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Popularity-Based Approach to Promote Cooperation in The Prisoner's Dilemma Game

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***Abstract*—Examining the interaction between agents in a well-mixed population has been a prevalent area of research. Previous studies have emphasized the evolution of the impact of network architecture and payoff differences on agents' behavior in various games. There has been a recent surge in interest in incorporating popularity among researchers in this field. In this study, we employ a game theoretic approach to gain insight into the strategic behavior and decision-making processes of individuals in a network and how these decisions impact the diffusion of information when an individual's popularity is considered. The Fermi function is used to model the probability of information diffusion and the spread of influence within the network. We introduce a novel simulation module that models the dynamic process of evolutionary game theory in both synthetic and real-world networks, leveraging the Fermi update rule as a critical component. The simulation results provide valuable insight into the evolution of cooperative behavior in complex networks and hold potential for further exploration into various aspects of evolutionary game theory.**

***Index Terms*—Prisoner's Dilemma, game theory, evolutionary game on networks, Fermi function, Facebook, Watts-Strogatz, social networks**

I. Introduction

Researchers have long been fascinated by the evolution of cooperative behavior in populations for many years as it can have important implications for understanding the behavior of individuals in various settings, including social, economic, and biological systems. Foundational publications by Smith and Axelrod [1], [2], [3] in the 1970s marked the inception of evolutionary game theory, laying the groundwork for subsequent investigations. Following the publishing of the first papers on evolutionary game theory, researchers in various fields became interested. Over the following decades, the study of evolutionary game theory has been applied to a wide range of real-world problems, including the evolution of cooperation in social networks, the evolution of cooperation in multi-level systems, and the evolution of cooperation in the face of environmental change. The investigation of information flow within networks has garnered significant attention among researchers who seek to comprehend the behavioral patterns exhibited by individuals in such contexts [4]. Individuals' decision-making processes are inherently influenced by the environment in which they operate and the characteristics of their surrounding neighbors [5]. In particular, social networks have drawn much interest as they are central to shaping human interaction and behavior. The recent findings from studies on the evolution of cooperative behavior in social networks have provided valuable insights into the role of network structure, reputation, and the process of network formation. These studies, employing a game theory approach, have unveiled novel perspectives and enhanced our understanding of the dynamics underlying cooperative behaviors within social networks [6], [7], [8], [9].

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In today's world, the influence of social media on individuals is undeniably profound. People often follow others they perceive to share similar characteristics or aspire to resemble. Building upon this understanding, we present a popularity-based strategy in this paper to delve into the intricate process of cooperation evolution. This paper introduces a popularity-based strategy to investigate the evolution of cooperation. Our contribution to the field builds upon the foundational research conducted by Ohtsuki et al [6]. Furthermore, we extend this work by incorporating the insights and advancements made by Cameron and Arias [7]. Through our research, we uncover intriguing insights and unveil remarkable findings that offer valuable insights into the fundamental dynamics and necessary conditions for cooperative behavior.

The current working model of the Prisoner's Dilemma employs a payoff-based strategy. In this approach, each node calculates the probability of switching its current strategy with that of its neighbors using their payoffs and a variable β that determines the decision's intensity. However, this model consistently results in Watts-Strogatz Networks with a predominantly defector-dominated population. In contrast, when examining the Facebook dataset, certain games exhibit cooperator populations that are neither dominant nor extinct. Our investigation proceeds in two phases. First, we experiment with the existing method by testing it under conditions where the benefit-cost ratios exceed the average number of edges per node, along with different values of β. Second, we expand our research to include a popularity-based model. In this novel approach, we dynamically adjust the β value in each node's calculation. Instead of remaining a static variable, β changes depending on the neighboring node's degree. A higher degree, indicating greater popularity, results in a higher β value and, consequently, a stronger inclination to switch a player's strategy. In real networks, such as the Facebook dataset, nodes do not possess the same level of interconnectedness as those in Watts-Strogatz Networks. Instead, there are smaller sub-networks with limited connections, as well as nodes with significantly higher or lower degrees than others. This variation in network interconnectivity emphasizes the importance of popular nodes. Lastly, we compare the payoff-based strategy and the popularity-based strategy and discuss the main differences.

The remainder of this paper is structured as follows: Section II provides an overview of related work in this field. Section III presents the model employed for experimentation, detailing its underlying framework. The data utilized for the experiments is elucidated in Section IV, followed by the presentation of the experiment. Section V comprehensively discusses the obtained experimental results. Section VI concludes this article, summarizing the key findings and implications.

II. Related Work

Emergence in studies on evolutionary game theory directed researchers to analyze the impact of network structure and reputation on cooperative behavior. An early examination of the impact of network structure on cooperative behavior has been done by Nowak and May [10]. The authors use a mathematical model to study the evolution of cooperative behavior in spatially structured populations and show that individuals' spatial arrangement can significantly impact the evolution of cooperation. Then, seminal studies are conducted for a variety of games across many networks [11], [6], [12], [13]. One of those games, Prisoner's Dilemma, has been the focus of in-depth study in many disciplines, such as economics, psychology, political science, and computer science. In the prisoner's dilemma game, the structure of the game and the payoffs associated with different outcomes can play a critical role in determining the likelihood of cooperative behavior [14]. In addition, studies show that the importance of network structure on the development of cooperation plays a significant role [15], [16], [17], [18]. In particular, they show that the presence of certain types of network structures can promote the evolution of cooperation, while others can suppress it. These findings provide insights into how network structure can influence cooperative behavior in complex systems and have important implications for understanding the evolution of cooperation in real-world social and biological systems.

The Watts-Strogatz network [19] is often used to model the evolution of cooperative behavior in the Prisoner's Dilemma game. The Watts-Strogatz network combines characteristics of regular and random networks [20], making it suitable for simulating cooperative behavior in various systems. Studies investigating the Prisoner's Dilemma game on the Watts-Strogatz network contribute to a deeper understanding of how network topology influences cooperative behavior and how it can be promoted in real-world systems [7], [21], [22]. Different theories have been proposed to explain why people cooperate with strangers. The results of experiments played by humans indicate that the level of cooperation is similar for lattice or scale-free networks [23]. In a well-mixed population, where the Prisoner's Dilemma game is played, natural selection favors defectors over cooperators. In order to overcome this bias and promote the increase of cooperators within the population, special rules or mechanisms are required [24]. This idea is supported by research conducted by Ohtsuki et al. [6], and followed by Cameron and Cintr 'on-Arias suggests that cooperation can remain in social networks provided certain conditions are fulfilled [7]. Recent studies have investigated various strategies, such as the exposure-based strategy for gaining benefits by incurring costs to engage a player [25], [26], or the reciprocal reward strategy, which involves willingly sacrificing personal payoff for neighbors with the highest link weights [27], [28], [29]. Instead of relying solely on the straightforward payoff difference between agents and their neighbors to enhance network reciprocity, a modified approach has been adopted, one that incorporates the concept of the averaged payoff difference and leverages key concepts such as the enduring period and the expanding period [30], [31].

This study builds upon previous research by examining the effects of these unique rules and mechanisms on the promotion and persistence of cooperation within a well-mixed population. By utilizing an evolutionary algorithm, we can evaluate the effectiveness of different strategies and methods in reducing the number of defectors and promoting the growth of cooperators. This approach helps us thoroughly test and assess the effectiveness of different strategies, giving us valuable insights into how cooperation evolves in the Prisoner's Dilemma game.

III. Model

The traditional version of the Prisoner's Dilemma (PD) involves four fundamental values: T for Temptation, R for Reward, P for Punishment, and S for Sucker's payoff. A game must fulfill two essential conditions to be labeled the Prisoner's Dilemma. These elements comprise the fundamental criteria for identifying and categorizing the Prisoner's Dilemma game. First, the Temptation payoff (T) should be greater than the Reward payoff (R), which in turn should be greater than the Punishment payoff (P), and the Punishment payoff should be greater than the Sucker's payoff (S), $T > R > P > S$ [2]. Additionally, the following condition must hold: twice the Reward payoff ($2R$) should be greater than the sum of the Temptation payoff (T) and the Sucker's Payoff (S), which is $2R > T + S$. These conditions form the fundamental criteria for identifying and characterizing the Prisoner's Dilemma game. The two mentioned conditions, which are frequently related to the "Win-stay, lose-shift" strategy [32], also known as Pavlov [33], serve as the foundations of acceptable player behavior in this approach. Based on previous results in a repeated game scenario, these requirements are used to predict a player's forthcoming actions.

In our model, we have two strategies: cooperation (C) or defection (D), and the following is the payoff matrix for the Prisoner's Dilemma game.

	C	D
C	R	S
D	T	P

Fig. 1: Prisoner's Dilemma Game Matrix

The payoffs for each player are determined by the following matrix:

$$M=\begin{pmatrix} b-c & -c \\ b & 0 \end{pmatrix}$$

where $b > 0$ is the reward for mutual cooperation. In order to provide benefits, there is a cost involved, represented by the variable c, where $c > 0$. Hence, the average payoff for individuals who cooperate can be determined by subtracting the cost c from the benefit b, resulting in b - c. If one player cooperates while the other defects, the defector receives the reward b while the cooperator receives the cost c. Thus, the dominant strategy for each player is to defect, which leads to mutual defection and the lowest possible payoff for both players. The experiments are conducted with a benefit value of 1.8 and a cost value of 0.3. The payoff matrix used between cooperators and defectors,

$$M_1=\begin{pmatrix} 1.5 & -0.3 \\ 1.8 & 0 \end{pmatrix}$$

remained constant throughout the game.

In addition to the payoff matrix indicated above, an alternative payoff matrix is employed for specific experiments with a benefit value of 15 and a cost value of 0.5.

$$M_2=\begin{pmatrix} 14.5 & -0.5 \\ 15 & 0 \end{pmatrix}$$

The values assigned for b and c are selected based on a critical requirement for the persistence of cooperation. This requirement is defined by an equation that takes into account the benefit, cost, and average number of edges per node.

$$\frac{b}{c} > k \tag{1}$$

This equation is one of the necessary conditions for cooperation to be the dominant strategy in a network [7].

The experiments involve running multiple simulations with varying parameters to test their impact on the proportion of cooperators to defectors at the end of each game. Each player is set to either a defector or a cooperator. If node i is a cooperator, the strategy is denoted as:

$$s_i = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

This strategy implies that the player i will cooperate, aiming for the benefit of the group or cooperation with others.

On the other hand, for a defector, node i, the strategy is represented as:

$$s_i = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

This strategy indicates that the player i will defect, prioritizing their individual benefit over cooperation with others.

In each time step, players assess their payoffs in relation to their neighbors and make choices based on a comparative evaluation of their payoffs and other selection criteria, which will be further elaborated upon. The total payoff of a player i is calculated using

$$w_i = \sum_{j \in \Omega_i} {s_i}^T M s_j \tag{2}$$

A. Strategy Update Rule

The function used to define a node's chance of changing strategy with its neighbor is the Fermi Function. It is defined as:

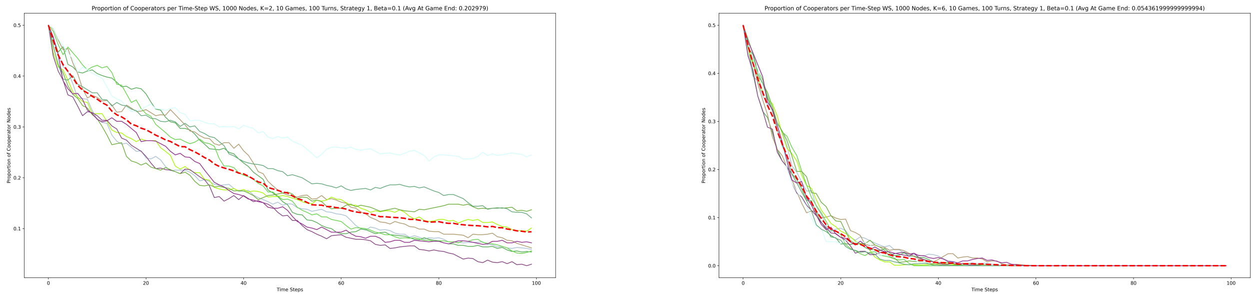
$$P_{i \to j} = \frac{1}{1 + e^{-\beta(w_j - w_i)}} > k \tag{3}$$

where β represents the intensity of the selection. w_i and w_j are the payoff of node i and node j.

Two types of strategies were used for nodes to decide on their role as cooperators or defectors. In strategy 1, payoff-based selection is used, and in strategy 2, popularity-based selection is used.

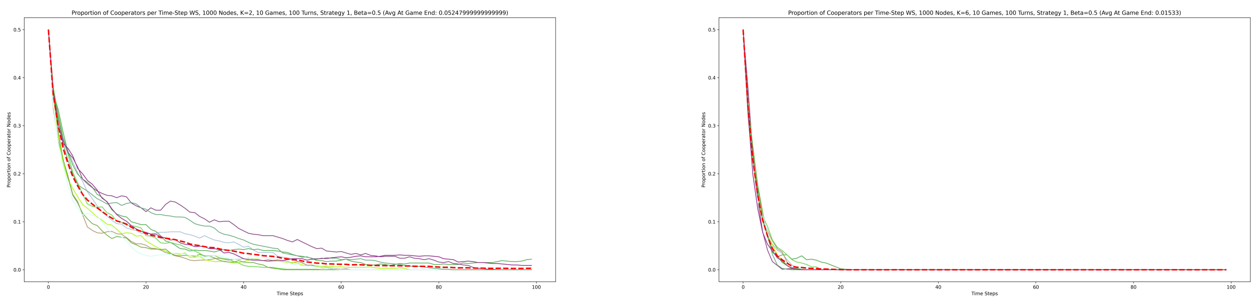
B. Payoff-Based Strategy

The payoff-based rule incorporates the payoffs of neighboring players to update strategies, aiming to enhance individual strategies and maximize gains. In this process, each player's strategy is determined using the Fermi function. In the Fermi function, β is set to different values to comprehend the decision-making process better. A higher value of β indicates greater risk avoidance in decision-making, whereas a lower value of β suggests a tendency towards random decision-making.



(a) k = 2 (b) k = 6

Fig. 2: Prisoner's Dilemma on Watts-Strogatz network with payoff-based strategy obtained with the intensity of selection value set to $\beta = 0.1$ for 10 games 100-time steps (a) displays the results when k=2 (b) displays the results when k=6



(a) k = 2 (b) k = 6

Fig. 3: Prisoner's Dilemma on Watts-Strogatz network with payoff-based strategy obtained with the intensity of selection value set to $\beta = 0.5$ for 10 games 100-time steps (a) displays the results when k=2 (b) displays the results when k=6

C. Popularity-Based Strategy

The popularity rule incorporates the payoffs and the popularity of neighboring players. The degree centrality is utilized as a metric to assess the popularity of neighboring players within the network. In Fermi function β is set to

$$\beta = \frac{\text{degree of neighbor node}}{\text{number of nodes} - 1} \tag{4}$$

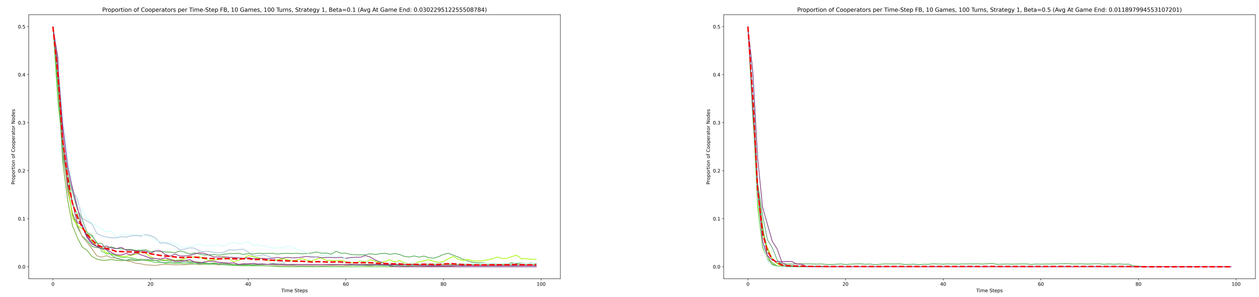
IV. Experimental Setup

In this study, we used both synthetic and real-world datasets, Watts-Strogatz and real-world network Facebook [34] dataset. In the Watts-Strogatz network, the number of nodes is specifically set to 1000 for our experimental setup. The Facebook data set contains 4039 nodes and 88,234 edges.

In the Watts-Strogatz network, k represents the network's average degree of connectedness. The parameter k explicitly refers to how many nearest neighbors each node is initially linked to. Each node in the initial regular ring lattice is connected to its two closest neighbors on either side when k is set to 2. As a result, the network structure is exceedingly regular and well-organized, with minimal communication between nodes. By contrast, when k is set to n where $n > 2$, the initial regular ring lattice connects each node to its n closest neighbors on either side. As a result, each node has a higher level of connectedness, which results in a denser and more linked network structure. In conclusion, while k = 4 or k = 6 results in a higher degree of connectedness and a denser network structure, k = 2 produces a network that is less linked and more erratic. In our experimental investigation, we looked at how changing the parameter k might affect the two different approaches in the Watts-Strogatz network. In particular, we looked at two distinct k values, k = 2 and k = 6 in the payoff-based strategy. Similar to how we did for the payoff-based strategy, we used k = 2 and k = 4 to examine the impacts of k in the popularity strategy. We attempted to get insight into the impact of this parameter on the two strategies. Furthermore, for the Facebook network, the average number of edges per node was calculated using the following formula:

$$\begin{aligned} \text{Average \# of edges} &= \frac{\text{Total \# of edges}}{\text{Total \# of nodes}} \\ &= \frac{88,234}{4,039} \approx 22 \end{aligned} \tag{5}$$

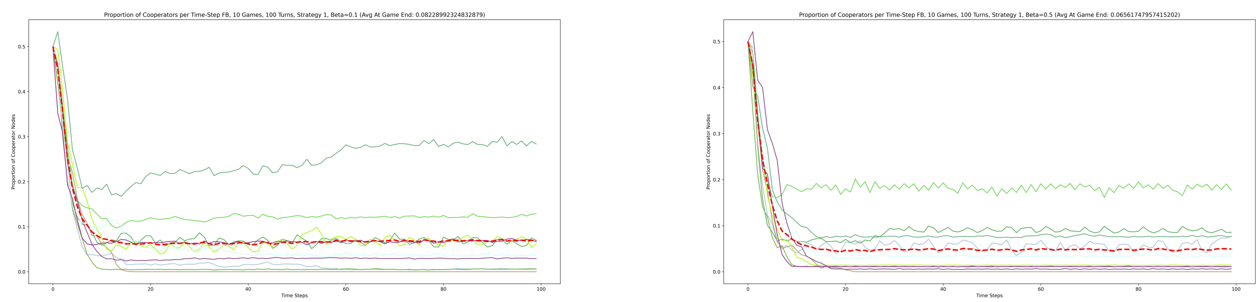
In addition to k value, we also analyzed the impact of



(a) $\beta = 0.1$

(b) $\beta = 0.5$

Fig. 4: Prisoner's Dilemma on the Facebook network with payoff-based strategy obtained with payoff matrix M_1 for 10 games 100-time steps (a) displays the results when $\beta = 0.1$ (b) displays the results when $\beta = 0.5$



(a) $\beta = 0.1$

(b) $\beta = 0.5$

Fig. 5: Prisoner's Dilemma on the Facebook network with payoff-based strategy obtained with payoff matrix M_2 for 10 games 100-time steps (a) displays the results when $\beta = 0.1$ (b) displays the results when $\beta = 0.5$

different β values in payoff-based strategy for Watts-Strogatz and Facebook Network. The parameter β is critical in defining the amount of noise that enters the decision-making process in the context of our investigation. In particular, a larger β value indicates a higher probability of individualistic choices being made during the strategy adoption phase [35]. This implies that when the β value rises, the impact of noise grows, resulting in a wider variety of strategic options for individuals. We can learn a lot about the dynamics and results of strategic interactions in our model by comprehending the effect of β on decision-making noise.

The game begins with an initial configuration where a certain number of players opt to be defectors and cooperators. The initial allocation of defectors and cooperators is evenly split, with a distribution of 50% for each group. To gain deeper insights into the dominant strategy, players engage in a series of 10 rounds of interaction. After each set of 10 rounds, the utilities are computed, and this process is repeated in 100 independent simulations. Within each game iteration, the payoff for each player is calculated using the formula specified in Equation 2. This approach allows us to explore the dynamics and outcomes of the game and provides valuable insight to understand the dominant strategy.

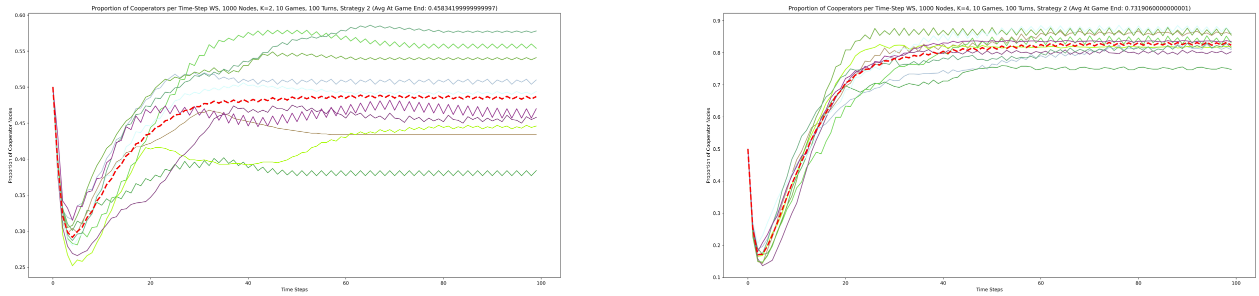
V. Experimental Results

The experimental results relating to the payoff-based strategy and popularity-based strategy used in the contexts of the Watts-Strogatz network and the Facebook network are shown and discussed in this part.

A. *Results for The Payoff-Based Strategy*

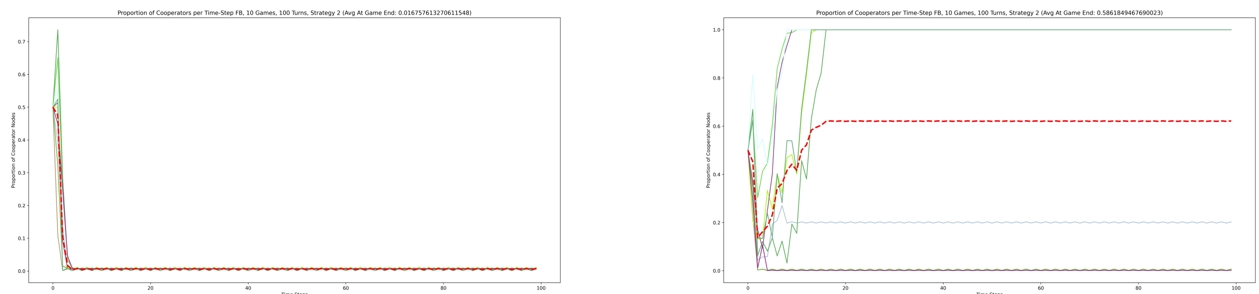
A clear observation emerges by systematically investigating different combinations of β and k values within the framework of the Watts-Strogatz network. It is evident that the dominant strategy prevailing in this context is the defector strategy, ultimately resulting in the complete eradication of the cooperator strategy within the population.

Figures 2 and 3 provide visual representations of the simulation results for the Watts-Strogatz network when the payoff-based strategy is employed. The cooperator strategy in the Watts-Strogatz Network exhibits enhanced longevity when a combination of lower β and k values is employed, resulting in a more extended period before its ultimate elimination. In particular, it takes roughly 80-time steps for the defectors to achieve a steady proportion of 80% on average when $\beta = 0.1$ and $k = 2$. Other parameter combinations, on the other hand, cause a quicker fall in the incidence of cooperative behavior.



(a) k =2 (b) k =4

Fig. 6: Prisoner's Dilemma on Watts-Strogatz network with popularity-based strategy obtained with different k values for 10 games 100-time steps (a) displays the results when k = 2 (b) displays the results when k = 4



(a) Strategy payoff matrix M_1 (b) Strategy payoff matrix M_2

Fig. 7: Prisoner's Dilemma on the Facebook network with popularity -based strategy obtained with different strategy payoff matrix for 10 games 100-time steps (a) displays the results when strategy payoff matrix is M_1 (b) displays the results when strategy payoff matrix is M_2

TABLE I: Average cooperator players and stabilization time using payoff-based strategy on Watts-Strogatz network at the end of 100-time steps with different k and β Values

β	k	Average Cooperators	Time Step
0.1	2	2%	80
	6	0.5%	40
0.5	2	0.5%	60
	6	0.2%	10

In order to gain insights into the dynamics of the system, we conducted investigations on the Facebook network, where we examined the effects of different β values, $\beta = 0.1$ and $\beta = 0.5$, and two different payoff structures, for cooperators and defectors within the framework of a payoff-based strategy. Two distinct payoff matrices were used in our experimental setup, denoted as M_1 and M_2, to investigate the system's dynamics. M_1 corresponds to a smaller $\frac{b}{c}$ value, while M_2 is characterized by a larger $\frac{b}{c}$ value. Our observations show a rapid and complete transition toward defection within the population regardless of the β value or the payoff. Figures 4 and 5 present the simulation results for the Facebook network, illustrating the outcomes when applying the payoff-based strategy with varying β values and different payoff values.

B. Results for The Popularity-Based Strategy

The simulation results depicted in Figure 6 display the outcomes obtained when applying the popularity strategy in the Watts-Strogatz network using different values of k. As indicated by Equation 1, the ratio of b/c plays a significant role in determining the existence of cooperation. When the value of k is smaller than b/c, cooperation emerges as the dominant strategy more rapidly, requiring fewer time steps. Conversely, when the value of k exceeds b/c, cooperation diminishes at a faster rate within the network. In the Watts-Strogatz network, the dynamics of the Prisoner's Dilemma game exhibit a distinct pattern when the popularity-based strategy is employed. Initially, the number of cooperators experienced a decline, followed by a rapid increase. Eventually, the cooperators stabilized.

The rapid decline can be attributed to a social dilemma, where each player finds it rational to defect regardless of the other player's choice. Consequently, there is a drop in the number of cooperators within the Watts-Strogatz network. However, as time progresses, cooperators have the ability to form clusters and outcompete defectors in their local vicinity, capitalizing on the network structure. As these cooperative clusters expand, more players are influenced to engage in cooperative behavior, as these clusters become less susceptible to invasion by defectors.

The influence of popularity within the population is evidently significant in the decision-making process within the Watts-Strogatz network. In contrast to the payoff-based strategy, even in the face of initial defection, players in the network tend to form clusters that promote increased cooperation within the population. This observation highlights the crucial role of social dynamics, specifically the influence of popularity, in shaping the behavior and outcomes within the network.

Our investigations on the Facebook network, employing the popularity-based strategy, have yielded intriguing results. Within the experimental framework, we explored two distinct payoff values, as depicted in Figure 7. Notably, when utilizing payoff values that satisfy a smaller fraction of $\frac{b}{c}$ (reflected by payoff matrix M_1), a rapid decline in the number of cooperators akin to the payoff-based strategy was observed. Conversely, when the payoff values were selected to fulfill the condition $\frac{b}{c} > k$ where k is set to 22 based on the value from Equation 5, a noteworthy trend emerged: cooperators began to increase, resulting in an average presence of slightly over 50% of cooperators within the population. This observed trend closely mirrors the simulated results obtained from the Watts-Strogatz network experiments. Interestingly, certain games exhibit a similar behavior where cooperation almost completely diminishes but then unexpectedly makes a recovery. Remarkably, nearly half of the 10 sets of games conclude with cooperative behavior. However, in a few games, defectors dominate the population, resulting in a decrease in the average game values. To further investigate this phenomenon, conducting experiments with a larger number of games would be beneficial. Our findings confirm that cooperative behavior can indeed exist within social networks, provided that certain conditions are met. These findings shed light on the intricate dynamics of the popularity-based strategy and its consequential impact on cooperative behavior within the Facebook network.

VI. Conclusion

This paper presents a novel framework for conducting a comprehensive analysis of the impact of both the payoff-based and popularity-based decision mechanisms within the Watts-Strogatz and Facebook networks. In this study, we conducted a comprehensive exploration of decision-making strategies, with a particular emphasis on the pioneering integration of the Fermi function into the decision-making process. The Prisoner's Dilemma game is renowned as a classic example of a non-cooperative game. However, our study has brought to light the potential to foster cooperation within the confines of the Prisoner's Dilemma game by strategically adjusting the reward-cost ratio and integrating each player's popularity into the Fermi function. This novel approach challenges the usual understanding of non-cooperative games and presents a new perspective, demonstrating the possibility of promoting cooperation in the Prisoner's Dilemma game. Through our extensive exploration using the Prisoner's Dilemma game, we have demonstrated the highly influential role of leveraging popularity as a decision-making factor in promoting information diffusion. The results of our research highlight the dominant emergence of cooperative behavior within the population. Moreover, this popularity-based decision-making process provides valuable insights into understanding social dynamics' broader impacts and implications in networked environments. By integrating popularity as a pivotal factor, our research endeavors provide valuable insights into the realms of information dissemination and cooperative behaviors.

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