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RESEARCH ARTICLE

Evolution of innovative behaviors on scale-free networks

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Innovation, which involves technological transformation and management reorganization, brings about significant changes in modern society. In this paper, to investigate how innovations can be promoted, we propose a game-based model to study the co-evolutionary dynamics of human innovative behaviors. A simulation on scale-free networks is conducted, in which the innovative behavior of each node is determined and updated based on the feedback regarding its innovation, namely the diffusion of the innovation status. Numerical simulations of the model generate a series of patterns, which is consistent with people's daily experiences and perceptions as regards real-world innovative behaviors. Specifically, various scaling spatiotemporal properties and rich structural impacts on dynamics can be observed. This model provides a novel approach to understand the evolution of innovative behaviors and provides insight for strategy studies of innovation promotion.

Keywords innovative behaviors, innovation diffusion, evolutionary game, coevolution dynamics, scale-free networks

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1 Introduction

Studying the macroscopic phenomenon of a complex system by investigating microscopic mechanisms is a popular physical paradigm. Human society is studied using physics theories [1–6] as well as the real world. In this paper, the evolution of innovative activities is studied. In general, only a few innovators can come up with significant breakthroughs, while others learn from innovators and develop improvements on a smaller scale. These features of innovative activities exist in a variety of fields in human society, such as production research and development and publication and propagation in social media. The complete process of innovation activities involves two stages: the emergence of innovative behavior, and the diffusion of innovation in which the innovation gives rise to technological and knowledge revolutions in society. The diffusion process has already been widely discussed from macro and micro perspectives [7–10], and several models based on various dynamics, such as percolation [11–13], cellular automata [14–16], Ising model [17], and Potts model [18], have been proposed. Recently, the complex networks theory has provided a new perspective to describe the relationship between agents. In other words, the process of innovation diffusion on complex networks [19–25] has been studied in detail.

However, the emergence process of innovative behavior is rarely discussed in previous studies. In general, there are two diverse behaviors during innovation activities: to take higher risks by exploiting a new technology or new idea, or to follow an existing achievement as the safe choice. Therefore, the innovative behavior explored in the view of a strategy choice can be studied by using an evolutionary game model [26, 27]. In an evolutionary game, one gains rewards based on one's own strategies as well as those of the neighborhood, and determines the next strategy according to the principle of profit maximum. The idea that profits drive evolutionary dynamics has been introduced into the research of innovation [28–31], opinion [32], and information diffusion process [33, 34].

The emergence and diffusion of innovation are closely related, so it is helpful to discuss the following problems that has been previously studied in the research of R&D (Research and Development): when and where innovation occurs, how agents respond to neighbors' innovations, and how the responses improve the technology level of the entire system. Many physical methods have been applied to several relevant scenarios. For instance, based on percolation theory, Silverberg *et al.* realized the emergence of innovation in complex technology spaces [35–37]. In 2011, Bornholdt *et al.* discussed the competition and coexistence of multi-opinions, attempting to approach the mechanism of scientific paradigms' development [38]. In this study, we combine the evolutionary game and innovation competitive diffusion to construct a game-based dynamics for innovative behavior [39], in which the behaviors of innovating or following are considered to be strategies of agents, and the evolutionary pattern of innovative frequency and statistical spatiotemporal properties, both related to innovative cost, are studied. Furthermore, in a previous study [39], to describe the social connection between agents, lattices with periodic boundary condition were commonly used, which could not reflect the fact that heterogeneous topology has a deep influence on network dynamics [40–43]. Therefore, we use a scale-free network instead of lattices to discuss how the heterogeneous structure impacts the evolution of innovation behaviors in the game-based model.

The rest of the paper is structured as follows. The game-based model of innovative behaviors on Barabási–Albert (BA) networks is described in Section 2. Section 3 describes the global patterns of the system. Section 4 discusses the heterogeneous behavior of agents with different degrees. Finally, Section 5 summarizes the results and presents concluding remarks.

2 The model

In a game-based model, for simplicity, agents hold binary strategies $S(I,F)$: to be innovators I or followers F. Innovators make significant progress themselves, while agents acting as followers make incremental improvements by following innovators. All participants consume costs C_i and receive rewards M_i in the game, where subscript i represents an arbitrary agent. In general, innovators pay a higher cost C_I than followers, and therefore we have $C_I = a > C_F = 1$, where a, the relative cost of innovation behavior (hereafter referred to as innovation cost or cost), is the main kinetic parameter in innovation game. Each agent, whether I or F, benefits from the diffusion range of its innovation. Specifically, when an agent's result is adopted by more individuals, it is considered to be more successful and consequently gains more rewards. As a result, the reward of agent i M_i is defined as the total number of agents whose innovation diffuses from agent i (including itself and its followers), i.e., the total number of agents on the propagation tree with the agent as the root. Therefore, the final payoff of agent i is set as the difference between its reward from the diffusion and cost of innovation:

$$P_i = M_i - C_i = \begin{cases} M_i - 1, & i \in F, \\ M_i - a, & i \in I. \end{cases} \tag{1}$$

In the basic model, the dynamics can be regarded as a combination of innovation diffusion and strategy decision. It has two timescales: the strategies synchronously-updating cycle t and the competing diffusion timescale τ, and each t contains multiple τ. In each cycle t, agents run a competing diffusion process [28, 44–47]. They synchronously decide their strategies of next cycle $t+1$ according to their respective payoffs $P_i(t)$ at the last time step in the current cycle t. That is to say, strategy updating is timed by cycle t, and the strategy of agent i during cycle t is recorded as $S_i(t)$. The innovation status of agent i is updated at step τ during cycle t, and is represented by $m_i(t,\tau)$. $m_i(t)$ represents the final innovation status of agent i during cycle t. The system evolves as follows:

i) At each step τ, an arbitrary agent i, whose innovation status has never been changed in the current cycle t, is chosen with the status $m_i(t,\tau) = m_i(t-1)$. Then i changes its innovation status according to its strategy $s_i(t)$: an I agent propounds a new innovation $m_i(t,\tau)$, while agent F attempts to learn from any one of his neighbors j. For F agent, there are two scenarios: if the innovation type of j is raised in current cycle t as $m_j(t) = m_j(t,\tau')$ $(0 \le \tau' < \tau)$, its innovation status updates to j's as $m_i(t) = m_i(t,\tau+1) = m_j(t,\tau') = m_j(t)$; if j has never changed its innovation in the current cycle t, the learning attempt fails and i maintains the status quo, with $m_i(t,\tau+1) = m_i(t,\tau)$.

ii) After the diffusion process, i calculates its payoff $P_i(t)$ and compares its own payoff against that of its neighbors, and then updates its strategy in the same manner as that of the winner (the agent k) who has the highest payoff as seen in the comparison. If more than one agent has the highest payoff, one of them is randomly picked as the winner. All agents update their strategies $s_i(t+1) = s_k(t)$ synchronously.

iii) When the two steps described above are complete, the system enters the next innovation–diffusion cycle with $t = t+1$ and $\tau = 0$, and repeats the above steps.

It should be noted that the innovation competing diffusion processes in different cycles t are independent: only an innovation raised during the current cycle can be learned by followers and spread abroad, and each agent updates an innovation successfully once. In this study, the BA model, with power law degree distribution which indicates high degree heterogeneity, is selected as the relationship network. Beginning with a tiny fully-connected network, a BA network with N nodes is established by adding a new node with m edges ($N \gg m$) into the network and following the preferential attachment rule when connecting. For $N \gg m$, we have the average degree of BA network $\langle k \rangle = 2m$. At $t = 0$, the strategies of agents are randomly set as I or F. In our study, we consider the first 1000 cycles from $t = 0$ to $t = 1000$ as the initialization phase, and all calculations and discussions are conducted after the initialization. Unless otherwise mentioned, the system stops evolving at $t = 3000$, the results are averaged over 20 independent networks, and each network begins at 20 independent randomly-set initial conditions. As the cycle t is more important than step τ in a dynamic study of an innovation game, the term "time" refers to cycle t in the following passages.

3 The global patterns

The number of innovators n_I evolves to a steady state with tiny oscillation in a short time. The average number of innovators as a percentage of total numbers of agents in steady state is defined as the innovative frequency of the system R_I. As shown in Figs. 1(a) and (b), R_I decreases as the cost a increases and the tail of the R_I curve is truncated for scale effect. We define the extinction probability of innovators p_{ex} as the probability that innovators completely disappear and all agents are followers in the system at steady state. From Fig. 1(c) we can see that p_{ex} increases with the rise of cost a, until agents are unlikely to be innovators $p_{ex} = 1$ beyond cost threshold a_c. As shown in Figs. 1(a) and (b), below the threshold $a \ll a_c$, the innovative frequency of the system R_I is insensitive to the size of system, and the relationship between R_I and a could be described as a power-law function $R_I(a) \propto a^{-\gamma}$ with $\gamma \approx 0.5$ [Fig. 1(b)]. Innovative frequency R_I in the system slightly rises with the increase of the average degree of the network $\langle k \rangle$ [Figs. 1(a) and (b)], whereas the cost threshold a_c is considerably reduced [Fig. 1(d)].

In general, the innovation cost a and the average degree $\langle k \rangle$ of a BA network have a significant impact on the dynamics of the model, whereas the influence of network size N on the system can be ignored. Because each neighbor has an equal opportunity to be the innovation provider in our model, the innovation is easier to promote an innovation from the innovator with higher degree $\langle k \rangle$. For this reason, the global innovative frequency R_I increases slightly with the rise of the average degree $\langle k \rangle$ on the condition of $a \ll a_c$ [see Figs. 1(a) and (b)]. Meanwhile the reward M is concerned with network size N: with fixed N, if the innovative frequency

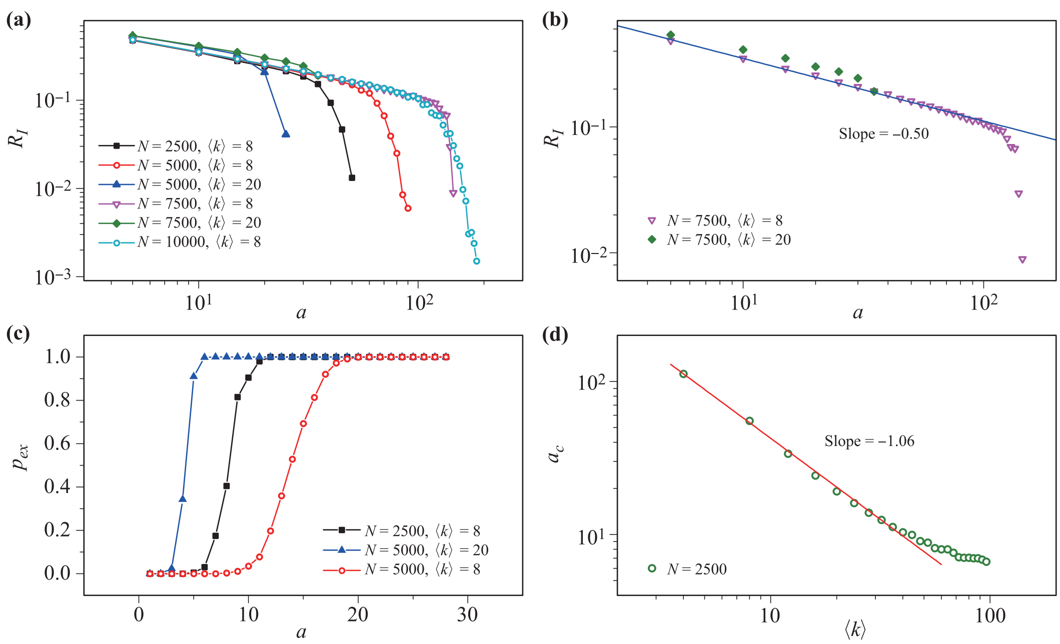

Fig. 1 **(a)** The average innovative frequency R_I vs. the innovation cost a, which obeys a scale-free behavior $R_I(a) \propto a^{-0.5}$ below the threshold [see Fig. 1(b)]. **(c)** The extinction probability of innovators p_{ex} vs. innovation cost a. **(d)** The cost threshold a_c vs. the average degree $\langle k \rangle$ of BA network, where the rad line denotes relationship $a_c \propto \langle k \rangle^{-1.06}$, which is obtained by the average over 200 independent runs respectively on 20 independent networks.

R_I is upgraded, i.e. the number of innovators increases, the average reward falls, which is a significant disadvantage to innovators in competition with followers. This is the reason that cost threshold a_c declines while $\langle k \rangle$ rises [see Fig. 1(d)]. In addition, when $\langle k \rangle$ increases, there are more strategy learners from one agent causing more frequent changes in an individual's strategy: the shorter the internal of I strategy adoption is, the faster I strategy diffuses during the early evolution of the system. Compared to network average degree $\langle k \rangle$, innovation cost a drastically affects the dynamics of the system. In the case with higher cost a, fewer agents can be innovators (Fig. 1), owing to the higher reward needed to pay higher cost a for the sake of maintaining the existence of innovators.

Each innovation put forward by innovators is promoted by followers. At the end of each cycle t, the ratio of the final diffusion scope S_I of disparate innovation is different because of the competition among them. The distribution of S_I is ruled by stretched exponential distribution $p(S_I) \propto C\exp(-\alpha S_I^{\beta})$, and is strongly influenced by the cost a, slightly affected by the average degree $\langle k \rangle$ of BA network, and generally insensitive to network size, as shown in Fig. 2. The stretched exponential distribution is mixed by power-law and exponential function, and becomes more analogous to power-law pattern when β falls. Ref. [39] has mentioned that this dynamic on lattices with periodic boundary condition shows quasi-localized property with a bimodal distributed S_I mixed by a power law head and a Poisson tail, considering the conclusion of Ref. [46] that the emergence of power-law-like property would be relevant to the criticality in the competing diffusion process. For the same reason, Fig. 2 shows that the quasi-localized property still exists in innovation dynamics on BA networks.

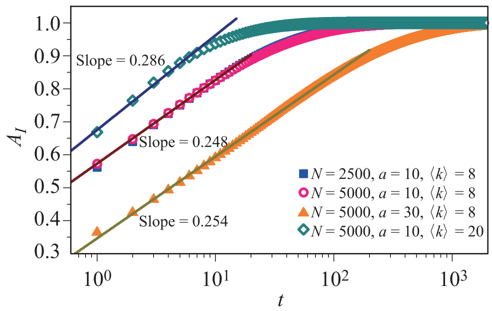

Fig. 3 The growth of the visited area of I strategies. The straight lines in the figure indicate the logarithmic function $A_I = \gamma \ln t$ with $\gamma = 0.286$, $\gamma = 0.248$, $\gamma = 0.254$.

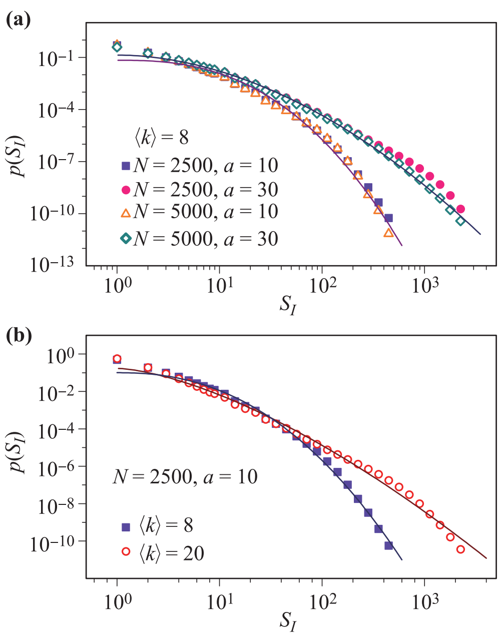

Fig. 2 The log-binning distributions $p(S_I)$ of innovators' innovation diffusing scope S_I. The curves in both figures indicate the stretched exponential distribution $p(S_I) \propto C\exp(-\alpha S_I^{\beta})$. The fitting parameters in panel **(a)** respectively are $\alpha = 0.20$, $\beta = 2.58$ when $N = 5000$ and $a = 10$; and $\alpha = 0.44$, $\beta = 1.90$ when $N = 5000$ and $a = 30$. The fitting parameters in panel **(b)** respectively are $\alpha = 0.32$, $\beta = 2.30$ when $\langle k \rangle = 8$; $\alpha = 0.91$, $\beta = 1.53$ when $\langle k \rangle = 20$.

At the end of each cycle t, agents adjust strategies by social learning. The growth of the visited area of I strategies, namely the percentage of agents who have ever been innovators, is shown in Fig. 3, where the slope of the tangent reflects the speed of diffusion of I strategies: the sharper the slope, the higher the speed. Differing from the lattice case, which has a slow diffusion of I strategies $A_I \sim t^{\gamma}$ (constant $\gamma < 1$, dependents on system parameters), I strategies spread at a fairly fast speed on the BA network with $A_I \sim \ln t$, at the beginning. However, the speed falls sharply to almost zero after some time owing to the scale effect, and is then nearly invariable for a long time. The spread process is not affected by system size N, but the spreading speed increases with the growth of average degree $\langle k \rangle$ and reduces with the growth of cost a.

The cumulative distribution $p_c(t_{dI})$ of duration t_{dI} as an innovator and the cumulative distribution $p_c(t_I)$ of time intervals t_I between each two consecutive adoptions of I strategy of an agent both obey the scaling property under the influence of cost a and average degree $\langle k \rangle$ rather than network size N (see Fig. 4). As the cost a grows, the interval t_I becomes longer [Figs. 4(a) and (b)], and meanwhile the persistence of I strategy t_{dI} drops (Figs. 4(c) and (d)). Both the interval t_I and duration t_{dI} decline along with the increase of average degree $\langle k \rangle$ [Fig. 4].

Hub nodes in BA networks usually earn large rewards because they have a higher probability of diffusing their

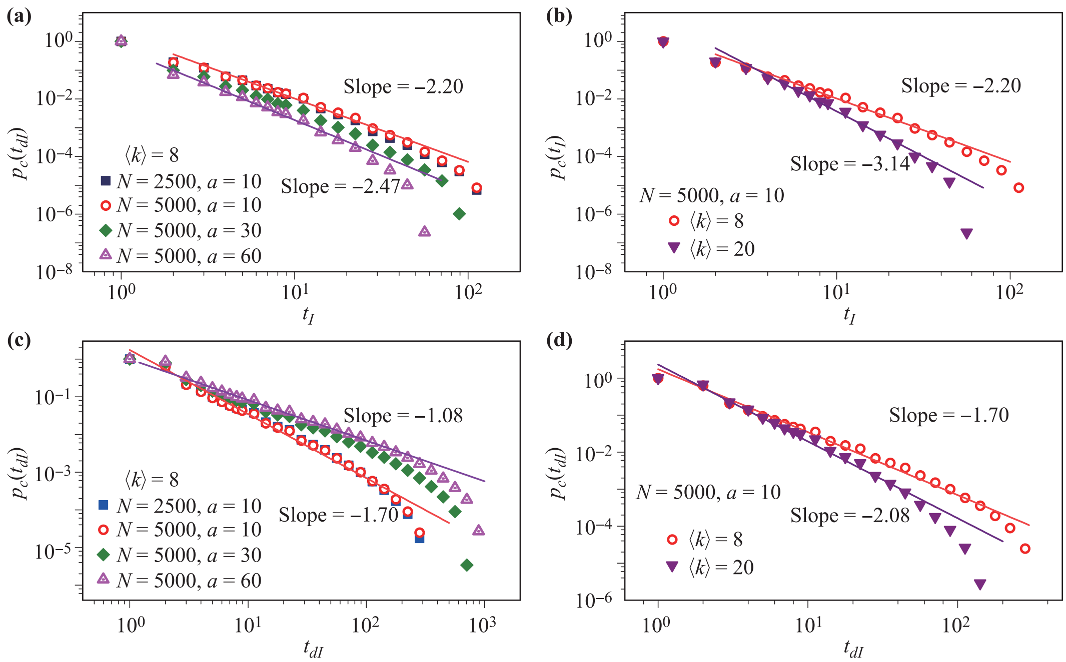

Fig. 4 Panel **(a)** and **(b)** respectively is the cumulative distribution $p_c(t_I)$ of time intervals t_I between each two consecutive adoptions of I strategy. The straight lines indicate the scale-free property with exponent, respectively. −2.20, −2.47 and −3.14, respectively. Panel **(c)** and **(d)** respectively is the cumulative distribution $p_t(t_{dI})$ of duration t_{dI} as an innovator. The straight lines indicate the scale-free property with exponent −1.08, −1.70 and −2.08. All the data are log-binning form.

innovation to their neighbors. Lowly-connected nodes amongst the neighbors of hub innovators tend to be innovators in the next cycle on account of hub innovators' large rewards, but they struggle to keep at being innovators for their uncompetitive innovation diffusion, and thus a considerable number of followers is ensured for hub nodes to generalize their innovation. While the cost a grows, along with the increasing ratio of followers, the duration of hub nodes staying as innovators increases with more rewards, and the others' diffusion opportunity and the duration of being an innovator reduces (Fig. 4). In other words, nodes with different degrees act differently in the dynamics. In the next section, further discussions on the heterogeneous behavior of agents with different degrees is carried out.

4 The heterogeneity in individual level

To investigate the differences on the role in the dynamics of the model for agents with different degrees, we first plot the distribution of the proportion of the innovators for different degree values:

$$\rho_I(k) = \frac{N_I(k)}{N}. \tag{2}$$

Fig. 5 shows that this distribution follows power law written as $\rho_I(k) \propto k^{-\gamma}$, and the distribution is insensitive to the cost a [Fig. 5(a)] and network size N [Fig. 5(b)]. It is important to emphasize that the value γ is less than 3, the value of power exponents parameter of degree distribution of the BA network, indicating that hubs have more potential to be innovators. From Fig. 5(d), the parameter γ tends to increase along with the average degree $\langle k\rangle$, implying that the difference between hubs and lower-degree agents tends to reduce.

This difference is more evident in the innovative frequency of agents for different degrees. Defining the number of agents with degree value of k is $N(k)$, the innovative frequency $R_I(k)$ of an agent with degree k is

$$R_I(k) = \frac{N_I(k)}{N(k)}. \tag{3}$$

As shown in Fig. 6, the pattern $R_I(k)$ increasing with k generally follows a logarithmic-like form of $R_I(k) = \gamma\ln(k+\omega)+c$ accordant to the corollary of Fig. 4. And also, $R_I(k)$ goes down along with the rising of innovation cost a or average degree $\langle k\rangle$ no matter what value the degree k is. This phenomenon also echoes the global pattern shown in Figs. 1(a) and (b).

The average diffusion scope $S_I(k)$ of every innovation put forward by innovators with degree k is an increasing function of k and behaves approximately in a stretched-exponential format manifesting a mixed power-law and exponential nature, presenting significant heterogeneity (Fig. 7). Under the tough surviving situation of innova-

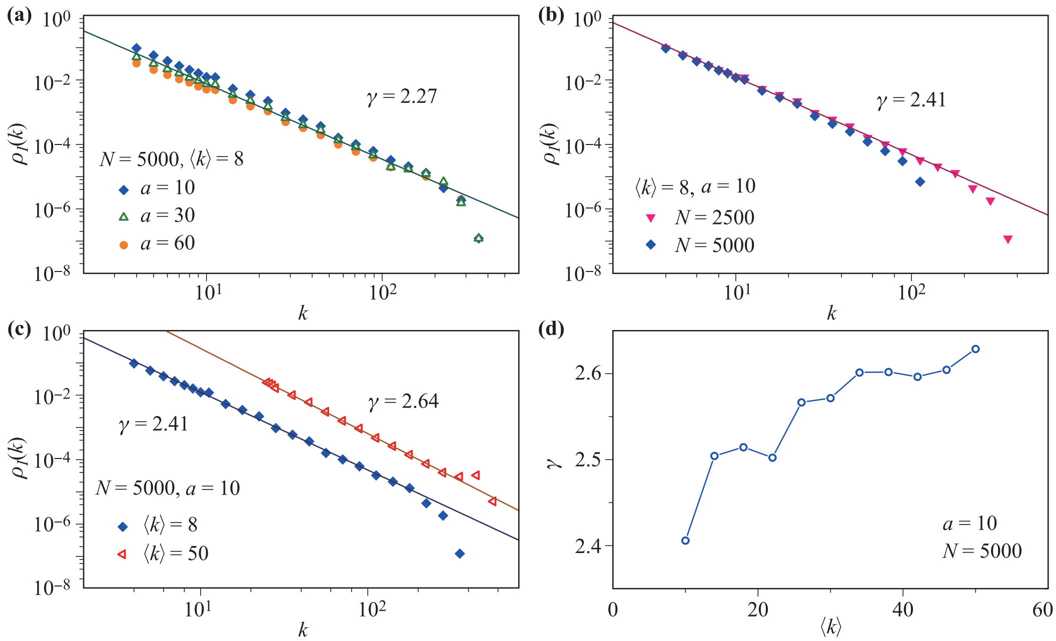

Fig. 5 The proportion of the innovators with degree value of k in the system, which obeys $\rho_I(k) \propto k^{-\gamma}$. **(a)** The line is the result fitting by data with $N = 5000$, $\langle k \rangle = 8$, $a = 30$. **(b)** The line is the result fitting by data with $N = 2500$. **(d)** The behavior parameter γ changing with average degree $\langle k \rangle$. The data in (a), (b), (c) are log-binning form.

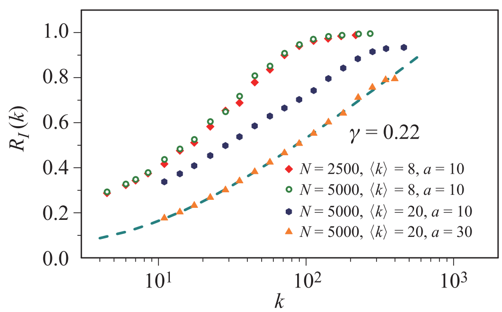

Fig. 6 The innovative frequency $R_I(k)$ of agents vs. the degree k of agents. The data points are in log-binning form. The dotted line shows the fitting function $R_I(k) = \gamma \ln(k + \omega) + c$, where $\gamma = 0.22$, $\omega = 10.18$, $c = -0.49$.

tors when innovative cost a is expensive, higher-degree innovators gain wider average diffusion scope $S_I(k)$ of innovation by changing more lower-degree innovators into followers for their reduced $S_I(k)$. This simulation result is concordant to the analysis in Section 3. When $\langle k \rangle$ grows, as the number of innovators increase [Figs. 1(a) and (b)], $S_I(k)$ of all agents declines [Fig. 7(b)].

To further demonstrate the behavior heterogeneity among nodes with different degrees, the separate distributions $p(S_I(k))$ of the average diffusion scope $S_I(k)$ of every innovation put forward by innovators with different degrees k are examined (see Fig. 8). With a view to the considerable degree heterogeneity in BA networks, we split range $(0, \ln(k_{\max})]$ into three approximately equal parts and divide the nodes into three classes: if $N = 5000$ and $\langle k \rangle = 8$, we have nodes whose degree $k \leq 10$ as low-degree nodes, $10 < k \leq 50$ as medium-degree nodes, and $k > 50$ as high-degree nodes. The distributions of three classes of innovation diffusion scope are separately plotted (see Fig. 8), in which the fitting stretched-exponential form with a small β presents fair power-law property. As the rewards are calculated by diffusion scope and the total reward of the system is equal to the size of the network, the competition among innovators is intense, leading to the scale-free ingredient of the curve, which mirrors the range correlation of innovators [46]. The result confirms that the quasi-localized property does not disappear in the case on BA networks.

The strategy-altering probability p_a of agents is a non-monotonic function of degree k, as show in Fig. 9. The probability goes up along with the growth of degree until it reaches a peak and then goes down, and it is fitted by a Giddings function where μ represents the center of the peak:

$$p_{\mathrm{a}} = p_{\mathrm{a}}^0 + \frac{A}{\omega}\sqrt{\frac{\mu}{k}} I_1\left(\frac{2\sqrt{\mu k}}{\omega}\right) \mathrm{e}^{\frac{-k-\mu}{\omega}}. \tag{4}$$

Combined with the knowledge from Fig. 6 that innovation frequency $R_I(k)$ grows sharply with degree, a picture of the dynamics on scale-free network is obtained: lower-degree agents and medium-degree agents prefer to retain the status of being followers and fence-sitters re-

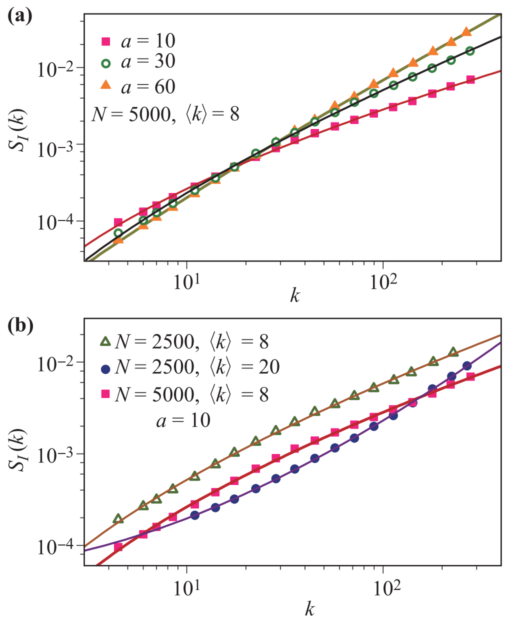

Fig. 7 Diffusion scope $S_I(k)$ of innovators' innovation vs. degree k of nodes. All the data are log-binning form. The curves in both figures indicate the stretched exponential function $R_I(k) \propto C\exp(-\alpha k^{\beta})$. The fitting parameters are: in panel **(a)**, when $a = 10, 30, 60$, α respectively is $0.38, 3.01, 2.08$, and β respetively is $0.54, 0.67, 0.86$; in panel **(b)**, $\alpha = 2.84$ and $\beta = 0.60$ when $N = 2500$ and $\langle k \rangle = 8$, $\alpha = 0.29$ and $\beta = 1.65$ when $N = 2500$ and $\langle k \rangle = 10$, $\alpha = 3.38$ and $\beta = 0.54$ when $N = 5000$ and $\langle k \rangle = 8$.

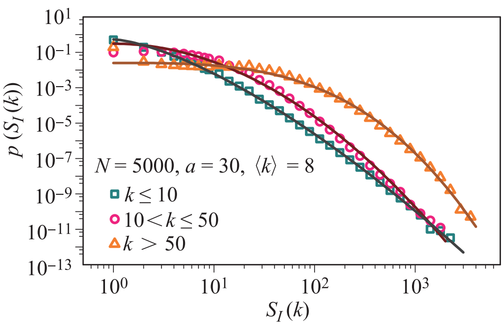

Fig. 8 The distribution $p(S_I(k))$ of innovation's diffusion scope $S_I(k)$ for innovators with degree k. The data points are in log-binning form. The fitting curves indicate the stretched exponential distribution $p(S_I(k)) \propto C\exp(-\alpha S_I(k)^{\beta})$. The fitting parameters respectively are: $\alpha = 1.32$ and $\beta = 1.46$ when $k \le 10$; and $\alpha = 0.46$ and $\beta = 1.99$ when $10 < k \le 50$; and $\alpha = 0.02$ and $\beta = 3.25$ when $k > 50$.

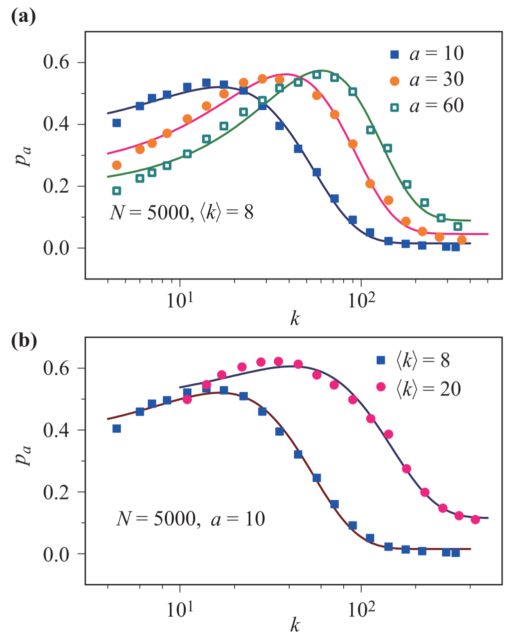

Fig. 9 The strategy-altering probability of agents with degree value of k. The data points is in log-binning form and fitted by Giddings function Eq. (4). Fitting parameters respectively are $\mu = 34.62, 61.43, 86.87$ when $a = 10, 30, 60$ for panel **(a)**, and $\mu = 34.62, 92.92$ when $\langle k \rangle = 8, 20$ for panel **(b)**.

spectively, and hub agents are frequently to be innovators and lack the will to change their strategies. For the case with higher cost a, a higher reward is needed for the survival of innovators, and therefore, a higher number of lower-degree agents have to be followers, the number of fence-sitters increases, and hub agents' ability of maintaining their innovation strategy also diminishes, which is reflected in the higher frequency of strategy updates. As the lower-degree agents are apt to be followers, the I strategies are difficult to diffuse at the end (Fig. 3).

In this section, we discuss the patterns of individual behavior brought about by heterogeneous degree distributions. Attributable to disparate node degrees, the competitive ability of innovation is different, and consequently the reward coming from innovation's spread is different. Therefore, agents with different degrees favor different strategies.

5 Conclusions

By combining evolutionary game and competitive diffusion, we established the evolution of innovative behaviors on a scale-free network with high node degree heterogeneity. The relatively higher cost of innovative behaviors, and the rewards of innovation diffusion, are the basic assumptions of the model.

Based on the simulation results, rich statistical phenomena of innovation behaviors are observed, on the global as well as individual level, including a series of non-Poisson spatiotemporal patterns (e.g., time intervals between consecutive adoptions of I strategy, duration as

I strategy, and innovation diffusing scope). More importantly, the innovation cost a considerably impacts all the spatio-temporal patterns of innovation behavior. Furthermore, some interesting properties concerned with the hierarchical structure are observed. One is the existence of the heterogeneity of innovation diffusion scope, indicating that hub innovators can gain much more than low-degree innovators and are usually more resilient to the change of innovation cost. Another observation is the difference between strategy selection for hubs and lower-degree nodes: hubs tend to be innovators, low-degree agents tend to be followers and medium-degree are fence sitters, especially in an environment with higher cost a.

Compared with traditional evolutionary games, neither the complete reciprocity among cooperators, nor the complete opposition between cooperators and betrayers, exists in our model. There are two reasons for this. First, innovators not only compete with but also depend on followers. As the cost $C_I > C_F$, innovators should earn more than followers to survive. At the same time, as the reward of agent i comes from followers learning from it directly or indirectly, their own reward is limited by the proportion of followers. Second, innovators also compete with and depend on each other: innovators compete with each other to attract followers in the diffusion of innovation, and correlate to other innovators through social learning of strategies between neighbors. Thus, the relationship between innovators leads to special dynamics compared to traditional evolutionary game theory, reflected in the impact of average node degree $\langle k \rangle$ on the ratio of innovators: with a lower cost a, owing to the social study of strategy, the increase of $\langle k \rangle$ improves the proportion of innovators; nevertheless, the population growth of innovators causes the average reward to drop, leading to the reduction of robustness to cost a, whence a_c is significantly reduced as $\langle k \rangle$ grows [Fig. 1(d)].

In summary, the motivation of human innovation is considered in our model, to investigate the co-evolution dynamics between innovation diffusion and emergence of innovation behavior. The simulation results are consistent with people's daily experiences and perceptions with regards to innovative behaviors, implying that the underlying mechanisms are efficiently captured by the model. Furthermore, our model provides a novel framework that is likely to be useful in further studies on innovative behaviors and strategies for innovation promotion.

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