity [42], and network adaptive

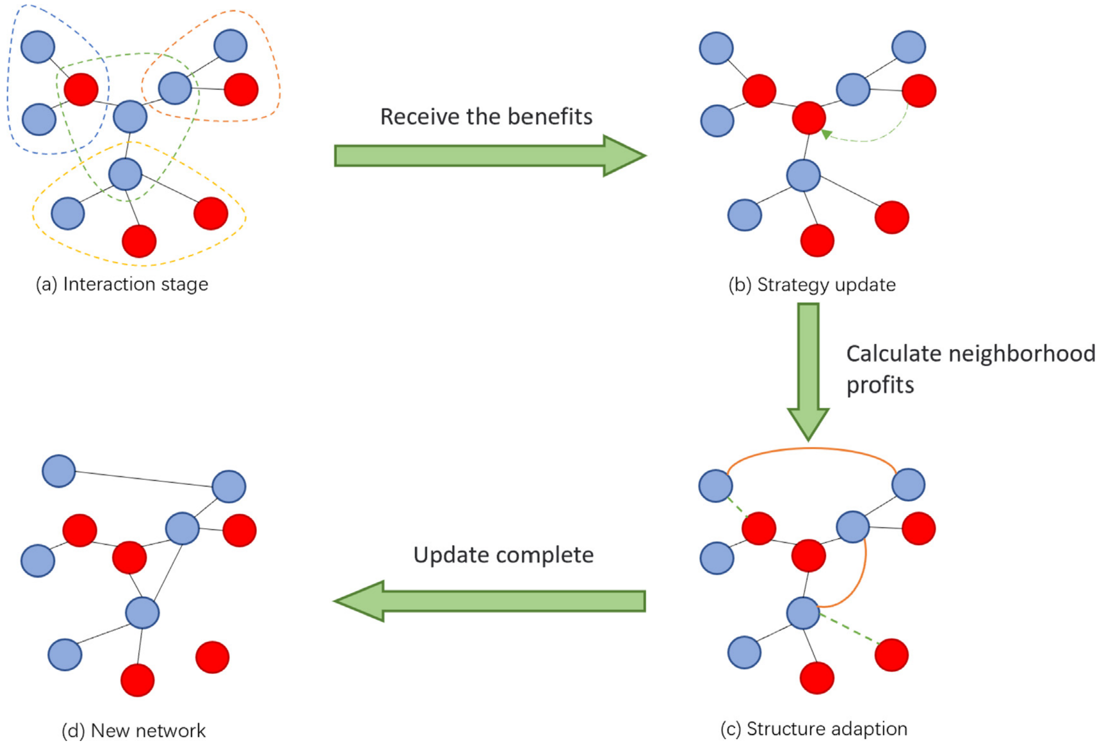


Fig. 1. Three kinds of basic actions of each individual in each Monte Carlo step. The red node represents the defector, and the blue node represents the cooperator. (a) All groups of public goods as circled by the dotted line interact. (b) All nodes randomly select a neighbor's neighbor for strategy update using Eq. (2). (c) All individuals are given the opportunity to select neighbors to update an edge with the calculated probability of Eq. (4) (d) The network is updated, and the next Monte Carlo step is taken.

processes have an important impact on the evolution of cooperation on complex networks. Based on what has been mentioned above, we propose a neighbor selection strategy and a strategy update rule based on neighborhood benefits and indirect learning, then we observe the influence of network topology and cooperation ratio on such rules based on self-identity considerations.

The rest of this paper is organized as follows, in Section 2, we introduce the basic model. In Section 3, we analyze the simulation results generated by different initial networks and different parameter settings and explain their inherent evolutionary logic and rules. In Section 4, we provide conclusions and outlooks.

2. Model

As mentioned above, in our model, individuals are more inclined to obtain information and learn strategies from their neighbors' neighbors. In particular, in a case similar to the public goods game, each individual's contribution to the public good is equalized and distributed to all the owners sharing the public good, that is to say, each individual's strategy is invisible to all the others in the same PGG group. This is a good hiding of individual strategy information, each individual can only estimate an individual's strategy through the income of other individuals in the community. In that case, it becomes more possible for individuals with intelligence to update their neighbors and strategies referencing the game information of individuals with common opponents. Therefore, based on the public goods game on the adaptive network, we make the individual use the edge-changing rule based on neighborhood profits and the learning strategy from the neighbor's neighbor, so as to make the model as close to reality as possible.

In the network, the nodes indicate the game players and the links indicate social interrelationships, the evolution of cooperation is carried out in a regular network and a BA scale-free network. At the start of evolution, each individual will have a strategy to be a cooperator (C) or defector (D) with equal probability, after the random initial conditions are applied, each individual completes a round of evolution in three steps, successively performs group game, strategy update, and network structure update, as shown in Fig. 1. First, each player accumulates its payoff by participating in all the PGGs they have to participate in. Then, each individual will have a chance to update their strategy and relink one of its edges. Based on the self-knowledge psychology mentioned above, individuals should learn strategies based on earnings and tend to learn strategies from their neighbor's neighbor whose earnings are higher than their own. Edge reconnecting will consider the profits of all other individuals' neighbors, and individuals will prefer to be neighbors of those with higher neighborhood benefits. At the same time, to simulate the irrational behavior of individuals, we make individuals reconnect edges considering the neighborhood profits with probability p_n, while randomly connected to individuals in the network without considering anything with the probability of $1-p_n$. The specific models of public goods games, strategy learning, and edge updates will be introduced in the following subsections.

2.1. Public goods game

For the public goods game on the network, each node acts as a center, the individual represented by this node and all its neighbors form a public goods group centered by it to play the public goods game, and each individual participates in a game of public goods centered on itself and all its neighbors, individual i invests amount c_i to all the PGG groups it participates in if it is a cooperator, then the payoff of player i that obtains from public goods game is

$$u_i = -c_i g + \sum_{j=1}^{g} \frac{\sum_{k=1}^{|N_j|} rc_k + rc_j}{|N_j| + 1}, \tag{1}$$

here r is the enhancement factor of PGG, g represents the groups participated by i. For each PGG group that i participates, j denotes the central node and N_j denotes all the neighbors of node j, $|N_j|$ represents the number of j's neighbors. And $g = |N_i| + 1$, which equals to the number of neighbors of i plus itself, the c_i in Eq. (1) represents the investment corresponding to the strategy of i, we set $c_i = 1$ if i is a cooperator, and $c_i = 0$ if i is a defector here, then $-c_i g$ calculates the value of the individual's investment to each group in each round. Based on the previous settings of c_i, the number of cooperators is the principal amount in the public goods pool on each PGG group, in each turn each group multiplies r to its principal and then equally distributes to all members of the group as their payoffs. In this process all of the players can get this payoff no matter whether one is a cooperator or a defector, the only difference is that a cooperator needs to make an investment while the defectors are not, giving selfish individuals the opportunity to free-ride. For one individual, the payoff of being a defector is always higher than that of a cooperator, therefore the public goods game can easily fall into the famous tragedy of the commons.

2.2. Strategy evolution

After all the players get their payoffs, an individual named x will have the opportunity to learn game strategies from its randomly chosen neighbor's neighbor y. Based on the individual's profit-seeking and selfishness, we suppose that an individual will learn strategies based on the income difference between the two parties. The learning probability should be positively correlated with the payoff gap. i.e., this pairwise comparison process takes the income difference between individuals as input and the replication probability of the strategy as output. The Fermi Dirac function can satisfy these requirements, which is often adopted in the evolution of cooperation on regular lattices, and regarding the cooperation on complex networks, replicators' dynamics are usually applied [52]. Thus, the player x imitates y's strategy with the probability given by the Fermi–Dirac function:

$$P(s_x \leftarrow s_y) = \frac{1}{1 + \exp{(u_x - u_y)/\kappa}}, \tag{2}$$

In Eq. (2), s_i represents the strategy of individual i, while u_i quantifies the payoff that individual i received in the previous turn. The higher the payoff u_y is compared to u_x, the more likely individual x is to learn strategies from y. If u_y is smaller than u_x, individual x still has a small probability of learning strategies from individual y to simulate the irrational behavior. The noise factor, denoted by κ, affects the intensity of learning based on the payoff gap. Individuals are more sensitive to small differences in payoffs with smaller κ, whereas they tend to learn more randomly with larger κ. If individual x fails to learn the strategy of its randomly selected neighbor's neighbor y in a given round, it will maintain its current strategy.

2.3. Structure adaptation

Each individual has a chance to change one of the neighbors after each round of repetition, this subsection introduces the relink rule of the individuals. Individuals tend to be a neighbor to those whose neighbors have a higher payoff, each turns when all the players get their payoffs from PGG, for each individual i, calculate the neighborhood profits u_n^i for it, that is, the average profit of all its neighbors.

$$u_n^i = \sum_{k=1}^{|N_i|} \frac{|u_k|}{|N_i|}, \tag{3}$$

In Eq. (3), N_i is the set composed of neighbors of individual i, $|N_i|$ is the number of neighbors of individual i, and u_k is the income obtained by the kth neighbor of i in the PGG. Then each individual cuts off an edge with the one with the lowest neighborhood profits in its neighbor and relinks this edge to individual i in the network with probability P_i which is expressed as follows.

$$P_i = \frac{u_n^i - u_n^{min}}{u_n^{sum} - Nu_n^{min}}, \tag{4}$$

here u_n^{sum} is the sum of the neighborhood profit of all individuals in the network in this turn, and u_n^{min} is the lowest neighborhood profit in the network, N is the number of the individuals in the network, the sum of the probability for an individual to build an edge to all the nodes is 1. Therefore, when an individual cut off an edge from the network, the individual must still be connected to at least one node in order to maintain a constant number of edges. In the process of evolution, each individual has a chance to update its strategy and reconnect one of its edges, this edge will be reconnected directionally based on the neighborhood benefits of other nodes in probability p_n and be reconnected randomly in probability $1 - p_n$.

3. Simulation and results

In this section, we demonstrate the simulation method and also the results and analysis of it. First, we observe the evolution process of cooperation under different p_ns and rs, and the influence of parameters on cooperation level f_c, then we analyzed the changes in the network topology and different kinds of links in the network to clarify the details of evolution and the specific influence of each parameter on the evolution process of the adaptive network.

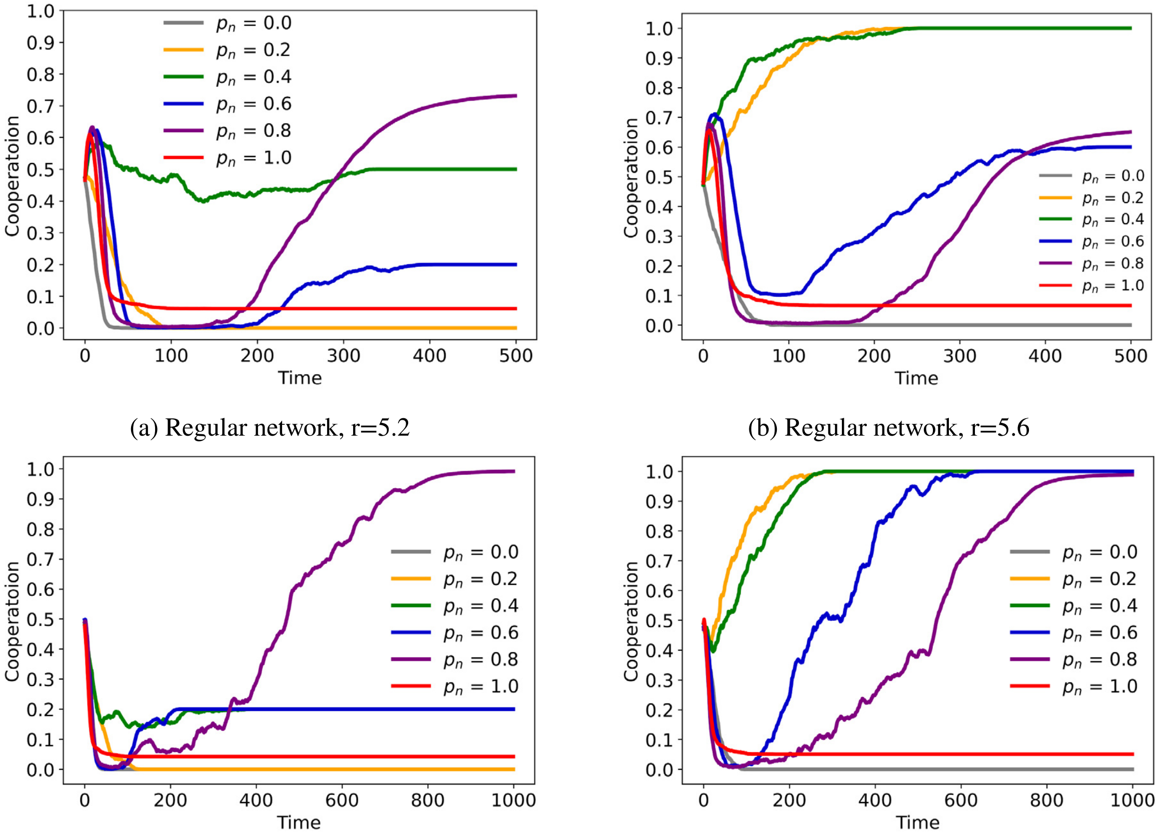
3.1. Method

At the beginning of each simulation, there are N=1500 players in both the regular and BA scale-free networks with an average degree of 4. We generate a random number between 0 and 1 for each individual according to the uniform distribution. When the random number is greater than 0.5, the individual becomes a cooperator, and when it is less than 0.5, the individual becomes a defector, so that each individual can obtain one of the two strategies with equal probability at the beginning. After the random initial conditions are applied, in each Monte Carlo step all the players will randomly choose an individual from its neighbor's neighbor and update their strategy by Eq. (2) where κ is set to 0.1, then change one of its neighbors by Eq. (4). Next, we will choose a target for this new edge using Russian roulette based on Eq. (4), if the individual chooses to establish an edge with itself, then rerun it to avoid self-loops, which means that every time an individual makes a link, it just establishes only one edge with one other node in the network. We run each simulation at about 500 steps on the regular network and 1000 steps per simulation on the BA network, which is enough for the network to evolve into a smooth state, each result is the average of more than 10 simulations to ensure accuracy.

3.2. Evolution of cooperation

We analyze the changes in cooperation level f_c under different parameter combinations and networks, and the influence of different parameters on the cooperation level is separately explored below. The experimental results are shown in Fig. 2, where we can see that when $p_n = 0$, the players are completely random reconnecting edges and the cooperator ratio drops rapidly to zero. For p_n takes some other value, there exists at least a short period of rapid increase of cooperators in the early stage of evolution on the regular network, the higher the p_n is, the faster the increase of f_c will be. However, this phenomenon does not occur on the BA network. On both networks, when p_n is set to 0.2 and 0.4, for r is 5.6, the evolution trend of the cooperator ratio does not change much, gradually increasing to a stable value. However, when r is 5.2, the cooperation is low first and then high before it evolves to stability as p_n is 0.4, and as p_n is 0.2, the change curve of cooperation level is similar to that when p_n is 0. When p_n is 0.6 or 0.8, the phenomenon of "bottoming out" occurs in both networks. As p_n is 1.0, i.e., the players consider neighborhood profits in all the edge changes, f_c rapidly drops to a value after a slight increase and then stops changing. Besides, we can notice that when r is 5.2, the cooperation level is not high when p_n is small, but when p_n is 0.6, the cooperation level is almost the same as when $p_n = 0.4$ on the BA network at the end of evolution. Then as p_n is set to 0.8 and r is 5.2, the final level of cooperation on both networks has significantly improved, especially on the BA network. While we can notice that, when p_n is set to 0.8, f_c remains almost unchanged when r is 5.2 compared with the case that r is set to 5.2. Under the condition that p_n is 0.6, the final cooperation level becomes larger with the increase of r, while the cooperation rate at the bottom is still low. Meanwhile, with the increases of r, on the regular network, the final cooperation level of when p_n is 0.2 or 0.4 is overtaking and becomes always higher than when p_n is set as 0.6 or 0.8. And on the BA network, for r taken as 5.2, when p_n is 0.4 and 0.6 the final cooperation level is very similar, only when p_n is taken as 0.8 the cooperation was significantly enhanced. When r takes as 5.6, the speed of cooperation to occupy the whole network increases with the decrease of p_n.

Thus, we know that when r is low, a high p_n first facilitates the defector's invasion of the cooperators, but when the number of cooperators drops to a certain point, it starts to rebound, this phenomenon is especially evident in the BA network. However, if the players completely use neighborhood profit to select their neighbors, the cooperation is out from the influence of r: f_c is always very low regardless of r, but not reached 0. When r is higher, a low p_n can obviously promote cooperation, and its effect is more significant than the case that the neighborhood profit is considered more.



(a) Regular network, r=5.2

(b) Regular network, r=5.6

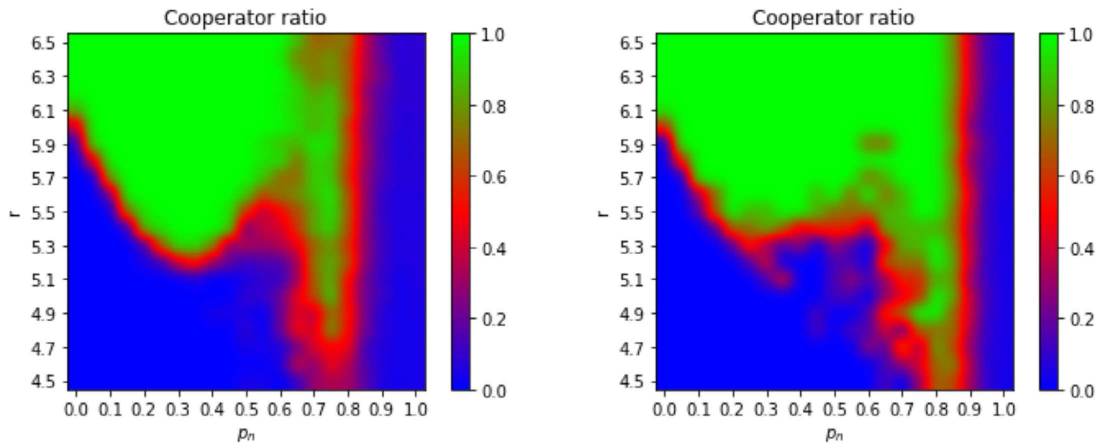
(c) BA network, r=5.2

(d) BA network, r=5.6

Fig. 2. The fractions of the cooperator changes over time. On the regular network we set (a) $r = 5.2$, (b) $r = 5.6$, and on the BA network we set (c) $r = 5.2$, (d) $r = 5.6$. Yellow, green, light blue, dark blue, pink, and red represent different p_ns, going from 0 to 1 in steps of 0.2. On the regular network, the evolution reaches stability when it reaches 500 time steps, while on the BA network, it needs about 1000 time steps. From this, we can see that p_n has a similar impact on both networks. When r is 5.2, a larger p_n leads to a higher fraction of cooperation, while when r is 5.6, a smaller p_n is more advantageous, and p_n values close to 1 or 0 consistently lead to lower levels of cooperation.

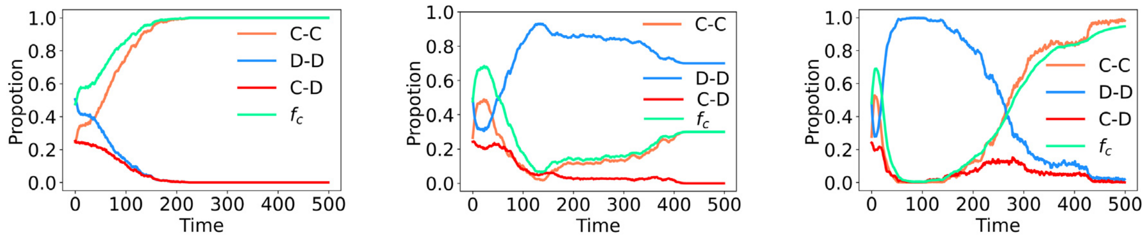
Therefore, it is speculated that the probabilistic of choosing the neighbor based on neighborhood profits can make two kinds of effects: a lower p_n (but greater than 0) directly promotes cooperation, and a higher p_n makes the cooperation probability more stable form the influence of r, it may either stabilize the cooperation to a very high level or to a very low level, depending on the value of p_n.

For exploring the comprehensive influence of different r and p_n, the final cooperation level is shown in Fig. 3. From this, we can clearly notice that when the regular network is selected as the initial network, two values of p_n reduce the value of r required for cooperation. When p_n is set to around 0.3 and 0.75, the final cooperation level will have a significant promoting effect, but when p_n is between these two, there is much less promotion to cooperation. When p_n is set to 0, the edge changes completely random, and the difficulty of cooperation is much greater than that when p_n is set to the middle value. On the BA network, the promotion effect of low p_n on cooperation is not so obvious, but when p_n sets to around 0.75, cooperation is still promoted. At the same time, it can be seen that when p_n is high (larger than 0.75), the final cooperation is less affected by the change of r in the figure, and when p_n is above 0.8, the network will not evolve to cooperation even if r increases to very high in both networks. This result further confirms the previous inference: when r is large, a small p_n can promote cooperation better, while a larger p_n can stabilize the final cooperation level of the network around some specific value. Even when r is small, the network can maintain a certain level of cooperation with a high p_n, but in this case, the rise of r will have only a little effect on promoting cooperation. This is reflected in both cases that choose these two networks as the initial network. The difference is that when the BA network is utilized as the initial network, the promotion effect of low p_n on cooperation is weakened, while high p_n can maintain cooperation in a lower r value.

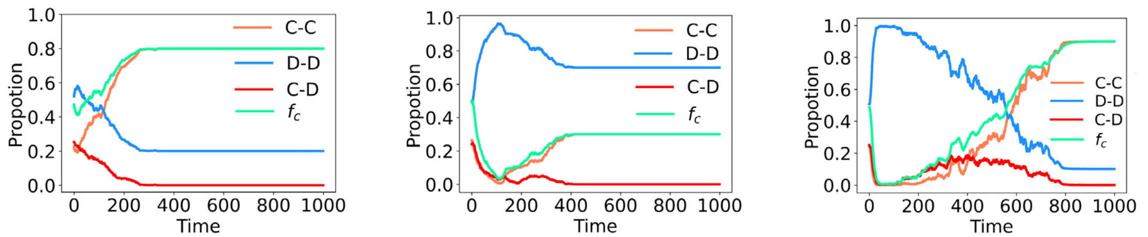


(a) Regular network (b) BA network

Fig. 3. The heat map shows the cooperation level depending on the intensity of select p_n and r. From blue to green, the color bar indicates that the cooperation level changes from 0 to 1 accordingly. Generally, a monotonically increasing effect of r could be found to promote cooperation, however, different p_n results in different sensitivity of cooperation to r, especially when p_n is greater than 0.8, cooperation is more insensitive to r.



(a) Regular network, r=5.4, p_n=0.3 (b) Regular network, r=5.4, p_n=0.5 (c) Regular network, r=5.4, p_n=0.75

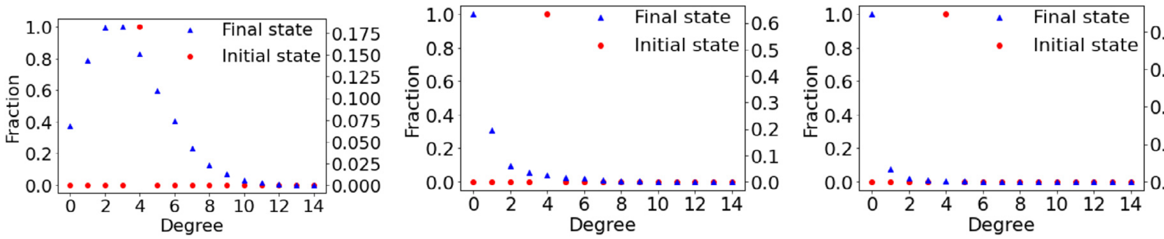


(d) BA network, r=5.4, p_n=0.3 (e) BA network, r=5.4, p_n=0.5 (f) BA network, r=5.4, p_n=0.75

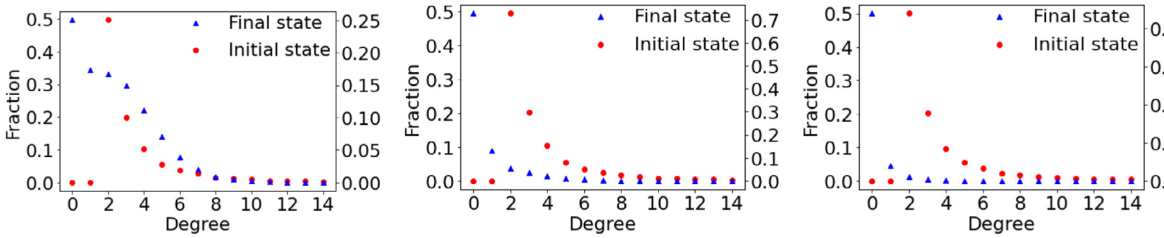
Fig. 4. The number of three types of different edges varies with time step in two initial networks and different sets of parameters. The top row shows the simulation results on the regular network, and the bottom row shows the case on the BA network, where the orange curve represents the change in the number of edges between cooperators, the blue curve represents the change in the number of edges between defector, and the red and green curves respectively represent the change in the fraction of edges between cooperators and defector and the change in the fraction of cooperators on the network.

3.3. Structural adaptive

In this subsection, we show the degree distribution of the network and the changes of different types of edges in the process of network evolution, to reveal the details of the role of the neighborhood profit evolution rule in the process of network evolution. As a result, Fig. 4 shows the changes in different types of edges in the evolution process. We can see from it that the edges between the cooperator and defector keep dropping and remain low in all the cases, meaning that there is a certain extent of separation tendency between cooperators and defectors, while the ratio of C–C edge is highly consistent with the ratio of cooperators. We can observe that when p_n is 0.5 and 0.75, there is a phenomenon of increasing and then decreasing f_c in the regular network, which can be explained by the relative speed of degree heterogeneity and cooperation clustering. In this case, since p_n is relatively large, edges on the network will quickly aggregate towards cooperators, which promotes the formation of both C–C and C–D edges and spreads cooperation in the same way as



(a) regular network, r=5.4, p_n=0.3 (b) regular network, r=5.4, p_n=0.5 (c) regular network, r=5.4, p_n=0.75



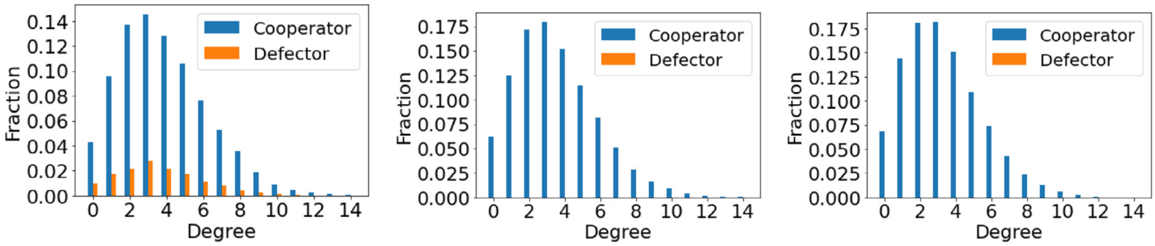
(d) BA network, r=5.4, p_n=0.3 (e) BA network, r=5.4, p_n=0.5 (f) BA network, r=5.4, p_n=0.75

Fig. 5. The comparison of initial degree distribution on the network and the final degree distribution of evolution. The regular network (row 1) and BA network (row 2) are taken as the initial network under different parameter settings, the initial degree distribution is represented as red and corresponds to the vertical scale on the left, and the final degree distribution of evolution is represented as blue and corresponds to the vertical scale on the right.

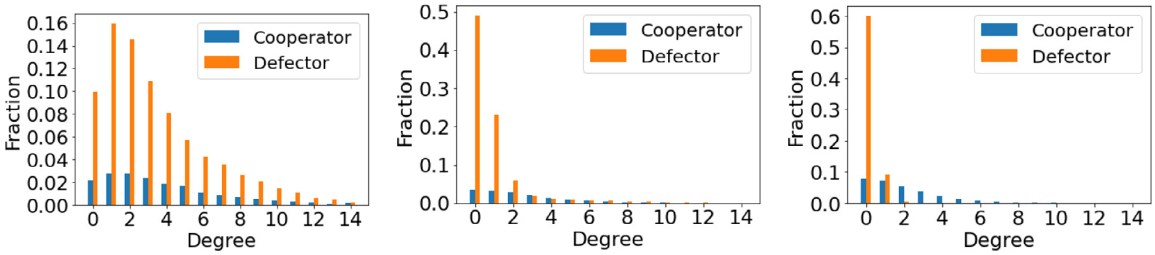
when $p_n = 0.3$, leading to a rapid increase in f_c. However, this also leads to faster formation of degree heterogeneity. From the figure, we can see that the number of C–D edges remains almost unchanged during the early stage of evolution, indicating that cooperators and defectors are still mixed. As the network heterogeneity increases, and cooperators and defectors do not separate significantly, the evolution approaches the initial situation of the evolution on the BA network. As a result, the number of cooperators transitions from an increase to a decrease. From the figure, we can see that after the initial peak of f_c, the changes in the quantities of these three types of links on the regular network are similar to those on the BA network from the initial time. Moreover, we can notice that when the evolution goes to some extent, the C–D edges completely disappear on the network, and the evolution is frozen. This is because at this time, almost all the defectors on the network are isolated and all the edges on the network are concentrated among some cooperators, and there is little interaction between individuals with different strategies. Even if the individuals in the cooperator cluster connect the edges to a defector, this defector is difficult to spread the defect strategy and easily becomes isolated again due to its few neighbors and low payoffs, so the network evolves into a frozen state. Besides, Fig. 5 demonstrates the degree distribution before and after the network adaptive. It can be found that when the p_n sets to intermediate and higher value, the degree distribution of the BA network and regular network after the evolution changed into a power-law distribution, and the power-law of the evolved network is higher when p_n is higher. Otherwise, when p_n is low, the degree distribution of the regular network tends to be normal after evolution, which is different from that of the BA network after evolution. The degree heterogeneity of the BA network is preserved to a certain extent after evolution, indicating that the initial structural features of the network have a certain impact on the evolution for p_n is low. This explains the similarity between the evolution results on the BA network and the regular network for p_n is high, and the difference between the evolution results on different initial networks when p_n is small shown in Fig. 3.

For more details, Figs. 6 and 7 show the degree distribution of cooperators and defectors at several different time steps in the evolution process. It is easy to observe that on the regular network, as p_n is small, the degree distribution of the cooperator is always close to normal distribution during and at the end of evolution, and in the BA network it is different. In the BA network, the defectors do not die out in large numbers at the beginning but obtain almost the same degree of distribution and number as the cooperators. At the same time, it can be noticed that the power-law property of degree distribution completely disappears. After a while, the cooperators still maintain a relatively normal degree distribution, but the defectors are gradually isolated, and their degree distribution of them shows a power-law nature, and finally, the whole network formed the degree distribution as shown in Fig. 5(d). When p_n is 0.5, the degree distribution of cooperator and defector is similar to that when p_n is 0.3, but the degree of cooperator is more evenly distributed, on average, the degree distribution of defector is more power-law. In this case, the degree distribution of the BA network also shows the power-law characteristic earlier, and the extinction of cooperators on this network is much greater than that on the regular network. Finally, the degree distribution forms of the two networks are similar, but the cooperation level on the BA network is lower.

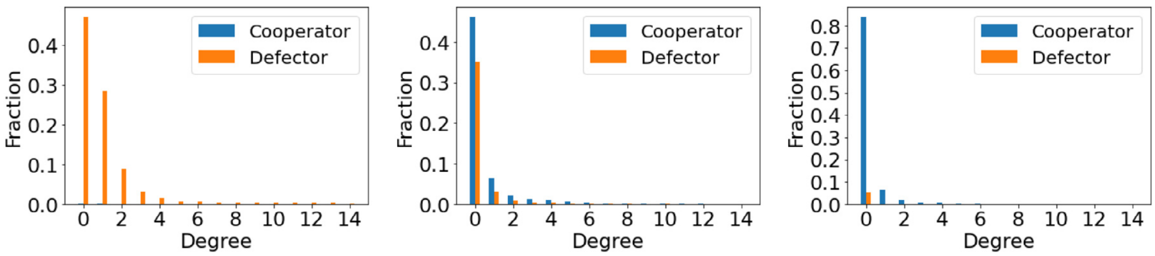
When p_n is up to 0.75, the cooperator ratio will be protected as we mentioned before, we see a much different situation here. In this case, the degree distribution changes in the two networks are similar, the cooperators almost disappear from



(a) regular network, r=5.4, p_n=0.3



(b) regular network, r=5.4, p_n=0.5



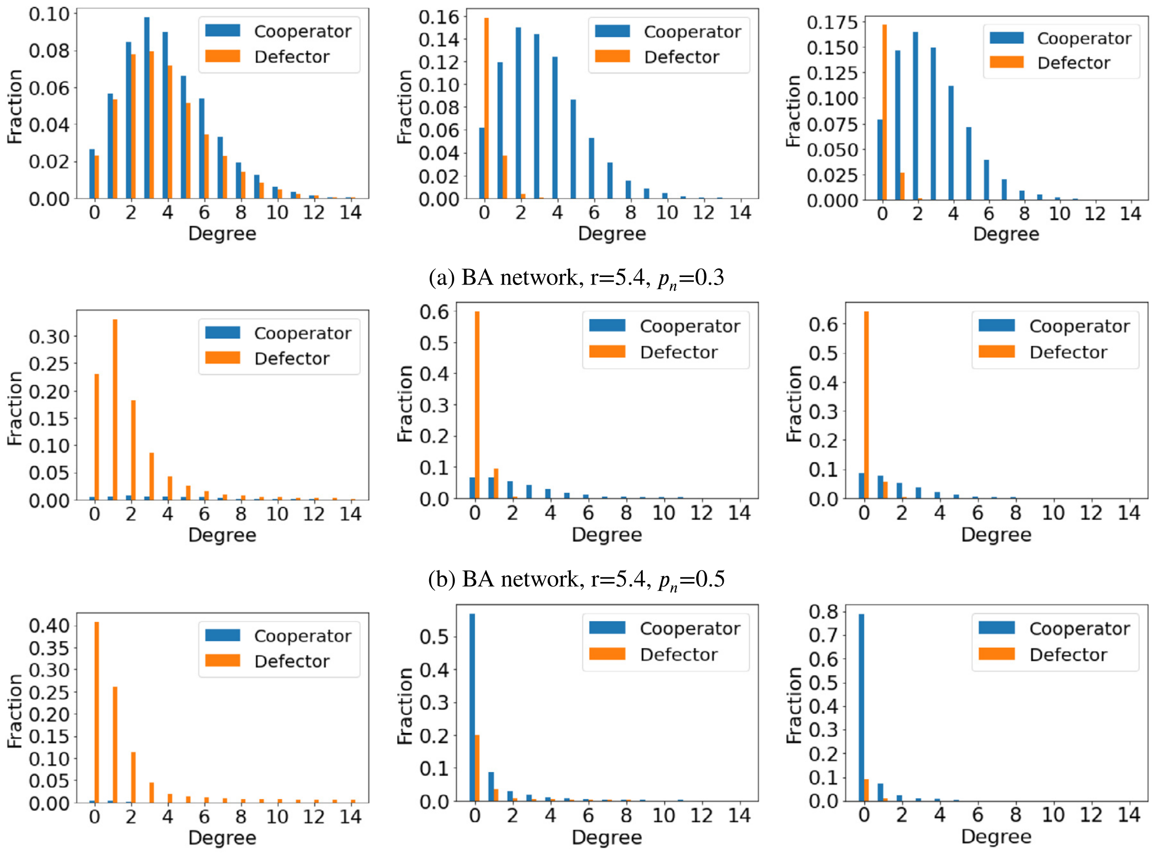
(c) regular network, r=5.4, p_n=0.75

Fig. 6. Degree distribution of cooperators and defectors. Sampling was conducted on various parameter combinations and at different time points, representing the early, middle, and end stages of evolution. Specifically, we took the 100th, 300th, and 500th steps of evolution to serve as representatives of these three periods on the regular network. The evolution of the early stage is depicted in the left line graph, while the middle and right graphs display the degree distribution at the middle and end stages of evolution, respectively. In these graphs, the blue bars indicate the degree of cooperators, while the orange bars represent the degree of defectors.

the start, the defectors almost occupy the whole network, and a power-law distribution structure is formed in the network, reaching the low point of cooperator proportion in the evolution process shown in Fig. 2. Then, as the number of C–D links maintains at a low level as shown in Fig. 4, defectors are gradually turned into cooperators, but the isolation status of a large number of nodes does not change. We can see a large number of cooperators are invaded by defectors in the early stage of evolution, but the few surviving cooperators turn a large number of defectors into cooperators one by one with a small number of edges that do not change the overall structure of the network. C–D links are just in the right small quantities, to keep the cooperators safe while giving them a chance to change the status of the network.

Under the condition that the neighborhood payoffs are widely considered, cooperators dying fast on the network because of their attraction to defectors, even if the initial cluster of partners can be formed, it will be quickly invaded due to the larger vision of policy replication, until most of the nodes in the network are quarantined then they form protection to cooperation, leaving a small amount of cooperators cluster. Then, the newly established links between cooperators and those isolated individuals will be very unstable. Each individual chooses their environment by reference to the other's profit, those isolated individuals are very difficult to connect with, even if it is connected, there is only a small amount of neighbors who can create very low earnings for it. That makes defectors stay naturally on the edge of the cooperator cluster, it is difficult for them to spread their strategies and in turn, they are gradually assimilated by cooperators.

Moreover, we examine the robustness of our results on the network size of different parameter combinations. We set $r = 5.4$ on both Regular networks and BA networks and choose p_n values of 0.3, 0.5, and 0.75, as shown in Fig. 8. From the figure, we can observe that compared to the regular network, the results on the BA network are more unstable to the network size, but there is no obvious trend of change. On the regular network, when p_n is 0.3 and 0.75, the fraction of cooperation is almost unaffected by network size. Still, when p_n is 0.5, there is a clear downward trend in cooperation fraction with increasing network size. Although the cooperation fraction is almost unaffected by network size in most cases, when the strength of individual consideration of neighborhood payoff is moderate, the level of cooperation achieved

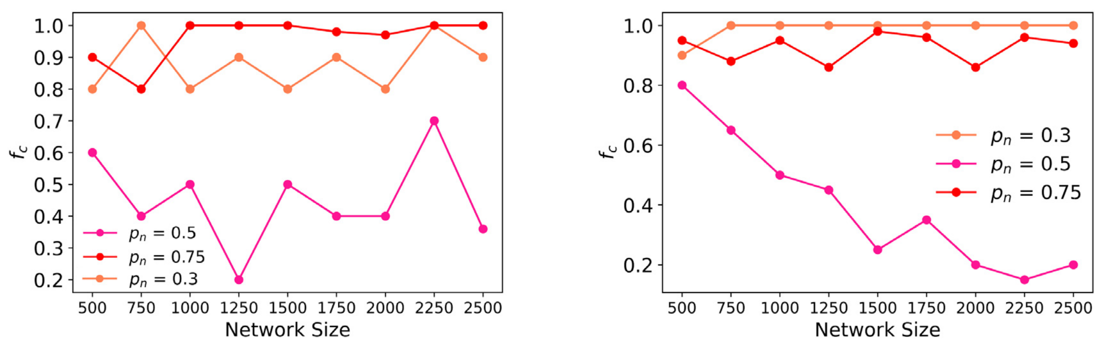


(a) BA network, r=5.4, p_n=0.3

(b) BA network, r=5.4, p_n=0.5

(c) BA network, r=5.4, p_n=0.75

Fig. 7. Degree distribution of cooperators and defectors. Sampling was conducted on various parameter combinations and at different time points, representing the early, middle, and end stages of evolution. Specifically, we took the 100th, 300th, and 500th steps of evolution to serve as representatives of these three periods on the BA network. The evolution of the early stage is depicted in the left line graph, while the middle and right graphs display the degree distribution at the middle and end stages of evolution, respectively. In these graphs, the blue bars indicate the degree of cooperators, while the orange bars represent the degree of defectors.



(a) Regular network

(b) BA network

Fig. 8. The proportion of cooperators changes with the network size. The cooperation fractions at the stable state of evolution on the Regular and BA networks changes with the network size for different values of p_n are shown in these two figures. In both figures, $r = 5.4$, the red, pink, and yellow colors represent the cases where p_n is 0.75, 0.5, and 0.3, respectively.

by the network at the stable state of evolution decreases with network size. While the cooperation fraction guided by some parameter combinations may vary with network size, the cooperation fraction at p_n values of 0.3 and 0.75 are higher than that at p_n=0.5 at all network sizes, and the cooperation level on the regular network is slightly higher than that on the BA network when p_n is 0.3 and 0.75. This is consistent with our previous results, indicating that our results are somewhat robust to network size.

4. Conclusions and outlook

In this paper, considering individuals' self-identity recognition, we propose a network adaptive rule based on individuals' neighborhood profits so that the individuals can choose their environment from the perspective of personal identity, and we make them learn the game strategies from second-level neighbors, who are likely to face a more similar situation to them. Different from the previous studies, the neighborhood payoff model in our research grants individuals a larger strategy learning radius and considers a group rather than an individual during rewiring the edges, which broadens the information scope for decision-making in the network. This provides individuals with a new and fair way to pursue their payoffs and increases the step size of strategy propagation. Compared with previous research, our work makes strategies more easily mixed, and our results demonstrate the cooperation evolution of individuals in a dynamic environment with an indirect learning perspective and faster strategy mixing speed. In the simulation, we study the cooperator sensitivity to the parameters p_n and r, and we observed the details of network topology changes during the evolution, we discovered two ways that p_n the probability of using the neighborhood profit edge-swapping rule can promote the cooperation. When individuals have less consideration for the neighborhood profits, there will be a certain tendency to isolate defectors, which protects the cooperators and gradually centralizes the edges owned by the defectors into the cooperative community, forming a cooperative cluster. In the end, a large number of defectors are isolated on the network, and cooperator clusters tend to be randomly distributed, the degree distribution of the whole network turns into a power-law distribution. When the value of p_n is in the middle, defectors will invade faster, making cooperation harder. When p_n is bigger, the invasion of defectors will be even faster, but a very small number of cooperators will survive, and because most of the other individuals in the network are isolated at this time, their low neighborhood profits make their connection with the existing cooperator cluster very unstable, and their sparse number of neighbors also makes their payoffs very low, so that their strategies are very difficult to spread and gradually assimilated by the partners. In this case, a high p_n plays a significant protective role in the ratio of cooperators. The size of p_n determines the extent to which the surviving cooperators can transform the other nodes in the network, but different from the case that p_n is small, most nodes on the network are isolated from the beginning and remain isolated until the end, even if the final cooperation level of the network can be maintained after transformation.

In previous studies, the impact of parameters on cooperation was mostly singular, with moderately less attention paid to the separation of topological properties between different individuals, and the coupling between the evolution of degree distribution and cooperation. In our study, we observed different impacts of the same parameter on cooperation within different ranges of its values and the emergence of different network degree distributions that led to the same cooperation. All of these provided an abundant picture of cooperation evolution and analyzed it from the perspective of changes in the topological properties of different strategic individuals, which is what sets our study apart. The collapse and protection of cooperation observed in simulations may reveal a form of natural protection to the cooperation that exists when the self-interest tendencies of the individual are high. And true nature may be in such a conversion between high p_n and medium p_n. When the group falls into a crisis of trust, the independent cooperation of a few individuals becomes the model of the group, and the cooperative behavior is carried forward again. However, when the group cooperation is good, the individual's vigilance becomes less, and the choice of environment is more random, leading to the situation of medium p_n and the crisis of trust occurs again. Such a process may be repeated in nature. Another important point is that in the simulation, the network structure in this process always presents a scale-free characteristic, which is consistent with reality to some extent. Therefore this structure adapting rule based on neighborhood profit may imply one of the reasons for the scale-free structure of social networks in the real world.

In our work, each individual has equal opportunity and speed in updating strategies and edges. However, if we make individuals update edge and strategy at different speeds and opportunities, or make individuals consider the degree of similarity between themselves and their counterparts when updating strategies, different evolutionary results may be obtained. Eventually, this research reveals the evolution of cooperation by network adaptive and self-identity recognition and explains the behavior of self-organization and self-adaptation in competitive games, we hope that our research will promote research of the conditions and forms of cooperation in groups and provide some guidance for addressing the social dilemmas.

CRediT authorship contribution statement

Yichao Yao: Designed and performed the research, Wrote the paper. **Bin Pi:** Designed and performed the research, Wrote the paper. **Ziyan Zeng:** Designed and performed the research, Wrote the paper. **Minyu Feng:** Designed and performed the research, Wrote the paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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