Optimisation of strategy placements for public good in complex networks

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ABSTRACT

Game theory has long been used to model cognitive decision making in societies. While traditional game theoretic modelling has focussed on well-mixed populations, recent research has suggested that the topological structure of social networks play an important part in the dynamic behaviour of social systems. Any agent or person playing a game employs a strategy (pure or mixed) to optimise pay-off. Previous studies have analysed how selfish agents can optimise their payoffs by choosing particular strategies within a social network model. In this paper we ask the question that, if agents were to work towards the common goal of increasing the public good (that is, the total network utility), what strategies they should adapt within the context of a heterogeneous network. We consider a number of classical and recently demonstrated game theoretic strategies, including cooperation, defection, general cooperation, Pavlov, and zero-determinant strategies, and compare them pairwise. We use the Iterative Prisoners Dilemma game simulated on scale-free networks, and use a genetic-algorithmic approach to investigate what optimal placement patterns evolve in terms of strategy. In particular, we ask the question that, given a pair of strategies are present in a network, which strategy should be adopted by the hubs (highly connected people), for the overall betterment of society (high network utility). We find that cooperation as opposed to defection, Pavlov as opposed to general cooperator, general cooperator as opposed to zero-determinant, and pavlov as opposed to zero-determinant, strategies will be adopted by the hubs, for the overall increased utility of the network. The results are interesting, since given a scenario where certain individuals are only capable of implementing certain strategies, the results give a blueprint on where they should be placed in a complex network for the overall benefit of the society.

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1. INTRODUCTION

Game theory is the science of strategic decision making among autonomous players[1]. Evolutionary game theory is the adaptation of game theory in populations of players, where game theory is used to explain the evolution of strategies in a population of players[2]. On the other hand, most of the real-world populations are not 'well-mixed' but are restricted by spatial limitations. Thus, the players distributed in heterogeneous networks provide an interesting premise to study evolutionary games. Particularly,the effect of topology of heterogeneous networks on the evolutionary stability of strategies has been studied thoroughly[3, 4].

Social structures of people have often been modelled as complex networks. While the 'well-mixed' or random models have been used earlier to characterise social interactions, the heterogeneous nature of some interactions, whereby some individuals have more links than others, is nowadays taken into account. It has been found that most social networks are, in fact, the so-called 'scale-free' networks, with power law degree distributions. As such, networked game theory has come into prominence, to analyse the payoff of individuals in such scenario. At the same time, public goods games have begun to be studied as a branch of games where the individual pay-offs for agents are less important than the overall payoff (utility) for the community. Not many studies have been done on networked public good games.

Evolutionary stability of a game refers to the ability of a particular strategy to dominate over any mutant strategy[2, 5]. There may be situations however, that weaker strategies are allowed to sustain within a network, due to the factors external to the game itself. A good real-world example of this is the welfare systems that are in place in many financial environments to safeguard the financially weaker individuals or organisations.

Normally, evolution within the context of game theory or networked game theory is taken to mean that individual agents adopt or evolve strategies with the view of maximising their individual payoff. This is indeed often the case: each deer in the forest adapts strategies to maximize its lifetime and food intake, and such strategies are passed on to the next generation, either by observation or as some kind of genetic memory. However, environmental pressures may also dictate collective evolution, whereby each individual tries to adapt the best strategy for the collective gain of the society, as opposed to its individual gain. For example, a society of deers may be forced to evolve collective strategies to better survive against a pride of lions. The strategy adapted by each deer, then, is dictated not so much by its individual gain but the collective gain of the society. It is easy to find similar examples in the human society as well.

In this work, we observe how the evolutionarily stable and evolutionarily unstable strategies should be distributed within a network in order to maximize the cumulative payoff of the entire network. That is, how best to assign the strategies over the nodes of a network to maximize the cumulative payoff of all players. In order to do that, first we try to determine whether the spatial distribution of players have an effect on the cumulative payoff of the network. Next, we observe the variation of average degree of players with each strategy to see which strategies tend to occupy the hubs and which occupy the peripheral nodes when the cumulative payoff increases. Since we need to keep the ratios of different strategies and their distributions fixed, we assume that there is no evolution of strategies among the players when a game is played iteratively. Instead, merely the initial configurations of players are varied to observe which configuration would provide the best overall utility of the network over time.

We use a genetic algorithm-based approach, where a population of networks, structurally identical but employing different placement of strategies, evolve to maximise the network utility. The evolving networks answer the question of how best to distribute strategies in order to maximise payoff for the society. We use the well known Iterative Prisoners Dilemma game as the game of choice. We use a number of well known strategies, including cooperation, defection, general cooperation, Pavlov, and the recently introduced zero-determinant strategies. We compare strategies pairwise, and our particular goal is to identify which strategy must occupy the hubs (highly connected nodes) against the other for maximum network utility.

Potential applications of such optimisation may be found in organisational structures. Quite often, even the weaker strategies are allowed to survive due to the external environmental conditions (e.g. welfare, legal or political pressures). Thus, the optimisation technique suggested in this work may help to determine the optimum distribution of strategies to maximise the overall utility of the network, while the strategies are not allowed to freely evolve and the ratios of players with each strategy remains fixed.

This paper is organised as follows. In the next section, we elaborate on the game theoretical background used in this work. Also, we give a brief introduction into genetic algorithms and scale-free networks. Then, we describe how genetic optimisation was used to optimise for the cumulative network payoff. Next, we present the results obtained, followed by the discussion and conclusion.

2. BACKGROUND

2.0.1 *Game Theory*

Game theory is the study of strategic decision making[1]. One of the key concepts of Game theory is that of Nash equilibrium[6]. Nash equilibrium suggests that there is an equilibrium state in a game, which neither player would benefit deviating from. The equivalent concept in evolutionary game theory, which is the adaptation of game theory in to the evolution of a population of players, is evolutionary stability[2]. Evolutionary stability refers to the dynamic stability and domination of a particular strategy over potential mutant strategies. Naturally, evolutionary games incorporate iterative games where a population of players play the same game iteratively in a well-mixed or a spatially distributed environment[7].

2.0.2 *Prisoner's Dilemma Game*

Prisoner's dilemma Game is a game that is found in classical game theory[8]. Given a payoff matrix in Fig. 1, the inequality $T>R>P>S$ should be satisfied in a prisoner's dilemma game. In other words, in the prisoner's dilemma game, the highest mutual payoffs are obtained by the players when both players cooperate. However, if one player cooperates while the other defects, the defector would obtain a higher payoff.

Player 1 \ Player 2	Cooperate	Defect
Cooperate	R, R	S, T
Defect	T, S	P, P

Figure 1: The payoff matrix of a prisoner's dilemma game.

A more simplified representation of the prisoner's dilemma game has been suggested in the literature, which we use in this particular work. Here, we assign the variables $2>T=b>1$, $R=1$ and $P=S=0$ and reduce the payoff matrix to a more simplified version[3]. With this representation, we can ensure that there is only one variable that we can vary to alter the payoff matrix and thus the game behaviour.

It has been observed that the topology of the network is significant in the evolution of cooperation of strategies in the PD game[3]. Cooperation evolves to be the dominant strategy in a Scale-free topology, while defection would dominate in a Erdos-Renyi random network. In this work, we analyse how these strategies should be distributed in a heterogeneous network in order to maximise the overall cumulative payoff of the network.

Even though prisoner's dilemma game is usually used in a micro-economic perspective, that is how the strategies affect individual players' payoffs, we use the PD game in a more holistic approach in this work. We observe how the cumulative payoff of the network can be optimised by placing the players in different spatial arrangements within a network. This is analogous to the public goods game[4] where each player contributes to the collective good, instead of choosing a strategy to play against a neighbouring opponent. Even though there isn't a notion of collective good in the PD game from the perspective of an individual player, the individual interactions would affect the cumulative payoffs of the network.

2.0.3 *Memory-one strategies*

Memory-one strategies[9, 10] are a special sub-class of strategies in prisoner's dilemma games, where the current mixed strategy of a game would depend on the previous interaction between the two players in concern. In a mixed strategy scenario, there is a probability distribution that defines the potential strategies that could be adopted by a particular player against an opponent strategy. In memory-one strategies, this distribution is conditional to the immediate previous state of the two players in concern. In fact, Memory-one strategies are a specialisation of a more general class of strategies called finite-memory strategies[9, 10], where the current strategy would be dependent of n number of historical states between the two players.

When considering the previous state between two players, in a PD game, there could be four possible states. Namely CC, CD, DC and DD, where C represents cooperation and D represents defection, respectively. Memory-one strategies are represented by stipulating the probabilities of cooperation by a player in the next move, given each type of interaction of the player with the same opponent. For example, a strategy (1,1,1,1) would imply that the Player A would cooperate with player B, irrespective of the previous encounter between Player A and B. Thus, the pure strategy cooperation and defection can be thought of as a special case of memory-one or finite memory strategies. By varying the probabilities of cooperation under each of the previous encounters, it is possible to define infinite amount of mixed strategies. Some of the well-known memory-one strategies include Pavlov strategy (1,0,0,1) and general cooperator (0.935, 0.229, 0.266, 0.42) strategy. We will consider both these strategies in this study.

Zero-determinant strategies[11, 12] are a special sub-class of Memory-one strategies that has recently gained much attention in the literature. As the name suggests, ZD strategies denote a class of memory-one strategies that enable a player to unilaterally set the opponent's payoff. Due to this inherent property, ZD strategies have the ability to gain higher expected payoff against an opposing strategy. However, it has been shown that ZD strategies do not perform well against itself. Due to this reason, ZD strategies have been demonstrated to be evolutionary unstable[9], particularly against the Pavlov strategy. In order to observe how the distribution of evolutionary stable and unstable strategies affect the overall utility optimisation in a network of players, we simulated the scenarios where ZD strategy is mixed with Pavlov and GC strategies.

Suppose p1, p2, p3 and p4 denotes the set of probabilities that a player would cooperate given that the player's last interaction with the opponent resulted in the outcomes CC (p_1), CD (p_2), DC (p_3), DD (p_4). ZD strategies are defined by fixing p2 and p3 to be functions of p_1 and p_4, denoted by Eq. 1 and Eq. 2.

$$p_2 = \frac{p_1(T-P) - (1+p_4)(T-R)}{R-P} \tag{1}$$

$$p_3 = \frac{(1-p_1)(P-S) + p_4(R-S)}{R-P} \tag{2}$$

It was shown by Press and Dyson[11] that when playing against the ZD strategy, the expected utility of opponent O can be defined using the probabilities p_1 and p_4, while p_2 and p_3 are defined as functions of p_1 and p_4. Eq. 3 gives the expected payoff of the opponent against the ZD strategy.

$$E(O, ZD) = \frac{(1-p_1)P + p_4R)}{(1-p_1+p_4)} \tag{3}$$

Here, P and R represent the payoffs earned when both players defect and cooperate, respectively.

Hence, ZD strategies allow a player to unilaterally set the opponent's payoff, effectively making them extortionate strategies. In the simulations performed here, we set the probabilities p_1 and p_4 as 0.99 and 0.01 respectively, as in the work done by Adami and Hintze[9], then deriving p_2 and p_3 to be 0.97 and 0.02, according to the ZD conditional probability equations.

2.0.4 *Genetic Algorithms*

Genetic algorithms[13] are widely used as an optimisation technique. Genetic algorithms adopt the established concepts in biology to optimize a population of candidate solutions based on a particular fitness function. Each potential solution is identified as a 'genome'. Recombination and mutation are the genetic operators that are used to 'evolve' a population, until a certain boundary condition is met. In recombination, two most fit solutions in the population are selected for 'reproduction' and they are randomly recombined to produce a new offspring solution. When each offspring is born, it would go through a mutation process with a relatively small probability to add new genetic information to the population. When generating each population set, the weaker solutions are allowed to die out, keeping the overall population size fixed. Genetic optimisation is ideal for optimising the payoff of a network game as there is no straight-forward computationally efficient algorithm to perform that task.

2.0.5 *Scale-free networks*

Complex Networks are self-organising networks with non-trivial topological features[15]. In this work, we mainly focus on the scale-free network topology when analysing the effect of network topology on the cumulative payoff. In scale-free networks, the network topology encompasses a power-law degree distribution[16]. In other words, the degree distribution of the network would fit in a equation of the form $y = \alpha x^{-\gamma}$. Here, γ is called the scale-free exponent. The scale-free exponent is obtained by fitting a particular degree distribution into a power-law curve. Higher the scale-free exponent, more the power-law nature of the degree distribution.

Scale-free networks are abundant in real-world networks, such as in social, biological and collaboration networks[15]. Scale-free networks make a perfect candidate to study the topological effect of a population of players due to this reason. For example, it has been shown that cooperation becomes that dominant strategy in a scale-free topology due to the heterogeneity of the network[3]. Moreover, scale-free networks can be generated efficiently using the preferential attachment based growth, proposed in the Barabasi-Albert model[15]. Preferential attachment model suggests that nodes with higher degree have a higher probability of attracting new nodes, when the network grows. In other words, there exists a 'preference' in attaching to existing nodes, when a new node joins the network. Therefore, we use scale-free networks generated using the preferential attachment model for all our simulations in this work.

3. RESEARCH METHOD

We used the genetic optimisation technique to test the hypothesis whether the strategy distribution in a heterogeneous network affects the cumulative payoff of all nodes. Here, we evolve the assignment the strategies to players within the network to maximise the overall payoff.

In a heterogeneous network of players, the players at hubs may play larger number of games compared to the players at the peripheral nodes. Therefore, depending on the spatial distribution of strategies, the cumulative payoffs of a particular game would be different. Thus, given a particular set of strategies and a spatial distribution, finding the optimum distribution of strategies over the network in order to maximise the total cumulative payoff could be regarded as an optimisation problem. Such optimisation may have applications where the overall benefit of a particular strategic decision making environment has to be maximised, instead of maximising a particular player's payoff.

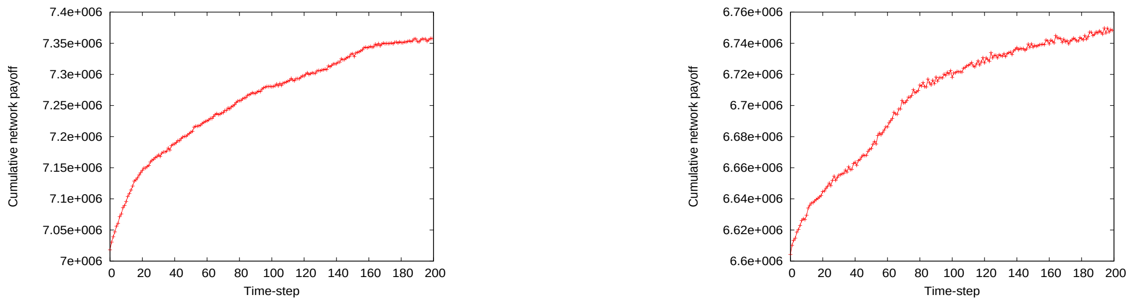
Initially, we wanted to test whether there's a correlation between the cumulative payoff and the initial distribution of strategies. To do that, we distributed the cooperator and the defector strategy in 100 different initial configurations, with the underlying network topology being a scale-free topology. The configurations were made to remain static without any evolution. For each configuration, we repeated the game over 1000 iterations and compared the accumulated payoff against the average degrees of nodes with each strategy.

When using the genetic optimisation too, a scale-free network was chosen for observation. Scale-free networks make good candidates as heterogeneous networks as they are commonly observed in social networks. A genome is represented as a binary string to represent the collection of nodes, with 1 and 0's being used to denote the two strategies assigned to the nodes. Initially, n number of different initial distributions of players placed randomly, ensuring that exactly 50% of the players follow each strategy. Afterwards, the game in concern is played iteratively for t number of time-steps among the players within the network. In classical Prisoner's dilemma the parameter b was set to 1.8 while for the memory one strategies, the variables were assigned to constants as T=5, R=3, P=1 and S=0. Note that the strategies of the nodes remain fixed during these iterations, thus the game is not simulated as an 'evolutionary game' in the strict sense of the word. This is necessary as we are interested in observing the effect of topological arrangement of strategies of players on the cumulative payoff of the network, for which the topological distribution of strategies should remain unchanged. The fitness function of the network game is the total cumulative payoff of all the players after the iterative game is played. In each generation of candidate player distributions, the fittest 10% networks are chosen for recombination. Upon recombining, the positions of players are randomly mutated with a very small probability. Following each recombination and mutation, the strategies of players are adjusted to keep the ratio of two strategies the same. This is done to ensure that the changing ratios of players' strategies do not affect the cumulative payoffs and it is just the arrangement of the strategies that affect the cumulative payoff of the network. Following this process, we could observe that genetic optimisation of player positions does improve the overall payoff of the network. Hence, the cumulative payoff of a network of a players are affected by the spatial distribution of players with heterogeneous strategies. This also suggests that GA could be effectively used to identify the optimum distribution of players/strategies within a network.

4. RESULTS

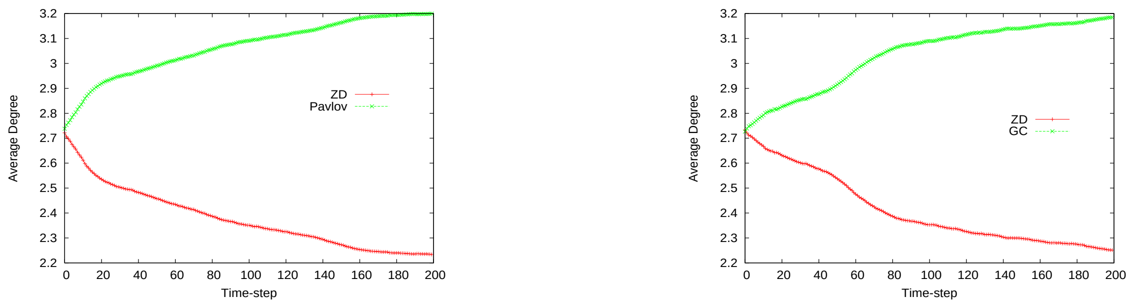
First we simulated the classical prisoner's dilemma game for the optimisation of strategy placement. It has been shown that the cooperation strategy is the evolutionary stable strategy in a scale-free network. Fig. 2 depicts the variation of the cumulative payoff of players in a collection of randomly distributed strategy distributions in a scale-free topology. The strategy distributions are sorted based on their resulting cumulative payoff. Fig. 3 shows the variation of the average degrees of cooperators and defectors in the same set of networks. As shown in the figures, there exists a clear correlation between the cumulative payoffs of strategy distributions and the average degrees of each strategy. Fig. 4 shows the average cumulative payoffs of network populations do increase over time when the initial configuration of the strategies is optimised using a genetic algorithm, suggesting that it is the networks with cooperators occupying the hubs that generate higher cumulative payoffs. While the cumulative payoff of the network is increasing, we can observe that the average degree of the cooperators of network populations do increase over time, while the average defector degree decreases, as shown in Fig. 5. This suggests that in order to maximise the cumulative payoff of a network, the cooperators should be placed as hubs.

Next we performed a similar optimisation on memory-one strategies of Prisoner's dilemma game. Memory one strategies are a branch of strategies in PD games where each the cooperation of each node depends on the previous move of each node. By varying the probabilities of cooperation based on each of the previous combinations (CC, CD, DC, DD), it is possible to derive different strategies. Some of the well-known strategies include General Cooperator, Pavlov and Zero-Determinant strategies. ZD strategies have been recently shown to be evolutionary unstable against Pavlov strategy. Thus, we use the Genetic optimisation technique to identify the optimum positioning of the



(a) $ZD - Pavlov$ (b) $ZD - GC$

Figure 6: The variation of cumulative network payoff of the network of players consisting of ZD-Pavlov and ZD-GC strategies. The network is a scale-free network consisting of 1000 nodes. The game was iterated for 200 time-steps.



(a) $ZD - Pavlov$ (b) $ZD - GC$

Figure 7: The variation of the average degrees of the network of players consisting of ZD-Pavlov and ZD-GC strategies. The network is a scale-free network consisting of 1000 nodes. The game was iterated for 200 time-steps.

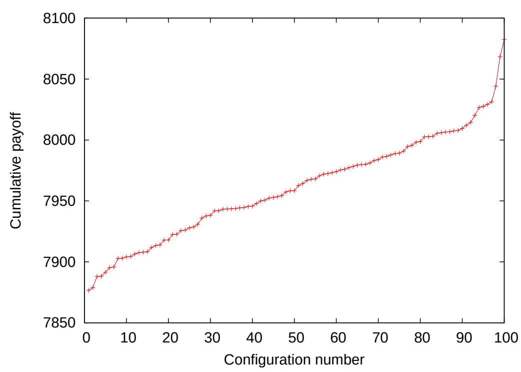


Figure 2: The variation of cumulative network payoff of a collection of random strategy distributions on a set of players playing the prisoner's dilemma game. The variable b was set to 1.8. The underlying network has a scale-free topology, consisting of 1000 nodes. The game was iterated for 10,000 time-steps. The strategy distributions are sorted based on the cumulative payoff.

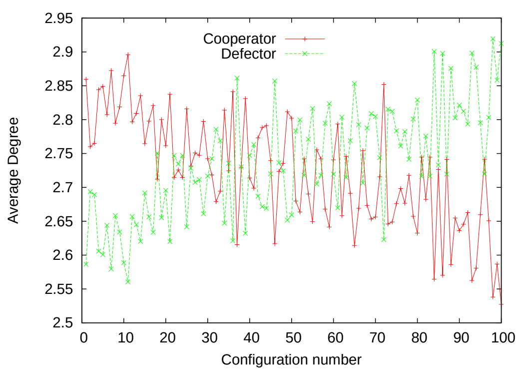


Figure 3: The variation of the average degrees of the cooperators and defectors of a collection of random strategy distributions on a set of players playing the prisoner's dilemma game. The variable b was set to 1.8. The underlying network has a scale-free topology, consisting of 1000 nodes. The game was iterated for 10,000 time-steps. The strategy distributions are sorted based on the cumulative payoff.

ZD and Pavlov strategies. Fig. 6[a] depicts the increase of the cumulative payoff of the players when the networks are being evolved, suggesting that in memory-one strategies too, strategy placement does contribute to the optimisation of cumulative network payoff. Fig. 7[a] shows the evolution of player configuration using genetic optimisation. As the figure shows, there is an apparent increase in the average degree of the Pavlov strategy compared to the ZD strategy, within the network population as the average cumulative payoffs of the networks are optimised. Even though the payoff of a ZD node would be higher against a Pavlov node, Pavlov performs well against itself compared to ZD strategy, making it the evolutionary stable against ZD. This suggests that when Pavlov and ZD strategies are mixed in a population of players, cumulative payoff of the entire network could be maximised by assigning the hubs with the Pavlov strategy.

Similarly when the ZD strategy mixed with the General Cooperator strategy, GC strategy would tend to occupy the hubs, as the networks are evolved over time. As with the case of ZD vs Pavlov strategies, the cumulative payoffs of the networks would continue to increase when the initial configuration of the strategies are changed, as shown in Fig. 6[b]. Fig. 7[b] shows the evolution of the average degree of the nodes occupying the two strategies over time.

Next, we mixed the Pavlov and general cooperator strategies to observe which strategy tends to occupy the hubs as the cumulative payoff of networks evolve as in Fig. 8. Again, it is when the Pavlov strategy is placed on the hubs that the cumulative payoff of the network tends to increase, as shown in Fig. 9.

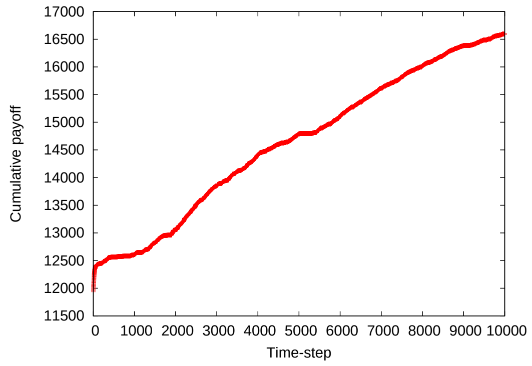


Figure 4: The variation of cumulative network payoff of the network of players playing the prisoner's dilemma game. The variable b was set to 1.8. The network is a scale-free network consisting of 1000 nodes. The game was iterated for 10,000 time-steps.

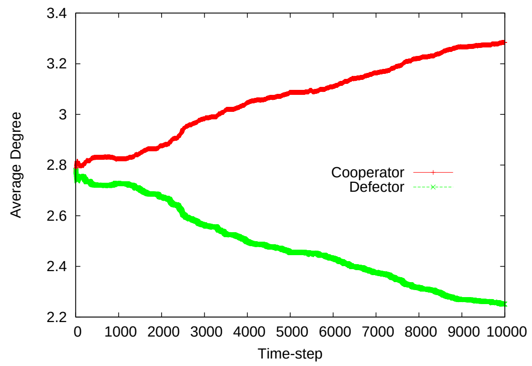


Figure 5: The variation of the average degrees of the co-operators and defectors of a network of players playing the prisoner's dilemma game. The variable b was set to 1.8. The network is a scale-free network consisting of 1000 nodes. The game was iterated for 10,000 time-steps.

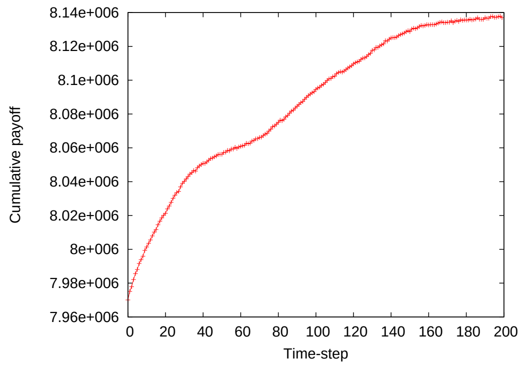


Figure 8: The variation of cumulative network payoff of the network of players consisting of GC and Pavlov strategies. The network is a scale-free network consisting of 1000 nodes. The game was iterated for 200 time-steps.

5. DISCUSSION

The observations made above can be summarised as follows:

Given a society which can be modelled as a scale-free network (bearing in mind the fact that most social networks have been indeed proven to be scale-free), and considering a scenario where nodes in that social network can choose from one of two strategies, and the overall balance of strategies across the network should be maintained such that at

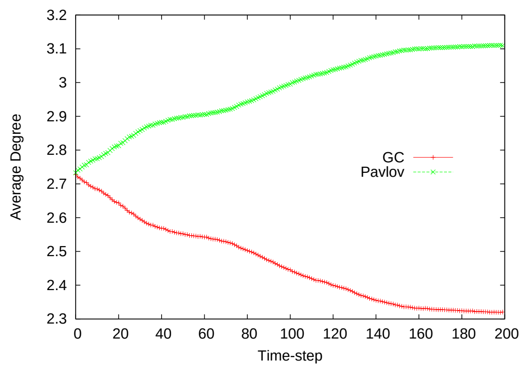


Figure 9: The variation of the average degrees of the network of players consisting of GC and Pavlov strategies. The network is a scale-free network consisting of 1000 nodes. The game was iterated for 200 time-steps.

any given time, the number of agents playing either strategy must be the same, certain strategies evolutionarily win the competition against certain other strategies in occupying the hubs (highest connected nodes) in the network.

- Cooperation occupies the hubs against defection
- Pavlov occupies the hubs against general cooperation
- Pavlov occupies the hubs against zero-determinant strategies
- General cooperation occupies the hubs against zero-determinant strategies

These results are arrived at by comparing the average degrees of nodes implementing each strategy, after 'evolution'. Let us note well here that nodes evolve (switch strategies) not to maximise their own pay-off, but to maximise the cumulative network payoff. Thus, the environmental pressure is for maximisation of the 'public good'.

These results are significant for the following reasons. The constraint of the network having to have an equal number of nodes implementing a pair of strategies might seem artificial at first. However, if we consider a scenario where nodes are merely 'place-holders' for individuals who roam in the network, while the strategies for these individuals is actually fixed, it is conceivable that such a scenario may indeed occur in real world. Therefore, nodes do not actually change strategies, but swap individuals who themselves always use a certain strategy. Thus, all individuals 'coordinate' by swapping positions for the 'public good'. For example, consider a soccer team, which has eleven fixed positions (left extreme, right extreme, centre back, goal keeper etc). The positions can be thought of as a complex network (the goal keeper position is connected to the three backs, and so forth). There would be certain players who are better at offence and others who are better at defence. The coach could rotate players around the positions in order to maximize the 'public good', which, in this case, is to increase the 'net' number of goals (goals scored by the side minus goals scored by the opposition). Similar scenarios can be described in the case of an army comprising many strategic units advancing, or a cooperate moghul placing his subordinates in various parts of his business empire to derive maximum benefit to his business. Therefore, understanding which classical strategies must be used by the hubs as opposed to peripheral nodes for maximum overall utility is of vital importance.

6. CONCLUSION AND FUTURE WORK

Game theory can be successfully applied to understand the dynamics of a society. The concept of public goods games has recently gained prominence, where the emphasis is not on the individual gains of agents but the overall payoff for the society. In this paper, we take a novel approach by utilising the classical Iterative Prisoners Dilemma game as a public goods game. That is, agents play prisoners dilemma repeatedly, and yet adapt their strategies with the goal of increasing the total network utility. We simulated evolution by implementing a version of genetic algorithm optimisation, where each member of the population is a network, with a particular distribution of strategies. Thus, we consider the evolution of networks (social structures), rather than evolution of individuals.

We found that networks evolve which prefer a certain type of strategy to be at their hub over another type, for high network utility. As such, the evolved networks preferred cooperation over defection, general cooperation over zero-determinant, pavlov over general cooperation, and pavlov over zero determinant at their hubs. This indicates that when societies compete, societies that can efficiently order individuals within those societies according to their strategies have a better chance of gaining high overall payoff. This is a significant result in understanding 'cooperation' for public good.

Genetic algorithm is only one form of optimisation. In future, we plan to undertake similar experiments with another optimisation techniques, including simulated annealing, ant-colony optimisation etc. We also intend to consider a broader range of memory-one and other strategies (tit-for-tat, for example). Furthermore, we may perform experiments on particular application domains, such as defence and project management, to better demonstrate the utility of our results. Still, we believe that the results as reported here are of value to the scientific community.

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