Applied Mathematics and Computation 496 (2025) 129364

Contents lists available at ScienceDirect

Applied Mathematics and Computation

journal homepage: www.elsevier.com/locate/amc

Full Length Article

Evolutionary games for cooperation in open data management

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ARTICLE INFO

Keywords:
Open data management
Evolutionary games
Social dilemmas
Cooperation
Complex networks

ABSTRACT

In the era of big data, open data has become a critical factor in production. To establish a stable and long-term open data management mechanism, we investigate the evolution of cooperative behaviors in open data management based on networked evolutionary games, where complex networks are used to model the interaction structure between open data managers and game theory is employed to illustrate the social dilemmas faced by these managers. In addition, we account for the dynamic nature of social dilemmas in the interactions between managers, recognizing that the dilemmas they encounter are not static but rather evolve over time. To model this, we use different game models to represent various social dilemmas and propose social dilemma transitions to capture the evolving dilemmas faced between open data managers. In our simulations, we explore how payoff parameters and transition rates influence the emergence and sustainability of cooperation across different population structures, finding that both factors play a significant role in the evolution of cooperation. Furthermore, the cooperative evolution dynamics is analyzed on a square lattice network with periodic boundaries from a microscopic perspective. We also study the influence of different patterns of social dilemma transition on the evolution of cooperation. The findings presented in this paper may offer valuable insights for open data managers, helping them make informed decisions, and fostering the evolution of cooperation within open data management systems.

1. Introduction

With the rapid advancement of information technology, data has become a crucial resource for driving social progress and national development [1]. Open data, an emerging concept in data management, refers to data that is freely accessible, usable, and shareable by anyone. Typically released in structured formats that facilitate machine processing and analysis, open data promotes transparency,

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https://doi.org/10.1016/j.amc.2025.129364
Received 8 January 2025; Received in revised form 12 February 2025; Accepted 14 February 2025

sharing, and unrestricted access [2,3]. Its primary goal is to dismantle information silos, foster the dissemination and application of knowledge, and enhance transparency and public participation in governance, business, and society. The opening and proactive utilization of diverse data sources, including government and enterprise data, can unlock vast economic and social potential, providing significant impetus for the development of the digital economy, digital culture, and digital society [4].

Open data provides startups and developers with a wealth of resources that can drive innovation in new products and services. By analyzing open data, companies can identify market needs and develop more competitive solutions. Besides, open data enhances the transparency of governments and organizations, thereby increasing public trust in policy-making and decision-making processes. Providing access to detailed data on environmental, financial, and social issues, among others, enables the public to gain a deeper understanding of government operations [5]. As such, open data plays multiple roles in modern societies and carries significant social, economic, and political implications. Furthermore, open data has broad applications across various sectors, including transportation [6,7], government [8,9], and environmental management [10,11]. For instance, in traffic management and urban planning, analyzing traffic flow data allows city managers to optimize traffic signals and public transportation routes, improving the overall efficiency of urban systems. In environmental protection and monitoring, the release of data on water resources, meteorological conditions, and air quality indices empowers the public to understand environmental issues better and supports sustainable development initiatives.

Despite the numerous benefits of open data, its implementation still faces several challenges [12,13]. As the information age progresses, concerns about privacy protection are becoming increasingly prominent [14]. The release of open data must carefully consider personal privacy and data security, making the prevention of sensitive information leakage a critical aspect of open data management. Moreover, the quality of open data directly influences the effectiveness of its use [15], with accuracy, completeness, and timeliness being essential factors to ensure its utility [16]. A comprehensive open data management system must be established to drive the development of the digital economy, digital culture, and digital society. In this context, open data managers play a crucial role, alongside data providers and users [17]. These managers, who may include personnel from specialized management agencies, government staff, or even members of the public, have the option to engage in the management of open data. When deciding on their strategies for whether or not to participate in the management of open data, they evaluate their payoffs through a learning mechanism, continually adjusting their strategies until they identify the most favorable one, which is a dynamic game process. In addition, since not all open data managers interact directly with each other, and interactions typically occur with neighboring managers, complex networks offer an ideal framework to model these interactions [18,19]. In this framework, nodes represent open data managers and edges capture the interactions between different managers.

Networked evolutionary games, which combine complex networks with evolutionary game theory [20,21], provide an effective framework for modeling the relationship between open data managers and their decision-making processes through learning mechanisms. It provides a powerful tool for studying the emergence and maintenance of various self-organizing behaviors in both natural and social systems [22], attracting attention from researchers across a variety of fields, including biology [23,24], physics [25,26], mathematics [27,28], computer science [29,30], and so on [31–33]. Many scholars have applied networked evolutionary games to explain the mechanisms behind the emergence of widespread cooperative behaviors and have identified factors such as conformity [34,35], reward [36,37], and game transitions [38,39] as key drivers in this process. In addition, evolutionary games have recently been utilized to analyze strategic behaviors in the development of artificial intelligence and the adoption of new technologies [40–42], demonstrating their significant role in applications within the era of artificial intelligence and data science. Besides, many researchers have employed the powerful framework of networked evolutionary games to study various real-world management problems. For example, Song et al. [43] investigated the decision-making processes of participants in the collaborative air pollution management network based on networked evolutionary games and proposed countermeasures to address the synergistic effects of air pollution caused by regional heterogeneity. Kong et al. [44] developed an evolutionary game model to examine knowledge-sharing behavior within cluster innovation networks. They explored how bounded rational firms can achieve evolutionary equilibrium through continuous adaptive learning and strategy optimization, and further analyzed the factors influencing evolutionary trajectories. Xu et al. [45] constructed an evolutionary game model for marine plastic waste management, applying networked evolutionary games to investigate the impact of economic factors, relational structures, and game configurations on the evolution of management cooperation in marine plastic waste through simulation techniques.

In this paper, we utilize this powerful framework to explore cooperative behaviors in open data management. Specifically, the participation of open data managers in the management process is considered cooperative behavior, while non-participation is regarded as defective behavior. Recognizing that the social dilemmas faced between open data managers are not static, we propose an innovative mechanism for social dilemma transitions. Concretely, the duration of the social dilemma faced between managers follows a certain distribution, and once the duration is over, they will be faced with another different type of social dilemma. Through extensive simulations, we investigate the impact of this mechanism on the managers' participation in open data management. The purpose of this paper is to analyze open data management using networked evolutionary games, contributing new insights to the field and offering a clear direction for promoting the green development of open data.

The structure of the rest of this paper is as follows. In Section 2, we present a detailed explanation of the model for open data management incorporating social dilemma transitions. In Section 3, we conduct extensive simulations and analyses to assess the impact of the proposed model on cooperative behaviors in open data management. Finally, in Section 4, we summarize the key findings of this study and outline potential directions for future research.

2. Model

In this section, we present a comprehensive description of the model for cooperative behavior in open data management, employing the framework of networked evolutionary game theory. This section is organized into three main parts: Model Description, Social Dilemma Transition, and Payoff Calculation and Strategy Update.

2.1. Model description

In practice, open data managers do not interact with all other managers in the population but typically engage with their neighboring managers. To accurately capture this phenomenon, we employ complex networks to model the interaction structure among managers. In this framework, nodes represent managers and edges indicate the interactions between them.

The management of open data can be considered a public good, akin to social security, which is subject to free-riding behavior in cooperative settings. If open data managers opt not to participate in the management process, they can avoid the costs associated with participation. However, this choice also means they forgo potential benefits, such as an enhanced public reputation, which ultimately harms society as a whole. In contrast, if all open data managers choose to participate, they will gain greater rewards through the sharing of skills and experiences, benefiting both the market environment and society at large. Moreover, the interactions between different open data managers are often dynamic and varied. Strategic decision-making in this context mirrors several well-known dilemmas in game theory, such as the prisoner's dilemma, the snowdrift game, and the stag hunt game. These games are commonly used to study the potential for cooperation among self-interested individuals seeking to maximize their personal benefits. For example, the prisoner's dilemma has received significant attention as a model for exploring the evolution of cooperation, with recent applications in climate and environmental governance [46,47]. Given the dynamic nature of the dilemmas faced between open data managers, we incorporate three distinct and classical game-theoretic models, including the prisoner's dilemma, the snowdrift game, and the stag hunt game, to describe the payoffs in the evolutionary games between open data managers.

2.2. Social dilemma transition

As we have stated before, the dilemmas faced between open data managers are not fixed. Thus in this subsection, we provide a detailed description of the transitions between different social dilemmas, assuming that the durations of the various social dilemmas encountered by managers follow an exponential distribution, i.e., the duration of social dilemma i faced between managers satisfies

$$T_i(t) = 1 - \exp(-\lambda_i t), \tag{1}$$

where λ_i denotes the exponential rate. Once the duration has elapsed, the social dilemma between open data managers will transition to a different scenario. We emphasize that the social dilemmas faced by the same manager interacting with different managers can be different. In this paper, we primarily focus on three distinct scenarios of social dilemmas, which are modeled by three different dilemmas in game theory, including the prisoner's dilemma, the snowdrift game, and the stag hunt game. Specifically, the prisoner's dilemma is a non-zero-sum game typically characterized by whether two captured prisoners choose to defect or cooperate, with the only Nash equilibrium being mutual defection. Although cooperation would be mutually beneficial, it is often difficult to achieve due to a lack of trust. The payoff matrix of the prisoner's dilemma is given by

$$M_1 = \begin{pmatrix} 1 & -r \\ b & 0 \end{pmatrix}, \tag{2}$$

where $b \in [1,2]$ and $-r \in [-1,0]$ separately denote the temptation to defect and the sucker's payoff.

The snowdrift game describes a situation in which two individuals face a pile of snow and need to cooperate to remove it. In this game, there exists a mixed Nash equilibrium where each individual has a certain probability of choosing either cooperation or defection. The outcomes of the game encourage partial cooperation but do not converge to a state of complete cooperation or complete defection. The payoff matrix of the snowdrift game can be expressed by

$$M_2 = \begin{pmatrix} 1 & 1-r \\ 1+r & 0 \end{pmatrix}, \tag{3}$$

where $r \in [0,1]$ represents the cost-to-benefit ratio when both individuals select the cooperative strategy.

The stag hunt game models a scenario in which two parties can either cooperate to hunt a large prey, such as a deer, or act alone to capture a small prey, such as a rabbit. This game has two pure-strategy Nash equilibrium, i.e., (cooperation, cooperation) and (defection, defection). It highlights the importance of trust and coordination, offering the potential for high payoffs through cooperation, though there is also a risk of coordination failure. The payoff matrix of the stag hunt game is shown as follows

$$M_3 = \begin{pmatrix} 1 & -r \\ r & 0 \end{pmatrix}, \tag{4}$$

where r is a flexible parameter that takes a value in the range of 0 to 1.

Overall, cooperation is difficult to sustain in the prisoner's dilemma, partial cooperation is possible in the snowdrift game, and full cooperation is both achievable and advantageous in the stag hunt game. Additionally, defection is the dominant strategy in the

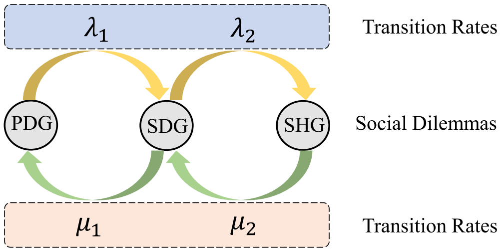


Fig. 1. An illustration of social dilemma transition. The interaction dilemmas between open data managers do not remain constant, but shift over time at specific transition rates. PDG, SDG, and SHG represent three different types of social dilemmas, and the arrows, along with the letters above and below, indicate the direction and rate of the transitions between these social dilemmas.

prisoner's dilemma, mixed strategies are possible in the snowdrift game, and the stag hunt game features multiple equilibria that require trust and coordination. These differences make such three game models particularly suitable for analyzing various types of strategic interactions and cooperation challenges, which can be effectively applied to describe the social dilemmas between open data managers. To provide a clear illustration of social dilemma transitions, we show an example diagram in Fig. 1. All the interaction dilemmas between open data managers evolve as time progresses, with the social dilemmas between open data managers shifting from PDG (SDG) to SDG (PDG) at a rate of λ_1 (μ_1) and from SDG (SHG) to SHG (SDG) at a rate of λ_2 (μ_2).

2.3. Payoff calculation and strategy update

Next, we describe the payoff calculation and strategy update for open data managers. Concretely, at each discrete time step, the manager in the network needs to synchronously decide whether to participate in the management of open data, where participation in management can be regarded as a cooperative behavior and is represented by the vector $s = (1, 0)^T$, while non-participation in management is considered as a defective behavior and denoted by the vector $s = (0, 1)^T$. Afterward, each open data manager x engages in the respective game with all adjacent open data managers in the network to obtain his/her cumulative payoff Π_x, which is given by

$$\Pi_x = \sum_{y\in\Omega_x} s_x^T M_{xy} s_y, \tag{5}$$

where Ω_x indicates the neighbor set of open data manager x, determined by the network structure, and M_{xy} denotes the social dilemma faced between open data managers x and y.

After each open data manager in the complex networks plays the respective game with their neighbors and accumulates the payoff, they will consider updating their strategies based on the cumulative payoff, which is modeled by the classical Fermi function. Specifically, open data manager x randomly selects a manager y from his/her neighbor set Ω_x for payoff comparison and decides to adopt manager y's strategy with a probability given by

$$P(s_x \leftarrow s_y) = \frac{1}{1 + \exp[(\Pi_x - \Pi_y)/\kappa]}, \tag{6}$$

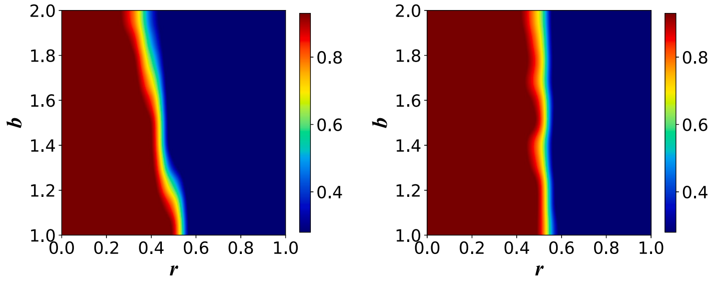
where s_x and Π_x are the strategy and payoff of open data manager x, respectively, and κ means the noise factor, which accounts for the irrational choices made by the open data manager during the game [48]. In other words, if the noise factor is large, the probability derived from Eq. (6) will approach 0.5. In this case, the manager becomes completely irrational and will randomly either retain his/her original strategy or adopt the strategy of the neighbor y with equal probability. Furthermore, if the payoff of open data manager x is greater than that of manager y, then manager x will maintain his/her original strategy with a higher probability. However, due to individual irrationality, there remains a small probability that open data manager x will adopt the strategy of his/her neighbor y.

3. Simulations and results

In this section, we perform a series of simulations to explore the impact of the model proposed in this paper on the adoption of cooperative behavior. Concretely, we first provide a detailed description of the population structure and simulation setup among the open data managers. Subsequently, we investigate the impacts of the payoff parameters and transition rates on the managers' decisions to participate in open data management, observing the emergence and maintenance of cooperative behaviors from a micro perspective. We eventually consider the influence of different patterns of social dilemma transition on the evolution of cooperation.

3.1. Methods

To simulate the population structure of open data managers, we primarily use small-world networks and scale-free networks, which are both classical models in the field of complex networks. These two types of networks have wide practical applications due to their unique properties. For example, small-world networks are commonly utilized to model social networks, transportation networks, and



(a) SW network (b) SF network

Fig. 2. Heat maps of the frequency of open data managers participating in the management concerning the payoff parameters b and r. The x-axis and y-axis denote the payoff parameters $r \in [0,1]$ and $b \in [1,2]$ in different social dilemmas. Each open data manager randomly decides to participate or not in the management at the initial moment. Subplots (a) and (b) show the cooperative proportion regarding payoff parameters b and r under the interaction structure among open data managers as small-world networks and scale-free networks, respectively.

ecological networks, etc. In these networks, nodes tend to have strong local connections, characterized by high clustering coefficients and short average path lengths, which means that neighboring nodes in small-world networks are likely to be interconnected, forming dense clusters. Additionally, despite having a large number of nodes, the distance between any two nodes in a small-world network is typically short, requiring only a few edges to connect them. On the other hand, scale-free networks are frequently employed to model the Internet, financial networks, and virus propagation, among other systems, and they emphasize the heterogeneity among nodes and the importance of hub nodes. The degree distribution of a scale-free network follows a power law distribution, i.e., $P(k) \sim k^{-\gamma}$, where $P(k)$ denotes the probability that a node has degree k and γ usually falls between 2 and 3. In a scale-free network, most nodes have small degrees, while a small number of nodes, the "hubs" possess large degrees and play a crucial role in the network. While scale-free networks are robust to the random removal of nodes, they are highly vulnerable to the removal of hub nodes, which can lead to network collapse.

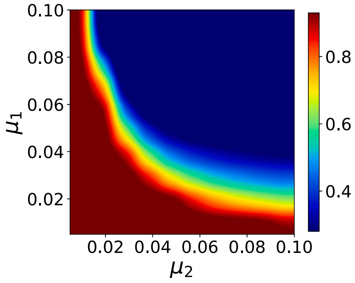
In practice, there exists frequent close cooperation and information flow among open data managers. For example, managers within the same domain typically have more direct connections, resulting in a high clustering coefficient. In addition, these managers can establish connections with others, even across distant regions, via a few intermediary managers, leading to a short average path length. Small-world networks precisely capture this balance between local connections and global reach. Local cooperation within small-world networks facilitates the sharing of information and resources, while the short paths between distant nodes help address cross-regional or cross-organizational coordination challenges, which are vital for effective cooperation and information flow in open data management systems. On the other hand, open data management systems often feature certain managers with greater resources, experience, or influence, who function as "hub nodes". These managers play a key role in coordinating and influencing the decision-making processes of the entire system. This dynamic is well represented by the power law distribution of scale-free networks, where a few managers possess high degrees of "connectivity" or influence. Additionally, scale-free networks can evolve adaptively as new managers are introduced, aligning with the dynamic nature of open data management systems. Therefore, the use of small-world networks (SW) [49] and scale-free networks (SF) [50] to model the structure of interactions among open data managers is particularly appropriate. These two network models effectively capture the essential characteristics of interactions in open data management, especially in terms of cooperation, competition, and information flow between different open data managers.

In the simulations presented below, both the SW and SF networks are fixed at a size of $N = 10000$. Each result is obtained by averaging multiple independent simulations, where each simulation involves a total of 10000 Monte Carlo steps, with the final result averaged over the last 500 steps. Moreover, the noise factor, consistent with most previous studies [51,52], is set at $\kappa = 0.1$. In all simulations, the open data managers initially make their decisions with equal probability on whether to participate in open data management. This means that, at the start, the frequency of cooperators in the network is approximately 0.5.

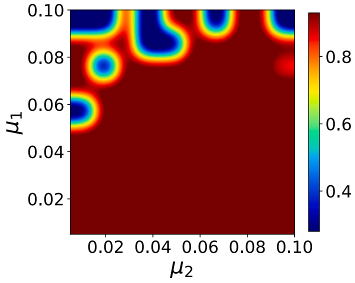
3.2. *Effect of payoff parameters on cooperative behavior*

In this subsection, we study the effect of the payoff parameters b and r, as presented in Eqs. (2), (3), and (4), on the adoption of participatory management behaviors by open data managers with social dilemma transitions, where the rate of social dilemma shifts from PDG (SDG) to SDG (PDG) is set to $\lambda_1 = 0.05$ ($\mu_1 = 0.04$), and the rate of transitions from SDG (SHG) to SHG (SDG) is set to $\lambda_2 = 0.03$ ($\mu_2 = 0.02$). The results of open data managers adopting cooperative behaviors on SW and SF networks with respect to the payoff parameters b and r are illustrated in Figs. 2(a) and 2(b), respectively. The ranges of the x-axis and y-axis are separately set to [0, 1] and [1, 2]. Each result is averaged for 15 independent simulations for each set of parameters to ensure accuracy.

When the interaction structures among open data managers are represented by small-world and scale-free networks, the results displayed in Figs. 2(a) and 2(b) indicate that the payoff parameters b and r significantly influence whether open data managers participate in management. Specifically, when the payoff parameter b is fixed, increasing the parameter r leads to the emergence of defective behaviors among the open data managers. As r increases further, all open data managers eventually cease participation in the management. The effect of b on cooperative behaviors depends on the value of r. When the value of r is relatively small (large), changes in b do not impact the outcome. In contrast, when the value of r is moderate, i.e., r is around 0.5, increasing b causes



(a) SW network



(b) SF network

Fig. 3. Influence of transition rates on cooperative behaviors of open data managers. The y-axis and x-axis represent the transition rates from SDG to PDG (μ_1) and from SHG to SDG (μ_2), where both μ_1 and μ_2 are in the range of $[0.005, 0.1]$. Each open data manager randomly decides to participate or not in the management at the initial moment. Panels (a) and (b) demonstrate the cooperative frequency regarding transition rates μ_1 and μ_2 under the interaction structure among open data managers as small-world networks and scale-free networks, respectively.

a decline in the number of cooperative managers. Moreover, a comparison between Figs. 2(a) and 2(b) reveals that the scale-free network more effectively encourages open data managers to participate in management compared to the small-world network. This is evident from the significantly larger dark red region (indicating full cooperation) in Fig. 2(b), alongside the notably smaller dark blue region (indicating full defection) compared to Fig. 2(a). These results suggest that population structure has a significant role in shaping the decisions of open data managers.

3.3. Influence of transition rates on cooperation

Considering that social dilemma transitions are typically complex in practice, we next examine the impact of different social dilemma transition rates μ_1 and μ_2 on the evolutionary outcomes, and the results are presented in Figs. 3(a) and 3(b), which correspond to the population structure of open data managers as SW and SF networks, respectively. Each result is obtained by taking the average of 15 independent simulations for each set of parameters to ensure accuracy. Both the transition rates from SDG to PDG (μ_1) and from SHG to SDG (μ_2) are set to $[0.005, 0.1]$, and the other two transition rates from PDG to SDG (λ_1) and from SDG to SHG (λ_2) are separately fixed to $\lambda_1 = 0.05$ and $\lambda_2 = 0.03$.

It is evident from Fig. 3 that the population structure has a critical impact on the decision-making of open data managers. Specifically, if the population structure is a SW network, the result displayed in Fig. 3(a) illustrates that all managers are involved in open data management when both transition rates μ_1 and μ_2 are relatively low. However, as these transition rates μ_1 and μ_2 increase, some managers gradually opt out of the management process, leading to a situation where no open data managers participate once μ_1 and μ_2 surpass the certain threshold. This phenomenon occurs due to the fact that as the transition rates μ_1 and μ_2 grow, it will lead to an increased prevalence of the prisoner's dilemma, which is the least conducive to sustaining cooperation compared to the snowdrift game and stag hunt game. The result in Fig. 3(b), corresponding to the SF network, shows that in most cases, open data managers continue to participate in management, as indicated by the dominance of the dark red color in the figure. However, when the transition rate μ_1 becomes too large, most social dilemmas encountered by open data managers are PDG, causing no managers to participate in the management of open data, which is consistent with the result in the SW network demonstrated in Fig. 3(a).

3.4. Snapshots of the evolution of cooperators from micro perspective

To more clearly and intuitively observe the emergence and persistence of cooperators from a micro perspective, we replace the population structure of open data managers with a square lattice network with periodic boundaries possessing Von Neumann neighborhoods, i.e., each manager has four neighbors. The size of the network is set as $N = 100 \times 100$, and we investigate the evolution of open data managers adopting cooperative behaviors under three different groups of parameters (b, λ_1) = (1.5, 0.050), (1.7, 0.050), (1.5, 0.035). Other parameters, including the payoff parameter and transition rates, are fixed as $r = 0.4$, $\lambda_2 = 0.04$, $\mu_1 = 0.04$, and $\mu_2 = 0.02$. The snapshots of cooperators and defectors at time steps $t = 10$, 200, 1000, and 2000 are shown in Fig. 4. In these snapshots, each square lattice denotes an open data manager, with red squares indicating defectors (those not participating in management) and green squares indicating cooperators (those participating in management).

From Figs. 4(1), (5), and (9), we can see that although the cooperators and defectors are initially distributed randomly across the square lattice network, the number of defectors significantly exceeds that of cooperators as the evolution proceeds to $t = 10$. Subsequently, the cooperators in the three scenarios spring back up again, with different levels of cooperation in the end, and it can be observed that cooperators mainly resist the invasion of defectors by forming clusters. Specifically, by comparing the results demonstrated in the first row with the second row, we find that for the parameter set (b, λ_1) = (1.5, 0.050), the system eventually evolves to a state of pure cooperation, where all open data managers are involved in the management. In contrast, for the situation of (b, λ_1) = (1.7, 0.050), there are still a small number of open data managers in the network who are not participating in the management, indicating that higher values of b hinder the emergence of cooperation. This is consistent with the results observed in the SW and SF networks in subsection 3.2, where a decrease in b favors the emergence and maintenance of cooperators. Furthermore,

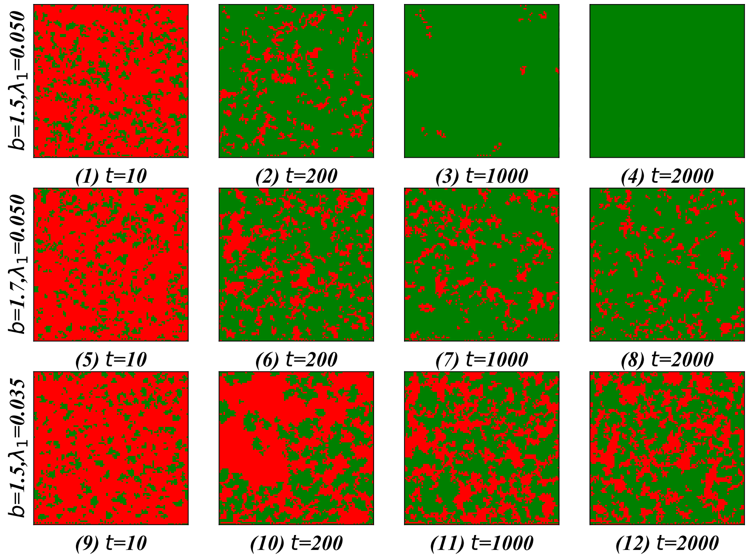


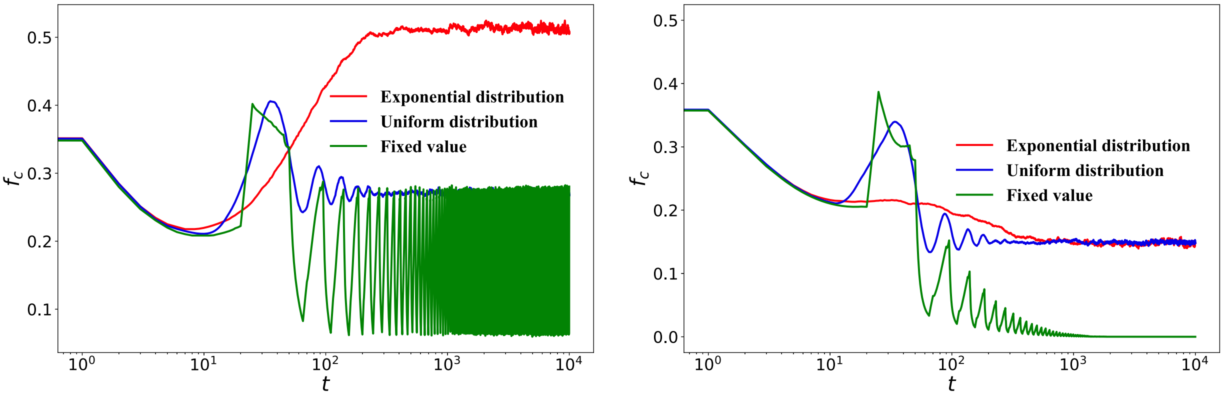
Fig. 4. Snapshots of the evolution of cooperators from the micro perspective. The population structure and scale are set to the square lattice network with periodic boundaries possessing Von Neumann neighborhoods and 100×100, where each square lattice represents an open data manager. Red and green colors indicate open data managers taking the strategy of not participating and participating in the management, respectively. The rows represent snapshots of the evolution of the cooperators at evolutionary time $t = 10$, 200, 1000, and 2000 under the specific parameter pairs (b, λ_1) of (1.5, 0.050), (1.7, 0.050), and (1.5, 0.035).

comparing the results of the first line with the third line, we get that in the case of (b, λ_1) = (1.5, 0.035), the number of cooperators in the network is slightly higher than that of defectors at $t = 2000$, whereas in the situation of (b, λ_1) = (1.5, 0.050), the defectors are eventually extinct. Therefore, an increase in the transition rate λ_1 promotes the evolution of cooperation since it reduces the prevalence of the PDG, which is the most detrimental social dilemma for the persistence of cooperative behaviors.

3.5. Impact of social dilemma transition patterns on the evolution of cooperation

It is worth noting that in all previous simulations, the durations of the different social dilemmas faced between managers are assumed to follow the exponential distribution. In this subsection, we examine the impact of different patterns of social dilemma transitions on the results and primarily focus on two additional scenarios besides the exponential distribution, including durations of the social dilemmas that are fixed and obey the uniform distribution. The results of the evolution of the cooperation frequency over time in SW networks and square lattice networks with periodic boundaries (SL) under these different patterns of social dilemma transitions are shown in Figs. 5(a) and 5(b), respectively, where red and blue represent durations following the exponential and uniform distributions, respectively, while green indicates the fixed value for the duration. The parameter settings associated with the duration of social dilemmas obeying the exponential distribution are: $\lambda_1 = 0.05$, $\lambda_2 = 0.03$, $\mu_1 = 0.04$, and $\mu_2 = 0.04$. To ensure comparability of the results, the means of the random numbers generated for the other two scenarios are set to match the exponential distribution. For example, in the scenario of uniform distribution, the duration of the social dilemma PDG $T_{PDG}(t)$ obeys a uniform distribution ranging from $1/\lambda_1 - 10$ to $1/\lambda_1 + 10$, i.e., $T_{PDG}(t) \sim U(1/\lambda_1 - 10, 1/\lambda_1 + 10)$. In the situation of fixed value, the duration of the social dilemma PDG remains constant at $1/\lambda_1$, i.e., $T_{PDG}(t) = 1/\lambda_1$. The remaining parameters, including network size and payoff parameters, are fixed to $N = 10000$, $b = 1.35$, and $r = 0.41$, respectively. All results are obtained by averaging 50 independent simulations.

Given that the stabilization rate of the cooperation frequency f_c is relatively fast on both networks, we employ a logarithmic coordinate for the evolutionary time t on the x-axis to more clearly observe the trend of cooperation evolution. From the results, we find that the number of cooperators on both networks initially decreases before fluctuating around a certain value. By averaging the cooperation frequency over the last 500 steps of a 10000-step Monte Carlo simulation, we obtain the following results: for the SW network depicted in Fig. 5(a), the cooperation frequencies under the scenarios of the exponential distribution, uniform distribution, and fixed value are 0.5099, 0.2702, and 0.1689, respectively. For the SL network shown in Fig. 5(b), the corresponding cooperation frequencies are 0.1459, 0.1493, and 0.0, respectively. These results suggest that when the duration of social dilemmas follows the uniform distribution, it more effectively promotes the evolution of cooperative behaviors than when the duration is fixed. However, the uniform distribution has a weaker facilitative effect compared to the exponential distribution on the SW network, and the difference between the facilitative effect of the exponential distribution and that of the uniform distribution on the SL network is minor. Furthermore, a comparison of the results in Figs. 5(a) and 5(b) reveals that the SW network structure is more conducive to promoting open data managers' participation in management than the SL network, which means that the population structure plays an important role in the decision-making of open data managers.



(a) SW network (b) SL network

Fig. 5. Evolutionary curves of the cooperation frequency over time under different patterns of social dilemma transitions. Subplots (a) and (b) demonstrate the results for the SW and SL networks, respectively, where the x-axis is set to logarithmic coordinates for better observing the upward and downward trends in the evolution of cooperation frequency, and the y-axis denotes the cooperation frequency f_c, i.e., the ratio of cooperators in the network. Red, blue, and green colors separately indicate that the durations of social dilemmas faced between open data managers follow the exponential distribution, uniform distribution, and fixed values.

4. Conclusions and outlooks

Open data, a newly emerging concept, is profoundly transforming the way information is accessed and utilized. By establishing a comprehensive open data management system, open data provides new momentum for the sustainable development of the digital economy, digital culture, and digital society. In this paper, we investigate cooperative behaviors in open data management using networked evolutionary games, where complex networks model the interaction structure between open data managers, and evolutionary game theory is employed to study how bounded rational managers can maximize their payoffs through repeated interactions. Building on the widespread "small-world effect" and the "Matthew effect", we mainly consider two types of open data manager population structures, including small-world networks and scale-free networks. Additionally, we introduce the concept of social dilemma transitions to capture the dynamic evolution of social dilemmas faced between open data managers in practice. In our simulations, we first generate heat maps of the cooperation proportion on the SW and SF networks with respect to the payoff parameters. We find that lowering the payoff parameters b and r promotes open data managers' participation in management. We then explore the impact of transition rates on cooperation behavior and discover that to foster cooperation, managers should encounter as few PDG-type social dilemmas as possible, meaning the transition rates μ_1 and μ_2 should be minimized. Besides, we examine the evolution of cooperative open data managers on square lattice networks with periodic boundaries from a micro perspective and find that cooperators can effectively resist the intrusion of defectors by forming clusters. Furthermore, we analyze the evolutionary curves of cooperation frequency under three patterns of social dilemma transitions, including the duration of social dilemmas following the exponential distribution, uniform distribution, and fixed value. We find that the exponential distribution of social dilemma durations is the most favorable for open data managers to participate in management on the SW network, while the fixed value proves to be the least favorable on both SW and SL networks. Moreover, by comparing the results across all simulations, we highlight the significant impact of population structure on the decision-making of open data managers.

This study presents a valuable contribution to understanding cooperative behavior in open data management; however, there are several limitations and avenues for future research. On the one hand, the development of open data generally involves multiple stakeholders such as open data users, providers, and managers, but this paper primarily focuses on open data managers. Expanding the model to incorporate interactions among all relevant actors would provide a more comprehensive view of open data management. On the other hand, the social dilemma transitions considered in this study are limited to three classic types, and the direction of transitions is fixed. Future work could extend this model by introducing a more dynamic set of social dilemma types and transition patterns, allowing for greater flexibility and realism. Therefore, in future research, we can consider constructing a multilayer network structure [53,54] to better capture the complex interactions between different types of individuals in open data and add other social dilemma models and transition patterns [55,56] to enhance the realism of the model. Finally, we hope that the findings of this paper will serve as a foundation for further research on cooperation in open data management and inspire new perspectives and models to better address the challenges of fostering cooperation in open data management.

Acknowledgements

This work is supported by the Natural Science Foundation of Chongqing (Grant No. CSTB2023NSCQ-MSX0064), the National Natural Science Foundation of China (NSFC) (Grant No. 62206230), and The Slovenian Research and Innovation Agency (Javna agencija za znanstvenoraziskovalno in inovacijsko dejavnost Republike Slovenije) (Grant Nos. P1-0403 and N1-0232).

Data availability

Data will be made available on request.

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