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EMERGING COOPERATION IN N-PERSON ITERATED PRISONER'S DILEMMA OVER DYNAMIC COMPLEX NETWORKS

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Abstract. The N-Person Iterated Prisoner's Dilemma (NIPD) is an interesting game that has proved to be very useful to explore the emergence of cooperation in multi-player scenarios. Within this game, the way that agents are interconnected is a key element that influences cooperation. In this context, complex networks provide a realistic model of the topological features found in Nature and in many social and technological networks. Considering these networks, it is interesting to study the network evolution, given the possibility that agents can change their neighbors (dynamic rewire), when non-cooperative behaviors are detected. In this paper, we present a model of the NIPD game where a population of genetically-coded agents compete altogether. We analyze how different game parameters, and the network topology, affect the emergence of cooperation in static complex networks. Based on that, we present the main contribution of the paper that concerns the influence of dynamic rewiring in the emergence of cooperation over the NIPD.

Keywords: Evolutionary game theory, complex networks, multiple iterated Prisoner's Dilemma, rewiring, cooperation

Mathematics Subject Classification 2010: 91A06, 91A12, 91A22

1 INTRODUCTION

Game Theory [1], provides a set of analytical tools and models that represent real-life situations to understand what we observe when selfish individuals interact. Within this discipline, one of the most studied games is the Prisoner's Dilemma (PD) [6] that has been widely used and applied in many fields as biology, economy, politics, among others. It was initially popularized by the mathematician Albert W. Tucker, and used to simulate the real world, e.g. negotiations between countries, social interactions, war treaties, etc.; where participants have the possibility to choose between cooperative or defective (egoistic) actions. The main point in this game is analyzing which of previous two options is the most profitable for a rational player, concluding in many cases that the defective behavior is the one which imply a better payoff, and therefore the most rational option.

The Iterated Prisoner's Dilemma (IPD) [6] is a variation of the classic Prisoner's Dilemma, where the two players repeatedly compete throughout a certain number of iterations. The iterative competition allows agents to develop strategies based on previous plays. Since players base their decisions on more complex strategies, selfish behavior is no longer necessarily dominant and cooperation can emerge. In his study [6], Axelrod observed that when the Prisoner's Dilemma game is played repeatedly a high number of times with different strategies, unselfish strategies performed better.

However, the IPD models a one-by-one conflict situations. An extension of it, the N-Person Iterated Prisoner's Dilemma (NIPD) [5] is interesting to explore the emergence of cooperation in multi-player scenarios. NIPD models situations where an individual interacts with more than one opponent at a time. In this scenario, there may be individuals that take advantage of the efforts of others. If only one individual decides not to cooperate, it can take advantage of the rest. However, if many members of the group choose the defective strategy, the group benefits are dramatically reduced, and the existence of these free riders becomes clearly evident.

The way that agents are interconnected is a key element that influences cooperation [12, 31, 35]. Complex networks provide a realistic model of the topological features found in Nature, and many social and technological networks. Within the most common complex topologies, it is possible to distinguish between scale-free and small-world networks. Besides, in many real life networks, the links usually are not fixed, instead agents are able to change the individuals with whom they interact (dynamic rewiring).

In this paper, we present a model of the NIPD game where a population of genetically-coded agents compete altogether. The paper first explores how different parameters, related to the NIPD game and the network topology, affect the emergence of cooperation in static complex networks. Then, the main contribution of the paper concerns on how introducing dynamic rewiring, along the game simulation, can influence the emergence of cooperation, and the conditions to enhance it. Up to our knowledge, this is the first time that dynamic rewiring has been analyzed in the NIPD game.

The rest of the paper is organized as follows. Section 2 presents some background necessary to understand this work. Section 3 presents a description of the genetic model used in this evolutionary game. Then, Section 4 presents the results obtained for different topologies, parameters and considering also dynamic networks. Finally, Section 5 draws the conclusions, and hints some possible future work.

2 BACKGROUND

In this section we introduce the state of the art, and several topics needed to understand this paper.

2.1 State of the Art

The Prisoner's Dilemma (PD) game, and its iterated version (IPD), has been a subject of study for many researchers over the last years [20, 5, 27, 11, 13, 14].

In a seminal work, Axelrod [20] used genetic algorithms to evolve a population of strategies where each strategy plays the 2-person iterated Prisoner's Dilemma (2IPD) with every other strategy in the population. All the strategies in the population are co-evolving in their dynamic environments, and Axelrod found that such dynamic environments produced cooperative strategies that performed very well against their populations.

More recently, in [11, 13, 14], the authors study the effect of coalitions and rewiring (see Subsection 2.6) in complex networks (see Subsection 2.5) on IPD games, and present very positive results in matters of cooperation among players. This gives us a good reason to study the effect of complex networks and rewiring in the NIPD model, which presents a more demanding environment, concerning cooperation, than the IPD.

In [5] Yao and Darwen demonstrated that cooperation can still appear in the n-player iterated Prisoner's Dilemma (NIPD) game, where $n > 2$ agents play simultaneously. However, it was still difficult to evolve cooperation when the number of players increases. They have also presented some experimental results which show the importance of the environment in which each individual is evaluated, and their effects on generalization ability.

In [23], the authors study the impact of different payoff functions and local interactions on the NIPD game. Each payoff function is used to describe different behaviors of cooperation and defection among a group of players. They also investigate the impact of neighborhood size on the evolution of cooperation, which in the NIPD case becomes rather difficult when the neighborhood increases.

In [22] the author proves mathematically that autonomous agents that are used to collect information on the Internet are actually playing he NIPD, and show how cooperation among these agents can emerge, when it is established how the resources can be shared.

Recently, Chiong and Kirley produced a set of works over the NIPD, that we analyze next. In [24], these authors simulate the NIPD game on a two dimensional grid-world to test the effects of neighborhood structure on the evolution of cooperative behavior. They experiment with three different types of neighborhood structures (triangular, rectangular and random pairing) and conclude that cooperation emerge from the triangular neighborhood structure, while defection prevails on the other two structures.

Later on, the same authors investigate the ability of co-evolutionary learning to evolve cooperative strategies in structured populations using the NIPD [25]. In this case, they find out that topological arrangement of the neighborhood structures is an important factor that determines the level of cooperation.

On another study that attempts to reveal more information of the elements that promote cooperation among individuals in the NIPD game, Chiong and Kirley examine on [26] the effectiveness of two learning mechanisms: an evolutionary-based technique and a social imitation technique. According to them, the evolutionary-based technique performs better and, therefore, it should be used when there is a need to realize effective collective actions.

Chiong and Kirley [27] have also studied the use of complex networks on iterated games. They have performed a series of experiments with small-world networks and two different types of N-Player games (the NIPD and the N-player Iterated Snowdrift game) to test the influence of different parameters of these networks in the cooperation of the players. This paper is the closest one to our work, however, there is no thorough explanation of the causes for this reduction in cooperation when rewiring is applied. Besides, when they use the term rewiring, they only consider the effect of the initial rewiring probability when creating the small world network topology; that afterwards remains static along the whole simulation.

In [28], the authors improve the previous spacial test model to include periodic boundary conditions. The results obtained from experimenting with this new model show that random movements can promote cooperative behavior in N-player games. Also, in [29] they propose a multiplayer evolutionary game model in which agents play iterative games in spacial populations. The simulations with this model indicate that the cost-to-benefit ratio and group size are important factors in determining the appropriate length of beneficial repeated interactions.

2.2 N-Iterated Prisoner's Dilemma (NIPD)

The Iterated Prisoner's Dilemma (IPD) consists on repeating successively a set of basic Prisoner's Dilemma games. Players make their decisions on each round considering a certain number of previous opponent's actions without knowing the number of rounds to be played. This prevents individuals from building their strategies depending on a certain time horizon. A strategy in the IPD is a rule to decide the next action depending on the previous history. The success of a strategy depends not only on that strategy, but also on the opponent's strategies.

The basic 2-player IPD has been used to model several real-world problems (addiction research [15] and behavioral economics [16], arms races [17] or even climate change [18]). However, there are other scenarios that cannot be modeled with the 2-player IPD (2IPD). The N-player IPD (NIPD) is used to model situations where one player interacts with more than one opponent at the same time. In the NIPD game, each player can also choose between Cooperation (C) and Defection (D), but the selected strategy is used against all the opponents and at the same time (multiplayer game). This makes a big difference, to the point that strategies that work well for the 2IPD might fail for the NIPD [19].

		Number of Cooperators				
		0	1	2		$n-1$
Player's action	C	0	2	4	...	$2(n-1)$
	D	1	3	5	...	$2(n-1)+1$

Figure 1. NIPD payoff matrix

A possible payoff matrix for a N-Player IPD is shown in Figure 1, where in each iteration, each player receives a payoff that depends on its action and how many individuals have cooperated in a particular game iteration. In this game, the D option is dominant, i.e., each player is better off choosing D than C no matter how many of the other players choose C and, however the outcome if all players choose thei non-dominant C strategies is preferable from every player's point of view to the one in which everyone chooses D, no one is motivated to deviate unilaterally from D [19].

Making some basic algebraic operations, it is possible to obtain the average per-round payoff, which lets us measure how common cooperation was [5]. If N_c cooperative moves are made out of N moves of an n-player game, then the average per-round payoff is given by:

$$a = 1 + \frac{N_c}{N}(2n - 3). \tag{1}$$

2.3 Genetic Model

An individuals strategy determines which action will be performed in a certain situation. When using genetics, we can represent the strategy using a genome, i.e., an array of bits that specifies the decision to take in every possible context. We will base our work in the genotypical representation introduced by Yao et al. in [5].

As Yao et al. explain in their model, each individual is regarded as a set of rules stored in a look-up table that covers every possible history. As a game might have an enormous number of possible histories, and as only the most recent steps will have significance for the next move, we only consider every possible history over the most recent h steps, where h is less than 4. This means that an individual can only remember the h most recent rounds. Such a history of h rounds is represented by:

1. h bits for the players own previous h moves, where a "1" indicates defection, "0" cooperation.
2. Another $n-1$ group of $h \cdot \log(n)$ bits for the number of cooperators among the other $n-1$ players, where n is the number of players in the game. This requires that n is a power of 2.

For example, if we are looking at 8 players who can remember 3 most recent rounds, then one of the players would see the history as:

$$\text{History for 8 players, 3 steps: } 001\,111\,110\,101 \text{ (12 bits).}$$

The first 3 bits on the left represent the players own actions (see [5] for a detailed example). The next three bits that follows, gives the number of cooperators among the other 7 players in the most recent round, which is 7 in this case, as the value of the three bits is 111_2. The rest of the bits also indicate the number of cooperators among the other players, but for previous rounds, i.e., for 2 and 3 steps ago, always keeping the most recent events on the left.

In the example, we have $2^{12} = 2048$ possible histories, therefore, the same number of bits are needed to represent all possible strategies. In the general case of an n-player game with history length h, each history needs $h + h \cdot \log_2(n)$ bits to be represented and there are $2^{h+h\cdot\log_2(n)}$ of such histories. Since there are no previous h rounds at the beginning of a game, we need to specify them with another $h \cdot (1 + \log_2(n))$ bits. Hence, each strategy is finally represented by a binary string of length $h + h \cdot \log_2(n) + h \cdot (1 + \log_2(n))$.

The different strategies used by the players, and represented by this model, form the genetic diversity of the experiment. Introducing other factors, like mutations, increases the genetic diversity. The measurement of this diversity can be very important to analyze genetic algorithms, and can be used as a finishing condition when the genetic diversity falls below a certain threshold. There are many methods to measure this diversity, e.g., the entropy, the Hamming distance, and the moment of inertia. In [8] Morrison and De Jong have shown that the moment of inertia obtains the same results, to measure diversity, than the Hamming distance; but with a much lower computational cost, so it is the approach that we use in this paper.

2.4 Spatial Networks

Spatial networks (SP) [2] are a collection of nodes connected by links, with a certain relation determined by the spatial proximity among them. Each node, representing a certain player, is connected to a group of other nodes, i.e., neighbors that form its neighborhood. Therefore, the neighborhood of a cell can be defined by a radius to describe the maximum distance a neighbor can be. This configuration represents relationships conditioned by proximity, and it is related with regular graphs. An example is presented in Figure 2.

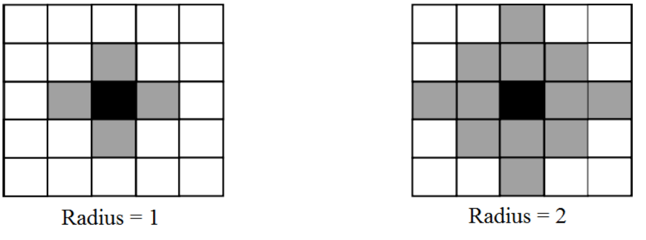

Figure 2. Neighborhood representations (in gray) as a function of the radius

2.5 Complex Networks

Many real networks present certain characteristics that suggest that, despite the fact of not being regular, they are not completely random either.

Complex networks can be classified in three basic types of networks [3]: random (RN), small-world (SW) and scale-free (SF).

Random Networks (RN) are randomly generated by placing a fixed number of edges between vertices at random with uniform probability [9]. Random networks are characterized by their short characteristic path length, i.e., the maximum distance between any two nodes in the graph is short.

According to Watts and Strogatz [7], small world (SW) networks are intermediate topologies between regular (e.g., spatial) and random ones. Their properties are most often quantified by two key parameters: the clustering coefficient and the mean-shortest path.

On the one hand, the clustering coefficient quantifies how the neighbors of a given network node (i.e., the nodes to which it is connected) are on average interconnected. It reflects the network capacities of local information transmission. The distance between two nodes of the network is the smallest number of links one has to travel to go from one node to the other. On the other hand, the mean-shortest path is the average graph distance of the network, and indicates the capacities of long distance information transmission.

Small-world (SW) networks [3] share properties of both random nets and regular lattices, because they have a short characteristic path length and a high clustering coefficient, i.e., there is a high connectivity degree among the vertices in the graph. This SW topology can be generated by the Watts and Strogatz algorithm [9]. Formally, we note them as $W_V^{k;p}$, where V is the number of nodes, k the average connectivity (i.e., the average size of the nodes neighborhood) and p the initial rewiring probability.

Scale-free (SF) networks follow a power law concerning degree distribution, at least asymptotically, i.e, the fraction $P(k)$ of nodes in the network having k connections to other nodes goes for large values of k as $P(k) \sim k^{-\lambda}$ usually having $2 < \lambda < 3$. Formally we denote them as $S_V^{k;-\lambda}$, where V is again the number of nodes. Scale-free networks show characteristics present in many real world networks like the presence of "hubs" connecting almost disconnected sub-networks. In [4], it has been proved empirically that many large-scale complex networks are scale-free. Among these type of networks we may cite the Internet, the World Wide Web, email network, protein interactions, etc. The "preferential attachment method" [4] can be used to build such topologies, reflecting also the dynamical aspect of those networks.

In [10] the synchronization of complex dynamical networks is analyzed. According to the authors, scale-free networks are inhomogeneous in nature; meaning that most nodes have very few connections, while few particular nodes have many connections ("hubs"). However, when introducing dynamical elements into the network models, which allows us to extend the models from static to dynamic, synchronization motion of its dynamical nodes is observed. This phenomena is the basis for convincing explanation of many processes in nature.

2.6 Dynamic Rewiring

Very often, when analyzing the effect of complex networks on the population dynamics, the link between nodes remain static throughout the whole simulation (cite). This means individuals are not allowed to change their neighbors regardless of their behavior and the effect it has on the individual's payoff. However this allows us to model and study the evolution of strategies within defined population structures, it does not fully capture the nature of social relationships, as humans tend to change their social ties when they are not beneficial anymore.

This situation can be included in our model by allowing connections to be modified dynamically depending on the individuals' interests. Therefore, when an individual considers that a player connected to him/her is not cooperative enough, he/she can cut this link and try to connect to a "better" neighbor (rewire). This process of rewiring allows players to dynamically create their neighborhoods based on their preferences [30, 33, 32, 34].

3 MODEL DESCRIPTION

This paper analyzes how cooperation in NIPD games is affected by several parameters, as well as by the topology used to connect the agents. Moreover, we are also interested on how the introduction of rewiring affects the emergence of cooperation. To achieve these goals, in this section we present a model that defines how agents play, interact, update their strategy and their links.

Firstly, we create a network where agents are nodes, and the links describe the relations between the agents. Once the network is established, each agent knows its neighborhood, which is formed by the agents directly connected. Then each agent plays the NIPD with all its direct neighbors. Finally, the payoff for each player is calculated.

The game is played a certain number of iterations. In each iteration, each player decides its actions depending of what has happened in previous ones. Thus, depending on the history that represents the context defined by the player's previous actions, and the number of opponents in the previous plays, it selects one action (how to select the action has been described in Subsection 2.3). Note that since the number of connections of an individual is not the same for every agent in a complex network, NIPD games can take place in neighborhoods with a variable number of players. Therefore, a player cannot use the number of cooperative neighbors as a reference to take a decision. For example, two cooperating players represent a 100 % of the cooperation in a two player neighborhood, but a 50 % in a four player neighborhood. To avoid this unevenness between neighbors, we consider the percentage instead of the total number of cooperators.

Once the action to take is selected for each agent, all of them play the NIPD. The payoffs are calculated as a function of the NIPD payoff matrix described in Table 1, and each player will obtain a payoff per iteration depending on its action and the amount of cooperators in its neighborhood. For example, in a 5IPD if a player decides to cooperate and only two neighbors cooperate the player obtains 2 points. However if all the neighbors cooperated he will receive $(2 \cdot (5 - 1) = 8)$ points. Since the size of the neighborhoods can be variable, the final fitness of an individual is obtained using the percentage of the payoff obtained competing in its own neighborhood, and also the other ones, where it is also a neighbor.

Once agents have played, and after a new generation is created, but before it is evaluated, agents may decide to rewire. For this, each player keeps track of the number of times a neighbor has cooperated with it. Moreover, once all the iterations of a NIPD game have been completed, agents know the others contributions. Thus in order to rewire, players firstly remove the connection with the less cooperative neighbor. After this, they ask the other neighbors about their more cooperative neighbors, and try to connect with the best one.

4 RESULTS

This section presents the experimental settings used in our game simulations, together with the results obtained for the different parameters and scenarios we consider.

4.1 Experimental Settings

In our experiments, we use the four types of networks introduced in Section 2, i.e., spatial networks, random networks, scale-free and small world networks. The radius used in spatial networks by default is 1.

Every experiment has run for 1000 generations. In each generation agents play for a certain number of iterations, configured as a game parameter. Each experiment is repeated 20 times, and finally the average values are calculated per generation. Regarding other parameters, Table 1 shows the default values used to perform the simulations, unless otherwise stated. These values have been selected, after a huge experimental set of tests, as we have found them representative and adequate for the present contribution.

Population Size	100
Crossover Type	Uniform
Mutation Probability[1]	1e−7
History Size	3
History Initialization	Random
Number of Iterations	50
Own Neighborhood Fitness	50 %
Rewiring	No

Table 1. Default values used in the simulations

4.2 Spatial vs. Complex Networks

In this subsection we consider the influence of the topology over our simulations. All the networks compared in this experiment have an average neighborhood of 4 nodes. This is done to avoid conditioning the result by having different average values for each network.

Following this policy, in Figure 3 we can see a comparison of the performance of different networks, i.e., a spatial network with a 1.0 radius, a Small World (SW) network with 4 neighbors and a initial rewiring probability of $p = 0.1$, a Scale Free (SF) network with 4 initial nodes; and, finally, a random network where every node connects randomly with other 4 neighbors. We can see that regular networks increase significantly the level of cooperation offered by random networks. The more organized a network is, the easier it becomes for the population to reach an agreement to increase the average payoff. This is coherent with the results found in [5].

Spatial networks are the most regular ones, and exhibit a higher degree of cooperation, which is coherent with literature (see [27]). However, most of real world

[1] The value for mutation probability has been set to 1e-7, because a higher probability had a negative effect on cooperation. We plan to further study this case in following work.

networks are not spatial, and in the following sections we will focus our attention on complex networks, especially on small world ones, as they present a higher level of cooperation than scale-free networks. The main reason for this difference among them is that the scale free heterogeneity makes it difficult to have a higher level of cooperation in the NIPD, as hubs contain a high number of nodes, and therefore cooperation on those nodes is more difficult to emerge under a NIPD model. At the same time, those nodes are in many other neighborhoods, so they have a strong influence over the rest of the network. Thus, we will focus over small world topologies in order to perceive more clearly the effect of several parameters over cooperation.

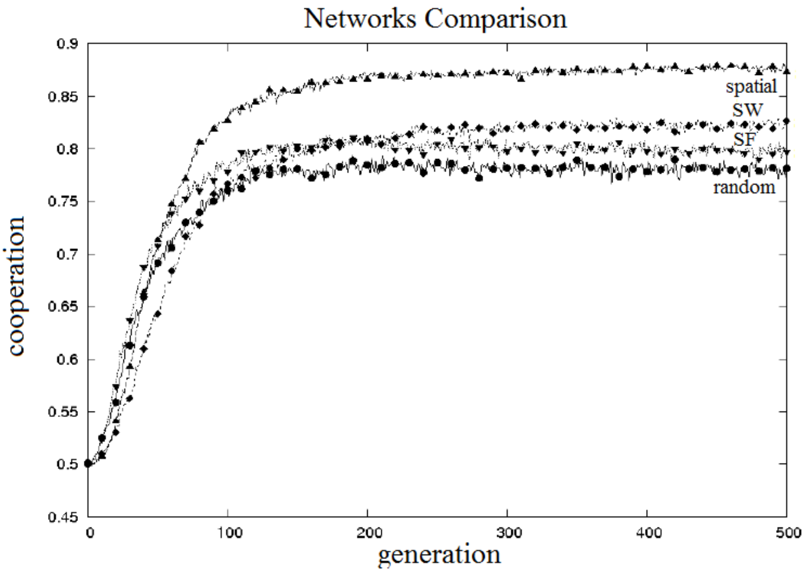

Figure 3. Comparison of spatial, small world (SW), scale free (SF) and random networks

4.3 Small World and Cooperation

In this section, we present the influence of several parameters of the NIPD game using a small-world topology, with an initial rewiring probability ($p = 0.1$).

4.3.1 Number of Players

In Figure 4 we can see the cooperation evolution for different neighborhood sizes for the small-world topology. The number of players that take part in a NIPD game simulation depends on the neighborhood size, which is variable depending on every individual. We can see in Figure 4 that when the average neighborhood increases, interactions take place between a higher number of players, reducing the final cooperation. This result is coherent and agrees with the work of Yao et al. [5], as cooperation becomes less probable in bigger groups, where the payoffs and the temptation to defeat are higher.

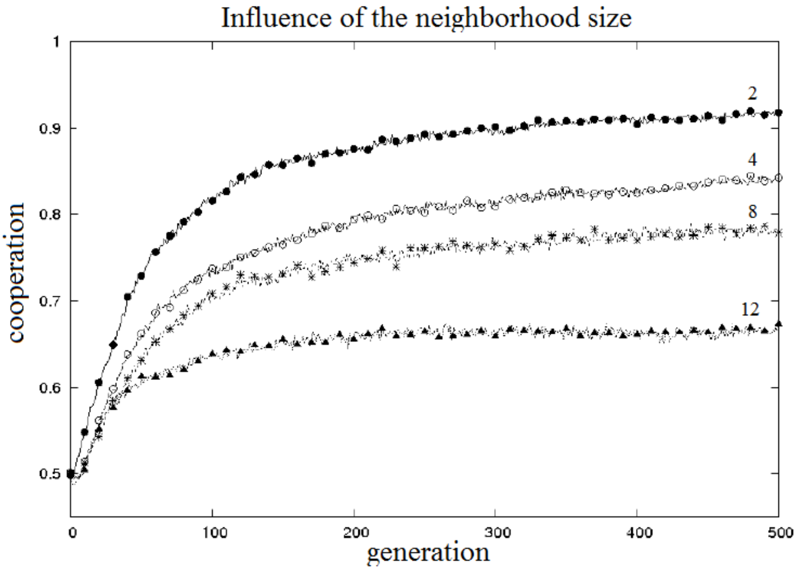

Figure 4. Influence of the neighborhood size

But, when the neighborhood size decreases, the players have less options to crossover their genes, since they are connected to fewer individuals. In Figure 5 we study the influence of the number of players on gene diversity. We can see that diversity decreases faster as the average number of players in the neighborhood increases.

4.3.2 History Size

Individuals decide their actions depending on what happened in previous plays. We model the memory of an individual using a certain history size. As the number of plays to remember increases, individuals theoretically can improve their behavior. However, an excessive value for the history size increases dramatically the size of the genome, which complicates the convergence to a specific behavior, either defector or cooperator.

In Figure 6, we can see that as the history size increases, cooperation among individuals is reduced. In populations with larger histories, cooperation is not so common. This is due to the fact that individuals take into account a larger number of previous actions, and can decide to punish their rivals for an action that happened long time before the current play. Moreover, according to the genomic representation introduced before, for each new play to remember the genome size increases 10 times

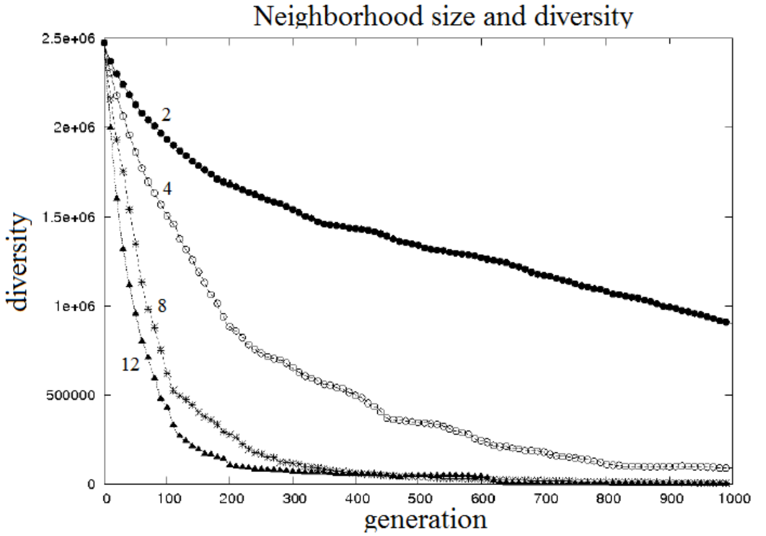

Figure 5. Population diversity for several neighborhood sizes

its size. This makes the convergence to cooperation really difficult, since the number of genes per individual is higher, and therefore the diversity of population much larger too.

4.3.3 History Initialization

During the first iterations there are not enough previous actions to complete the players' history. However, at the beginning of the game the players' histories must be initialized.

We consider three possible initializations: optimistic, pessimistic and random. The two first options consider that the individual has cooperated, or defected, respectively, in all the previous plays. In the third option the initial values are assigned randomly.

Figure 7 shows the implications of choosing any one of these three options. Cooperation becomes almost total with the optimistic initialization, since it encourages the cooperation from the first iteration of the game. The pessimist initialization reduces the degree of cooperation. However, since histories are always the same in the first iterations, it favors the evolution of the genes representing those contexts. After a few iterations, cooperation increases rapidly since it is an action that increases the average payoff.

Nevertheless, both the optimistic and pessimistic initializations are not very realistic, and bias the genome evolution to a few cases among all the possible contexts. Random initialization seems to be more pragmatic, as it models the behavior of those agents that take random decisions when they have no information. However,

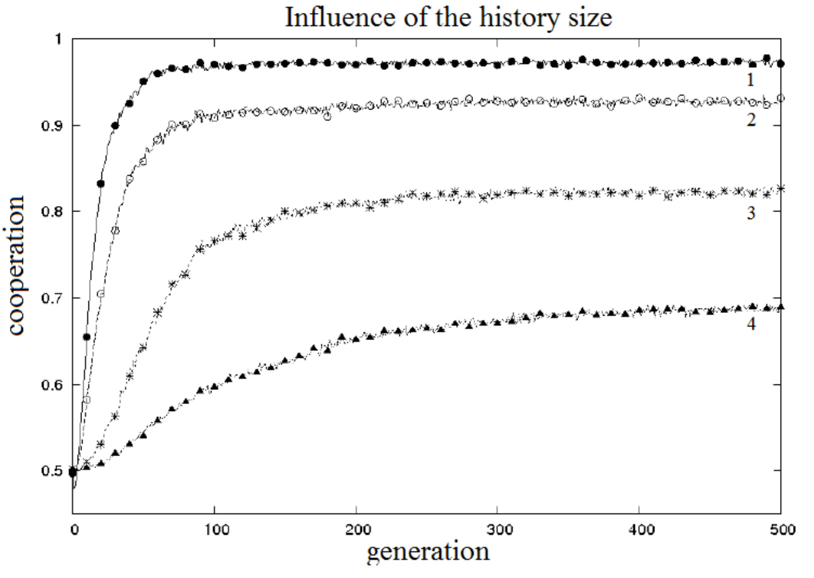

Figure 6. Influence of the history size in cooperation

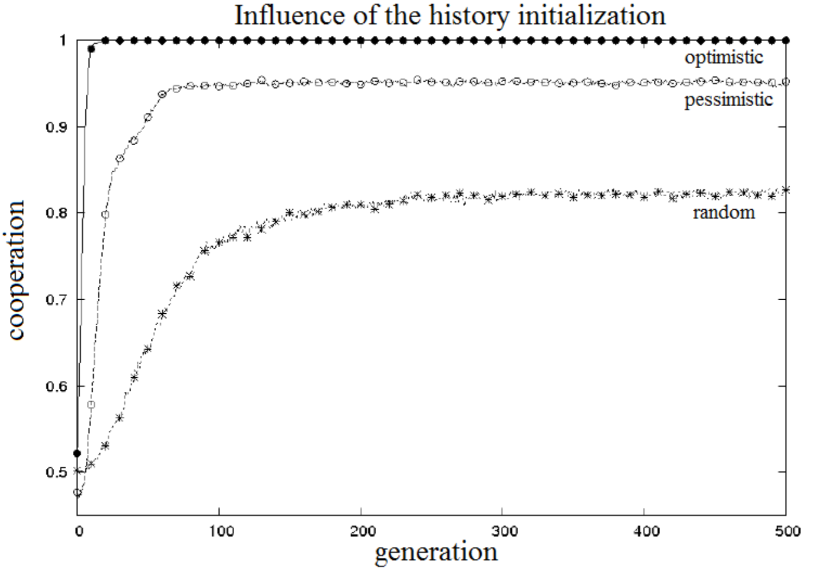

Figure 7. Influence of the history initialization

in this situation the cooperation results are the worst among the three alternatives.

4.3.4 Number of Iterations

The evaluation of an individual is made according to the payoffs obtained in the NIPD game. As we have seen in Section 3, each game is played for a fixed number of iterations. Since the first iterations cannot be based on previous actions, a transitory status is produced. We have seen in the previous section that this affects the behavior of the population at the beginning of the game. To avoid this effect, it is necessary to increase the number of iterations in each game, i.e., the higher the number of iterations, the lower the effect of the first ones.

The results obtained in Figure 8 show a higher degree of cooperation as the number of iterations increases. When the number of iterations is too low, as in the 10 iterations case, the individuals still have not converged to an optimal behavior. Notwithstanding, in the 100 iterations case we can see that the cooperation almost reaches the 90 % level.

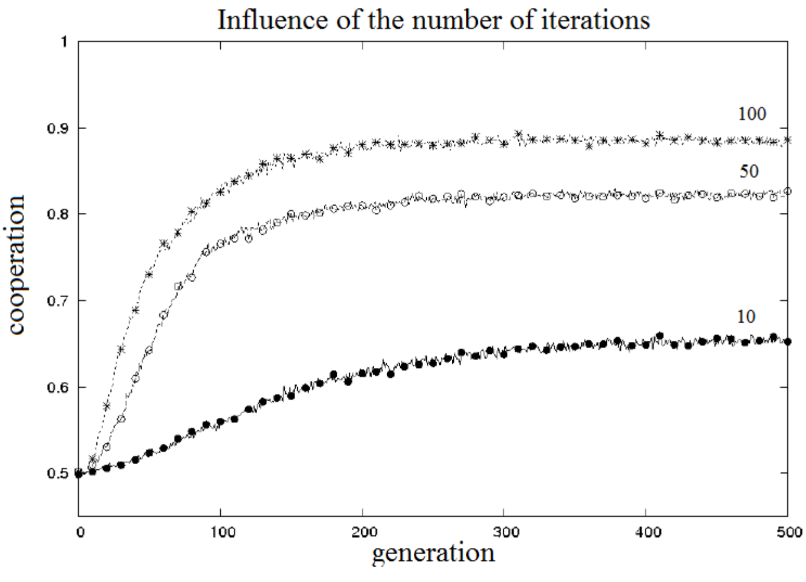

Figure 8. Influence of the number of iterations in each generation

4.4 Dynamic Rewiring

The networks considered up to now have been static in the sense that, once created, they did not change the links among the nodes along simulations. Therefore, individuals, belonging to these networks, did not have the possibility to modify their neighborhoods. Dynamic partner switching (dynamic rewiring) solves this problem, allowing agents to change their neighbors during simulation time.

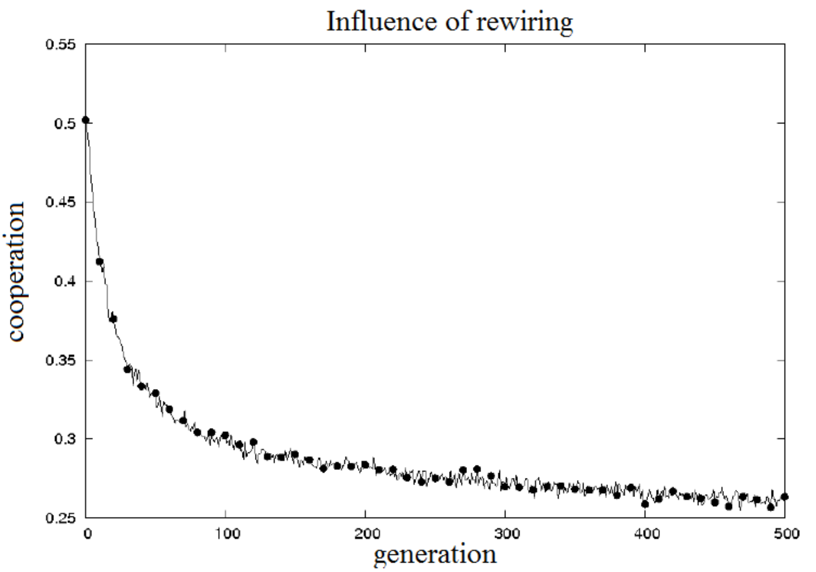

Figure 9. Influence of rewiring

Figure 9 presents a simulation with a scale-free network (4 initial nodes, 2 neighbors), where dynamic rewiring is applied in each new generation. The reduction in the cooperation shown in the figure is caused by the network configurations resulting from the rewiring process. This can be seen in Figure 10, where several individuals remain isolated from the population without any possibility to interact. However, the number of connections remains constant, which results in a few groups with a high number of players participating in the NIPD game, which leads to a reduction of the cooperation.

Figure 11 shows the evolution of cooperation taking into account only individuals that remain connected. Cooperation in this case fluctuates rapidly, but the result is worse than the case without dynamic rewiring. Here rewiring acts like noise, changing neighborhoods frequently, creating big neighborhoods, and preventing the emergence of higher levels of cooperation.

To avoid the increase of the neighbourhood size and the appearance of isolated individuals, isolated agents are allowed to rewire to any random individual after each game evaluation. The impact on cooperation is shown in Figure 12. The cooperation evolution is similar to the one obtained in the few groups formed by the rewiring (Figure 11). However, since now isolated individuals can reconnect again, cooperation spreads to all individuals in the population.

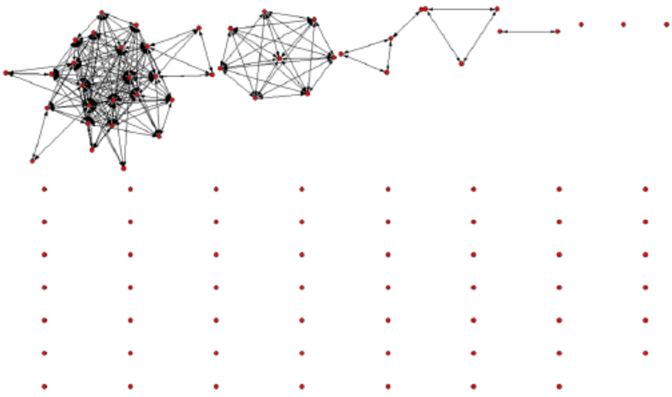

Figure 10. Example of network resulting after rewiring

In the previous figures, individuals always try to reconnect to the player who has been more cooperative within its neighbourhood. This makes cooperative players' neighborhoods bigger, and this behavior naturally prevents cooperation growth.

To counteract the effect caused by the continuous rewiring to the most cooperative neighbors, with the natural creation of big groups, we introduce a random individual selection probability in the rewiring process. The outcome of this mod-

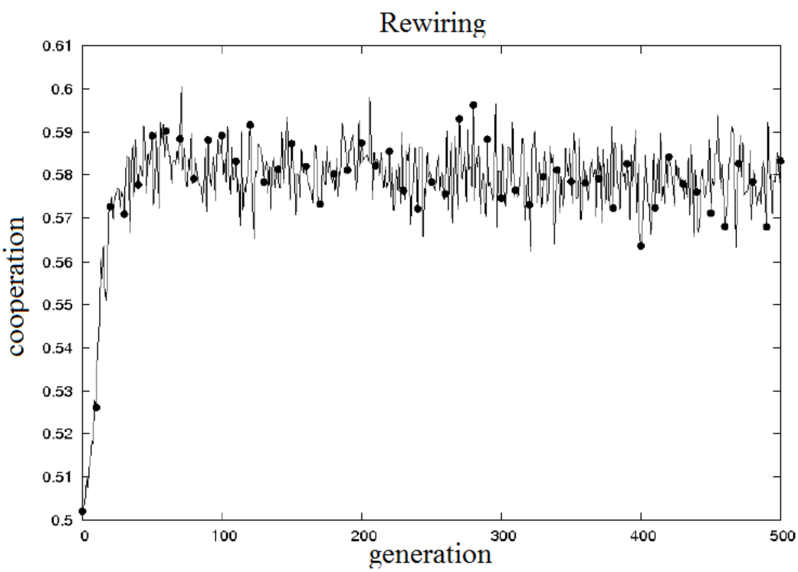

Figure 11. Influence of rewiring on connected individuals

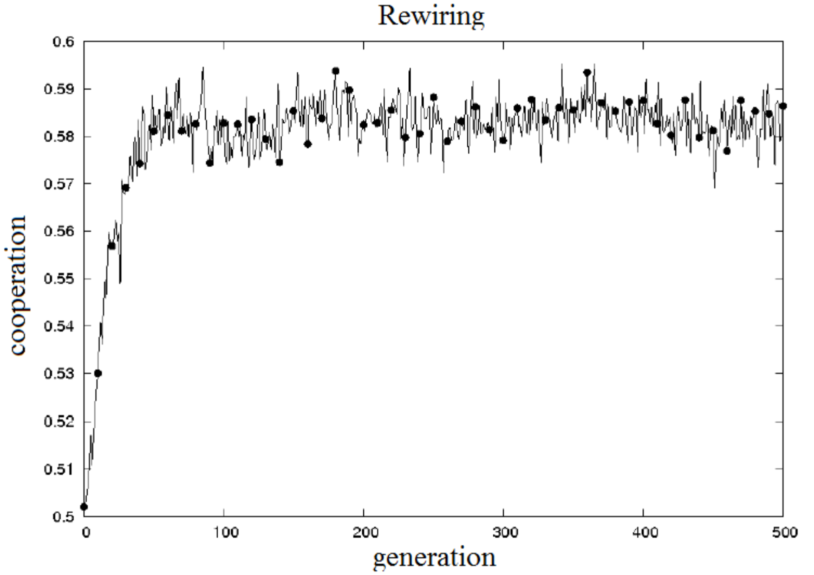

Figure 12. Influence of rewiring on disconnected individuals

ification can be seen in Figure 13, where results show an increase in cooperation. With the new random rewiring, neighborhoods do not grow so much, and, at the same time, individuals reject less cooperative players making their neighborhoods smaller, and both effects reinforce cooperation.

5 CONCLUSIONS

In this paper we have considered the classical NIPD model to analyze how several parameters and the network topology can affect the evolution of cooperation, using static or dynamic networks.

Firstly, we have seen that NIPD parameters like number of players, history size, initialization type and number of iterations play an important role in the emergence of cooperation. In fact, among the results obtained, we have seen that the more regular the topology is, the higher the cooperation tends to be. This means that in this case, spatial networks or small-world networks are better options for cooperation to emerge compared to other more irregular network topologies. We also have seen that cooperation becomes more difficult for bigger neighborhoods.

The main contribution of the paper is to study the effect of dynamic rewiring over the emergence of cooperation. Dynamic rewiring has proved to enhance the cooperation significantly, but the rewiring process should have a random component instead of always selecting the most cooperative neighbor. This result may seem counterintuitive, but we can understand it considering that, if the most cooperative

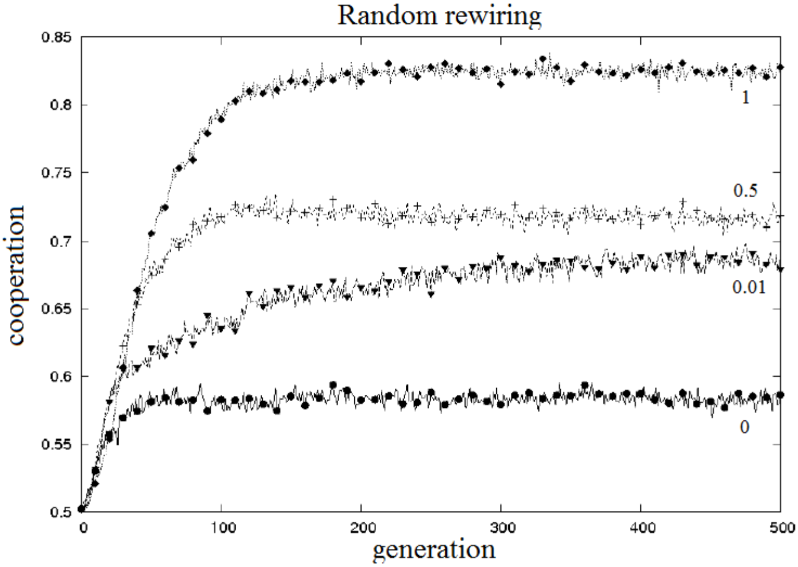

Figure 13. Effect of random rewiring with different reconnection probabilities

neighbor is always selected, then its neighborhood grows notoriously. This significant neighborhood growth usually ends in general defection in the NIPD game, as we have seen in the initial part of the paper.

For future work we plan to extend the NIPD model to other types of games, like the Public Good Games (PGG), as well as studying implications of different genome representations.

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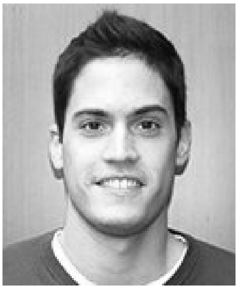

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