Evolution of Partner Selection

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Abstract

Partner selection is a mechanism that promotes sustainability of cooperators in cooperative dilemmas. In this paper we investigate the conditions that favour the evolution of a particular partner selection model that can be applied to any n-player game. The model allows a player to select partner combinations that satisfy his preferences. A limit case of the model is random choice of partners. Model parameters are under evolutionary control. We present simulations of our model that show evidence of the evolution of partner selection instead of random choice.

Introduction

In social interactions one of the main sources of distress is the proliferation of non-cooperative elements. A small percentage of unsocial behaviour is well accepted or even beneficial (Semmann et al., 2003). However, an unlimited growth of the percentage of free-riders is detrimental to cooperation and therefore to the maintenance of a society as a whole.

The study of social interactions has been modelled by several games presenting social dilemmas. For instance we have Iterated Prisoner's Dilemma (IPD), Ultimatum, Investment, Centipede, Public Good Provision (PGP) and Give-Take (Gintis, 2000; Fudenberg and Tirole, 1991; Axelrod, 1997; Mariano and Correia, 2002). Theoretical analysis of these games predicts the prevalence of exploiters or non-prosocial behaviour in general (Gintis, 2000).

Several approaches have been developed in order to limit proliferation of free-riders. Some of them use game specific strategies while others fall into mechanism design. In the former category, we have tit-for-tat as an example of a strategy to play IPD that in a variety of conditions is able to resist non-cooperative players. In the latter we have the possibility of partner selection (Izquierdo et al., 2010; Santos et al., 2006; Aktipis, 2004).

In this paper we investigate the conditions that favour the evolution of partner selection in any symmetrical n-player game. In particular, we examine the model proposed in Mariano and Correia (2010). That model assigns probabilities to combinations of partners that are updated in a process similar to Hebian learning. The process motivation is that, in the long run, cooperative players mostly select partners among themselves. When a positive interaction occurs, instead of reinforcing probabilities of combinations, probabilities remain unchanged. When a negative interaction occurs, the combination is replaced and its probability is decreased. As a result probabilities of combinations with positive interactions absorb decreasing probabilities. By positive interaction we mean that a player considers the result as acceptable or the interaction as cooperative. The model can be applied to any n-player game with any type of strategy (deterministic or stochastic).

Related Work

It has been reported in human experiments (Barclay and Willer, 2007; Coricelli et al., 2004; Ehrhart and Keser, 1999) that if players are able to select their partners they will seek cooperative partners while escaping free riders. In Price (2006) the author refers that in experiments involving human subjects, people tend to cooperate more when they can choose their interaction partners and, in that case, they cooperate when they perceive altruistic behaviour.

There is research on partner selection (Izquierdo et al., 2010; Pacheco et al., 2006; Santos et al., 2006; Zimmermann and Eguíluz, 2005; Aktipis, 2004; Semmann et al., 2003; Hauert et al., 2002; Stanley et al., 1995; Orbell and Dawes, 1993; Vanberg and Congleton, 1992) but this characteristic is granted in the model, i.e. players cannot choose between random partner allocation (Suzuki and Akiyama, 2008; Axelrod and Hamilton, 1981) or having the possibility to select with whom they will play. Moreover, these models are often tailored for a specific game such as PGP or IPD (Izquierdo et al., 2010; Aktipis, 2004).

Research similar to ours is Santos et al. (2006) and Pacheco et al. (2006) where population structure is able to evolve. Players are embedded in a network. If a player can change his links, selection favours cooperators that prefer to maintain links with their kin and to drop links with defectors. However, their findings were done in 2-player games and they only considered two types of strategies.

Model Description

The model of partner selection presented in Mariano and Correia (2010) is characterised by two vectors. One, $\mathbf{p}$, contains combinations of $n-1$ partners drawn from a set of candidate partners, which constitute the player's neighbourhood $\mathcal{N}$. Each combination is assigned a probability stored in vector, $\mathbf{c}$. In that paper three update policies of the above vectors are compared. In the present paper, we use the policy that has given the best results. In this policy, after a player plays a game with a combination drawn from vector $\mathbf{c}$ it compares the utility obtained u with parameter u_T and updates vector $\mathbf{p}$. The probability of the selected combination, k, is updated as follows:

$$p_k^{t+1} = \begin{cases} \delta p_k^t & \text{if} \quad u < u_T \\ p_k^t & \text{if} \quad u \geq u_T \end{cases} \quad . \tag{1}$$

The probabilities of other combinations are updated as follows:

$$p_i^{t+1} = \begin{cases} p_i^t + \dfrac{(1-\delta)p_k^t}{l-1} & \text{if} \quad u < u_T \\ p_i^t & \text{if} \quad u \geq u_T \end{cases} \quad , \tag{2}$$

where $i \neq k$, in order to maintain sum to unit and δ represents the probability decrease factor.

If the utility is lower than threshold u_T, slot k of vector $\mathbf{c}$ is replaced by a randomly generated combination, different from the ones in the other slots. Players of the new combination are randomly selected from $\mathcal{N}$.

Both vectors $\mathbf{c}$ and $\mathbf{p}$ have the same length represented by parameter l. This model has two particular cases of partner selection. When $l = 0$ the player randomly picks $n-1$ partners from $\mathcal{N}$ to play a game. The specific case of $l = 1$ is similar to the model presented in Aktipis (2004) and Izquierdo et al. (2010). In these works, which only consider IPD (a game with two players) if a player is not happy, he moves away seeking a new partner. In our case, a new random combination of partners is selected.

Player Chromosome

The description of the model has shown that it can handle random partner allocation as well as selection of best partner combinations. As we are using an evolutionary algorithm, the model parameters, namely l, δ and u_T, are part of the player's chromosome. In our simulations the domain of l is $\{0, 1, \ldots, \bar{l}\}$, where $\bar{l}$ represents the maximum value of l and the domain of δ is $[0, 1]$. The update policy is based on private information, namely the utility the player assigns to a specific partner combination. In this paper we simplify and assume $u = \pi$, the utility is equal to the payoff π ascribed by the specific game used. Therefore the domain of u_T is $[\underline{\pi}, \overline{\pi}]$, where $\underline{\pi}$ and $\overline{\pi}$ are, respectively, the lowest and highest payoff of the game. Besides these three parameters, the chromosome also contains the strategy, s, used to play the game. When talking about the chromosome we may designate the coded parameters as variables or genes. Table 1 summarises player's chromosome.

s	strategy
l	size of vectors $\mathbf{p}$ and $\mathbf{c}$
u_T	utility threshold
δ	probability decrease factor

Table 1: Player's chromosome

Evolutionary Setup

A plain genetic algorithm (Holland, 1975) with players' fitness as the total payoff obtained by a player favours players that are select more often, typically cooperators. On the other hand, if we average players' payoffs other types of players are favoured. For instance, an exploiter that played a single game and obtained the highest payoff is favoured compared to cooperative players that played more games among themselves, which produces a lower average.

Artificial Life systems such as AVida (Misevic et al., 2006), Tierra (Ray, 1992) or Polyworld (Yaeger, 1994) do not have an explicit fitness function. These systems are considered when the goal is the simulation of open-ended evolution (Chaumont and Adami, 2010). Individuals must continuously adapt their strategy to the environment they are faced with. Typically, individuals must manage their energy in order to survive and pass their genes to their offspring.

Here we use a similar model but we frame it in the context of game theory. We consider that players obtain energy by playing some game $\mathcal{G}$. A player reproduces when his energy reaches some threshold. Every newborn player starts with zero energy. A player's energy is incremented by the payoff π he obtains. In order to avoid negative energies due to negative payoffs, we adjust the payoff by the lowest payoff obtained in the game, $\underline{\pi}$. Summing up, the energy, e, of a player is updated as:

$$e^{t+1} = e^t + \pi - \underline{\pi} \quad . \tag{3}$$

Whenever a player's energy reaches the reproduction threshold, e_R, he produces an offspring. Reproduction is asexual and the offspring is a clone of the parent subject to mutation. The parent's energy goes back to zero.

The mutation operator is similar for all genes. Parameter l is perturbed by a discretized normal distribution with mean zero and standard deviation $\bar{l}/2$. Parameter u_T is modified by a normal distribution with mean zero and standard deviation $(\overline{\pi} - \underline{\pi})/2$. Parameter δ is perturbed by a normal distribution with zero mean and standard deviation 0.5.

Summarising, a player's phenotype is characterised by his strategy, the probability and combination vectors, his neighbourhood and his energy. We also record a player's age. Table 2 shows these parameters. When a player is born, vector

a	age
s	strategy
$\mathbf{p}$	probability vector
$\mathbf{c}$	combination vector
$\mathcal{N}$	neighbourhood
e	energy

Table 2: Player's phenotype

$\mathbf{c}$ is initialised with l random combinations of partners and vector $\mathbf{p}$ is initialised with constant value l^{-1}.

Environment

There are different artificial environments that influence how players interact. Research on cooperation uses toroidal lattices (Nowak et al., 2004), well-mixed populations (Pacheco et al., 2006), or small-world networks. Population structure influences the evolution and stability of cooperation. We opted for a well-mixed population, which means that a player can draw a combination from all the other players. Formally, for every player α in population $\mathcal{P}$ we have $\{\alpha\} \cup \mathcal{N}_\alpha = \mathcal{P}$. This is a typical structure in small communities (Price, 2006).

A simulation is composed of several rounds, N_R. In each round, all players select a combination of partners from their combination vector $\mathbf{c}$ using their probability vector $\mathbf{p}$. They play the game $\mathcal{G}$. For each played game, all participants update their energy as defined by equation (3). The player that selected the partners is the only one that updates his probability and combination vectors, according to equations (1) and (2). The other players may not know all their partners. Only the selecting player has all the players in his combination vector. This approach prevents players from copying others' combinations vectors.

The next step in a round is reproduction. All players that have reached the reproduction threshold generate one offspring. These players have their energy reset to zero.

Since reproduction increments population size, we need a mechanism to avoid an infinite growth of players. In the end of each round, a player may die with a probability given by the following sigmoid function:

$$P(\text{player dies}) = \frac{1}{1 + e^{B-|\mathcal{P}|-a}} \tag{4}$$

where B represents the carrying capacity, $|\mathcal{P}|$ is the population size and a is the player's age. Not only a player dies from overcrowding, but also he dies from old age. This implies that set $\mathcal{N}$ may vary from round to round with a strong dependency on B. Since we considered a well-mixed population, $\mathcal{N}$ is virtually the size of the population. Parameters that describe the overall behaviour of a simulation are presented in table 3.

$\mathcal{G}$	n-player game
B	carrying capacity
e_R	reproduction threshold
$\mathcal{P}^0$	initial population
N_R	number of rounds

Table 3: Simulation parameters

Comments

Players that are only exploited and cannot find sufficient cooperators, will not be able to reproduce. Also a population composed of a majority of exploiters may go extinct if the reproduction threshold is high.

The ratio $R_1 = e_R/(\overline{\pi} - \underline{\pi})$ represents the minimum number of games a player has to play to reproduce. The higher the former value, the more pronounced the effect of partner selection. It takes some time for the probability vector to converge to a situation where only cooperators are present in the best combinations of the combination vector. This was observed in a situation where set $\mathcal{N}$ is static (Mariano and Correia, 2010). In this paper we show that this may also happen in dynamic populations, meaning with variable $\mathcal{N}$. Notice that a cooperator will reproduce increasingly faster until the convergence of the probability vector.

An Evolutionary Stable Strategy (ESS) of some game $\mathcal{G}$ depends on the evolutionary mechanism. For instance, in a context of infinite populations where players play infinitely often (Hofbauer and Sigmund, 1998), defection is the ESS of the PGP game.

Using the energy model that we presented without partner selection (partners randomly picked) all players will play approximately the same number of games. If the game $\mathcal{G}$ is symmetric, its Nash Equilibrium (NE) will be maintained with this energy model. If some player deviates from the NE, energy obtained per game diminishes and consequently he will take longer to reach the reproduction threshold. This means that he will produce less offspring compared to those that stick to the NE. Due to the carrying capacity, the deviating player and his offspring have more chances of disappearing. The bottom line, is that in PGP with our energy model defection is still the ESS. However, with partner selection this may change. If a player can choose his partners, there may exist other ESS, namely cooperation, in the PGP game. This results from cooperators selecting preferably among themselves.

We have used a well-mixed population. Even in this case, since players select their partners, they are effectively constructing a network of contacts. The minimum and maximum number of contacts a player may have depend on n and l. The combination vector $\mathbf{c}$ can have l distinct combinations differing in a single partner, yielding a minimum value of $n + l - 2$ contacts. On the other end, all players in every combination may be unique, yielding a maximum

n	3 4 5 6 7
B	100 110 120 130 140 150
e_R	50 60 70 80 90 100

Table 4: Parameters values used in the simulations.

value of $(n-1)l$ contacts.

This contrasts with recent work that considered other types of population structure such as small-world and scale-free (Pacheco and Santos, 2005). With structure the contact limits above defined may be further reduced.

Experimental Analysis

The capability of the model we present to evolve partner selection can be assessed by tracking parameters l, u_T and δ. On the other hand, sustainability of cooperation can be measured by counting the number of cooperators that appear in a simulation.

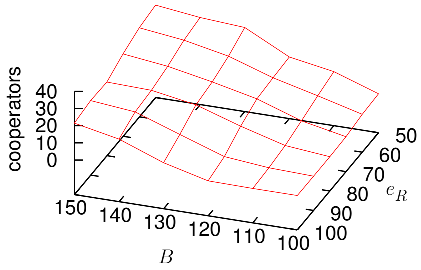
Game

We have performed simulations using the PGP game (Boyd et al., 2003; Hauert et al., 2002). This game is commonly studied to analyse cooperative dilemmas. Moreover, it is a n-player game. It is considered a generalisation of the Prisoner's Dilemma (PD) game to n players. In the PGP game, a player that contributes to the good, incurs a cost c. The good is worth g for each player. Let x be the proportion of players that provide the good. The payoff of a player that provides the good is $gx - c$ while players that defect get gx. The game has a single iteration. The strategy used by a player is probabilistic and is defined by probability s to provide the good. We assume that the utility of a player is equal to its payoff. In the simulations we set $g = 1$ and $c = 0.4$. The number of players in a game varied between three and seven. In this game, defection is the Nash Equilibrium and it is also the unique ESS.

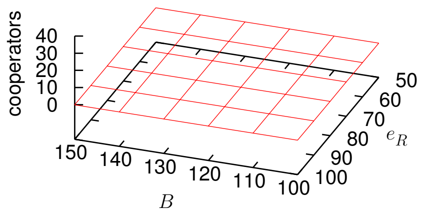
Tested Parameters

We have varied the carrying capacity and some parameters that influence the number of games a player has to play in order to reproduce. The latter is directly influenced by the reproduction threshold e_R but also by the number of players per game, n. Table 4 shows the values of the tested parameters thus giving an overview of the conditions where the evolution of partner selection was tested.

The size of initial population is 20. Those players all have the same chromosome: $(s = 1, l = 0, u_T = \underline{\pi}, \delta = 0)$, i.e. players are cooperative but perform random selection of partners. Whenever a new offspring is born, mutation occurs with probability 0.1. Mutation of genes l, u_T and δ has already been described. The maximum value of gene l was 10. Gene s is altered by a normal distribution with mean zero and standard deviation 0.1. Each simulation run



(a) 3-player PGP.



(b) 4-player PGP.

Figure 1: Average number of cooperators in the last round. e_R is the energy required for reproduction and B is the carrying capacity.

consists of $N_R = 10^5$ rounds. For statistical purposes, each result was taken from 30 independent runs, except otherwise noted.

Results

One major outcome was the identification of conditions for the survival of cooperators. This is important because in the plain PGP defection is the ESS. The use of partner selection modified this situation. Since we are using probabilistic strategies, we classified a strategy as cooperating if it cooperates more than 90% of the time. This is a strict threshold and results could improve if it was lower.

The survival of cooperators depends mostly on the number of players in a game. With 3-player PGP cooperators survive, but not with 4 or more players per game (see figure 1). It has been shown in Mariano and Correia (2010) that the number of possible combinations of partners grows exponentially with the number of players per game, n, and the number of candidate partners, $\mathcal{N}$, which is the size of the neighbourhood. Now, in a well-mixed population ($\mathcal{N}$ is the size of the population) with $n = 4$, the difficulty to find a favourable combination is already too high for cooperators to survive. In general, if the set of candidate partners is big and the number of players in a game is high, there are more

n	$\underline{\pi}$	$\overline{\pi}$	$\overline{\pi}-\underline{\pi}$	#C=n Δe C	#C=n–1 Δe C	#D=1 Δe D
3	−.27	.67	.93	.67	.33	.93
4	−.35	.75	1.10	.75	.50	1.10
5	−.40	.80	1.20	.80	.60	1.20
6	−.43	.83	1.27	.83	.67	1.27
7	−.46	.86	1.31	.86	.71	1.31

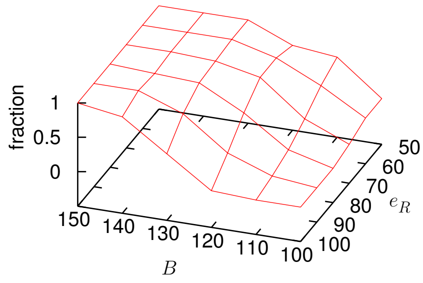
Table 5: Payoff range and energy obtained per number of players. The last three columns contain the energy obtained by a cooperator, represented by letter C, and by a defector, represented by letter D. In the first situation (#C=n column) all n players cooperate, while in the second (last two columns) all but one player cooperate.

combinations of players to explore. In these cases, the partner selection model requires more time to find the correct partner combination, which may not be available even with large life span and low reproduction threshold.

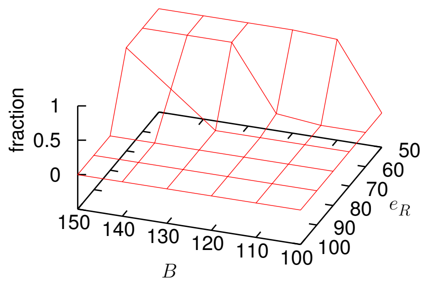
Results also show that there are conditions where the population decreases until there are not enough players to play a game. Such occurrence of extinctions depends on the number of players, energy required to reproduce and parameter B, as shown in figure 2. Extinctions increase with increasing e_R and decreasing B. While parameter B can be interpreted as a carrying capacity, it can also be interpreted as a player's average life span (see equation (4)). With low B values, high e_R and small n it is improbable that a player can attain sufficient energy to reproduce during his life span. This situation leads to high extinction rates.

We have already seen that 3-player PGP is the only case where cooperators survive. When we go to 4-or-more-player PGP the only survivors are defectors. In 4-player PGP, cooperators are early on wiped out by exploiters and the remaining exploiters cannot obtain sufficient energy to reproduce and die of old age. However, with growing n the probability of extinctions diminishes. This is due to the fact that each player is chosen more often to play by his neighbours. Therefore he may be able to attain the reproduction threshold, e_R, even when parameter B is low. In a population composed of only defectors, the payoff obtained by each one is zero. However, even in this situation, due to how energy is calculated (see equation (3)), defectors gain some energy. The more players in a game the more energy defectors obtain. Table 5 shows minimum and maximum payoff values for the tested number of players.

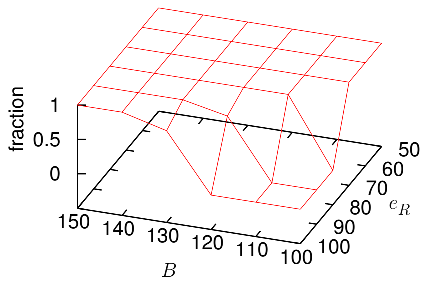
In the case of 3-player PGP, we analysed the evolution of the other three variables (genes) of the partner selection model, see figure 3. The pool size, l, increases from zero and stabilises around five. Variable δ also increases from zero and stabilises around 0.5. As for u_T it increases, stabilising just under the Pareto payoff obtained by a cooperator playing with only cooperators. The fact that these pa-



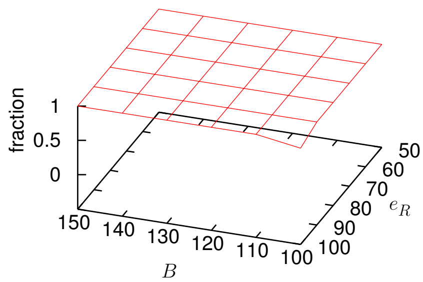
(a) 3-player PGP.



(b) 4-player PGP.



(c) 5-player PGP.



(d) 6-player PGP.

Figure 2: Percentage of simulations without extinctions. e_R is the energy required for reproduction and B is the carrying capacity.

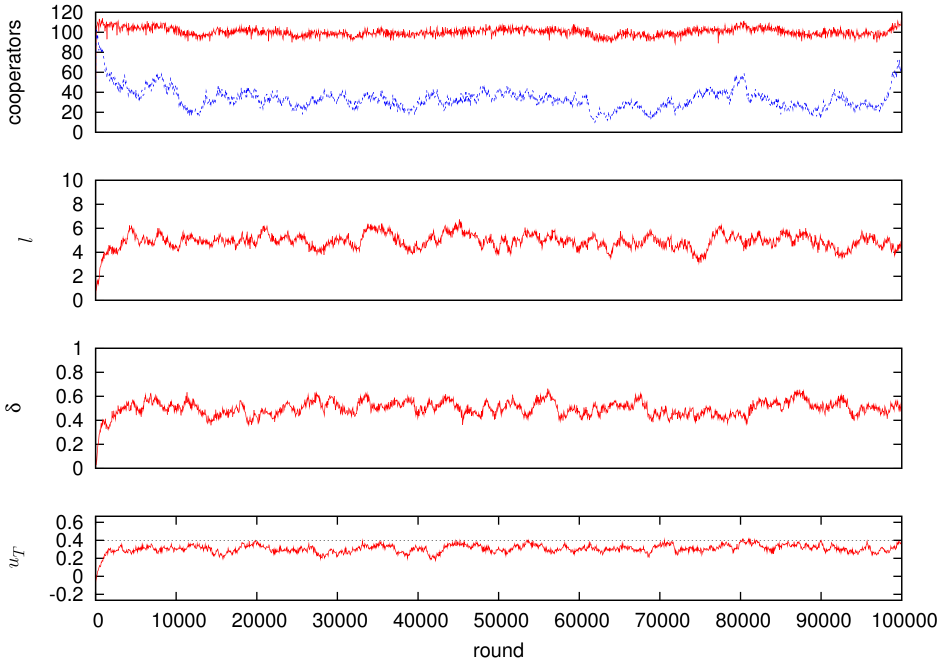


Figure 3: Example of a single simulation run (3-player PGP, carrying capacity B is 150, reproduction threshold e_R is 50) where cooperators are able to persist. In the cooperators plot, red solid line is population size and blue dashed line is number of cooperators (which fluctuates significantly without a corresponding influence on the average). In the plot of u_T the horizontal dashed line corresponds to the Pareto payoff. Results are plotted every 50 rounds.

rameters stabilise around some values means that there is no random drift. We confirmed such finding by measuring the variables under different e_R and B values, see figure 4. Remarkably, these variables are almost constant across all the values experimented for reproduction threshold, e_R, and B. Moreover, the memory length for partner combinations, l, is approximately 5, which is a quite small value. The fact these variables remain constant under different conditions reflects that a cooperator doing partner selection can find an adequate choice of partners, given time to achieve it.

Conclusions

We have analysed the conditions for the evolution of a partner selection model. With such a model, the average number of games played by some player depends on his characteristic. Cooperators that select among themselves play more often compared to defectors. Reproduction was based on an energy model. Players reproduce when they attain some reproduction threshold. In order to contain the population under some limits, players die from overcrowding and old age.

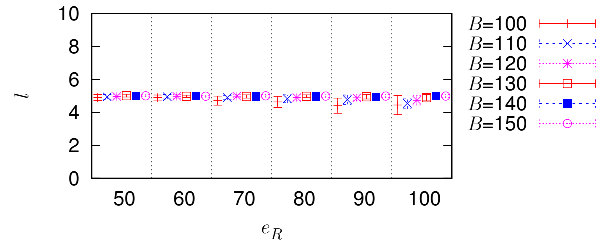
The results show that cooperators are able to persist in a population even if with low percentages. These results were only possible due to partner selection. Cooperators persistence was only observed in some conditions, namely, 3-player PGP, high carrying capacity and small reproduction threshold. In other conditions, we observed that defection, which is the ESS, was the sole strategy present in the population. The evolutionary dynamics of partner selection did not show any random drift in its variables. In fact the model is quite robust since the memory of partner combinations, l, the probability decrease factor, δ, and the utility threshold, u_T, are virtually independent of the carrying capacity, B, and the reproduction threshold, e_R.

We have shown the evolution of cooperators in the PGP. In contrast with others, (Izquierdo et al., 2010; Pacheco et al., 2006; Santos et al., 2006; Aktipis, 2004), this was obtained with stochastic strategies. Previous work has focused in specific games with only two strategies.

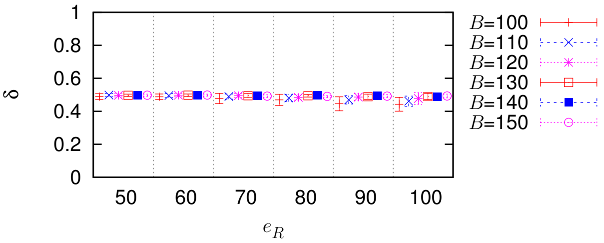
We are currently investigating how cooperators can persist in games with more than three players. Preliminary results show that with increasing carrying capacity cooperators live longer. Another possibility is to decouple the chance of player survival in two events: one for overcrowding and another for old age.

The fact that players are able to select with whom they play means that this model is suitable to study the emergence of niches. Suppose a game has multiple strategies to cooperate. This model of partner selection may favour the emergence of groups of players, where each group uses one of the different cooperating strategies available.

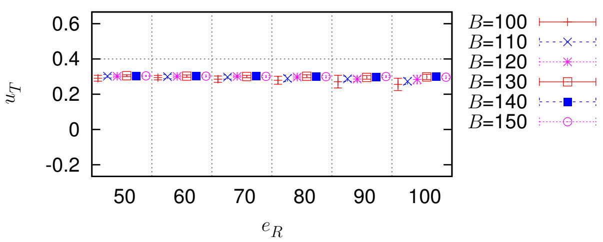
We have used a well-mixed population. However, this does not preclude the appearance of a network of players. With partner selection, a player is restricted to interact only with the partners in his combination vector. The use of another population structure, such as small-world, for instance, reduces the number of players available to form partner combinations. Consequently the number of partner combinations will be more limited. If we take into consideration the results with 3-player PGP partner selection may not evolve in some situations. This occurs specially for small populations (small B) and high reproduction energy, e_R. However, this is one avenue for future work.



(a) Average pool size.



(b) Average δ.



(c) Average u_T.

Figure 4: Plots show average data per simulation round across reproduction threshold (drawn on horizontal axis) and parameter B (each value has a specific point). Data are taken from simulations with 3-player PGP.

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