Selection of Imitation Strategies in Populations When to Learn or When to Replicate?

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Abstract. A question in the modeling of populations of imitators is if simple imitation or imitation based on learning rules can improve the fitness of the individuals. In this investigation this problem is analyzed for two kinds of imitators involved in a cooperative dilemma: One kind of imitators has a replicator heuristics, i.e. individuals which decide its new action based on actions of their neighbors, whereas a second type has a learning heuristics, i.e. individuals which use a learning rule (for short learner) in order to determine their new action. The probability that a population of learners penetrates in a population of replicators depends on a training error parameter assigned to the replicators. I show that this penetration is similar to a site percolation process which is robust to changes in the individual learning rule.

Keywords: Learning, Population Dynamics, Game theory, Percolation.

1 Introduction

Intuitively we know that being part of a community or a group makes us less vulnerable to external influences (or technically speaking, increases our fitness). The best strategy to being part of a group is behaving like its members, an attitude that requires good imitator abilities. Imitation is a paradigm that not only belongs to the study of social and biological sciences [1,2,3], but also to the study of artificial intelligence [4]. In populations the problem consists to find the rule that an individual uses to select an action from a finite menu. Every individual is conditioning its decision on his endowed private signal about the state of the world and observed predecessor's decisions, without knowing the private signals of these predecessor's. The problem is, with which criteria is possible to select the best heuristics to make imitation?

Several works analyze social dynamics that an imitator heuristics generates, assuming that a group of individuals behave according to the majority choice [5,6,7]. However, there is no criterion that dictates which specific heuristics is the right imitation rule. The diversity of imitation heuristics imposes a difficult problem in searching a criterion that matches to the desired rule [9]. One approach to solve this problem is to use an evolutionary perspective, assuming that imitation heuristics depends on natural selection [8,10]. In general imitation in

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social dilemmas can be explored defining individuals without memory. However, the reason to include individuals with memory in this investigation is based on an argument introduced by Bull, Holland and Blackmore [16], namely the larger the memory, the easier the imitation process is (where memory represents the individual's endowment of the private signals coming from its environment.). Hence, the selection of better imitators will favor individuals with larger brains, i.e. the human brain expanded in size by memetic and not genetic reasons.

In particular, the effect of memory in a social dilemma has been explored in previous works, showing that memory (in particular larger memories) could induce individuals to act in a more cooperative way [17,18]. The combined effect of this mechanism together with spatial extension allow individuals with a prospect cooperative character to disseminate, form clusters and minimize interactions with non-cooperative individuals [19,20,21,14]. In several of such models individuals are modeled as a kind of automata that give an answer depending of a mechanism that uses past information from the game. Two prominent examples from the literature are Pavlov, i.e. the individual's action switch whenever the individuals was punished in the last time step (Nowak and Sigmund, 1993 [22]), and TFT, i.e. the actual individual's action is just the opposite as its neighbor's action [1]. These examples consider individuals with memory size one, i.e. these individuals are able to store the information (either fitness or individual's action) from the previous time steep. However, there are other models considering individuals with longer memory size. In such case the individuals store several actions from its opponent in a vector; the new action is the result of the projection of this vector on the individual's strategy [21,17]. Recently an alternative learning schema combining past actions and past payoffs were introduced, allowing the individual to adapt to the character of its opponent as well as the must promising strategy behavior [24].

The present work is also based on the selection by evolution of different behavioral characteristics of a population. However, the present contribution is not aimed to select different learning rules, but to find how evolution selects two representative imitation heuristics in the context of a social dilemma (represented by a prisoner's dilemma game). As the author is aware, in the literature there is no analysis of the behavior and concurrence of different learning rules in large populations and spatial games. The present is the selection of two representative mimetic heuristics that goes beyond the simple individual imitation rules usually defined in these kind of problems.

The two basic rules to be considered are: mimetic rules based on replication, i.e. where the individual imitate the behavior of its neighbors, and mimetic rules based on learning, i.e. where the individual attempt to 'learn' and reproduce the behavior of its neighbors. The first kind of individual is called **replicator**, which tries to minimize the generalization error by utilizing the available information in a statistical optimal way [7,11,12], whereas the second kind of individual is called *individual with learning* (for short **learner**), which is based on the idea of coincidence training [13,12]. The behavior of both individuals is similar to the behavior of conformists with memory [1,14,15], i.e. individuals that basically makes an imitation of the action of its opponent. The aim of the present work is to consider if in a given population of learners can or cannot invade a population of replicators. The question is: is an individual with a pay-off based learning rule more effective than a simple imitator?

The remaining of this work is divided as follows. In the next section the model is explained, in particular imitation heuristics and the co-evolving dynamics, based on a game, are introduced as two coupled processes that determine the selection of individuals with a given imitation rule. In section three the simulation method and the main results are presented. In section four I present a discussion of the principal implications of this investigation. The last section is devoted to the main conclussions.

2 Model

Two learning heuristics are considered in this model. The first schema assumes that an individual takes decisions under the influence of an informational bandwagon effect. In this heuristics the individual tries to minimize the error in the implementation of a new action by utilizing the available information in a statistical optimal way [12,7]. The second schema assumes that the individual's decisions are made as the result of an individual learning process based on coincidence training [12,25]. Actions have uncertain payoffs. Additionally, individuals receive signals from other individuals and not from the environment.

Before choosing an action, the decision maker i observes the history of his private signal, $\sigma^i(t-l)$, and the history of the actions of the opponent j, $\sigma^j(t-l)$, where $1 \leq l \leq M$ is the step in the time history , where M is the number of signals that it is able to keep in its memory. This history is stored in a compact space Ω_i assigned to each individual i and is used in order to compute the probability distribution of the individual's new action $\sigma^i(t)$, which is an element of the set of the population's actions A.

Once an action is defined the individual becomes a payoff in the frame of a prisoner's dilemma game. Hence the individual's action can be either cooperate, C, or defect, D (Both actions will be defined in the next subsections). If the agent has low payoff respect its neighbors, then its learning schema is replaced by the complementary heuristics. Otherwise, the individual conserves its actual heuristics. In a nutshell, the population of agents owning a learning heuristics depends on the actions adopted by this population, and the population of actions depends on the population of learning heuristics. Furthermore remember that relative large memories are defined in order to facilitate the imitation process [16]. The agents are placed in a square lattice with periodic boundary conditions.

In the next subsections a detailed description of both the learning heuristics and the population dynamics is done.

2.1 Replicators: Bayes Rule

The input signal σ^i_I and σ^j_I can be either 1 for C or -1 for D. The individual i can follow a history Ω_i composed by the signals of $1 \leq l \leq M_i$ actions $(\sigma^j(t-l))$

of its opponent j and M_i own signals $(\sigma i(t-l))$, where m_i is the memory size of individual i. The decision maker i uses the observed action history and its own private belief in order to compute the probability of the new action WR^{ij} against individual j. The conditional probability that individual i cooperates, i.e. $\sigma^i = 1$, is given by

$$WR^{ij} = min[1, e^{-\beta \Delta \mathcal{S}^{ij}}], \quad (1)$$

where $\Delta\mathcal{S}^{ij} = \mathcal{S}^{ij}(t) - \mathcal{S}^{ij}(t-1)$. Here, $\mathcal{S}^{ij}(t)$ is the history of the signals $\sigma^i(t-M)$ and $\sigma^j(t-M)$ in the memory of individual i (this memory has a M_i size) given by $\mathcal{S}^{ij}(t) = \sum_{l=1}^{M_i} J^{ij}\sigma^j(t-l)\sigma^i(t-l)$, where J_{ij} is the connectivity between both signals. For simplicity, $J_{ij} \sim M_i$. Observe that j also makes simultaneously a new decision against i with a probability WR^{ji}. Hence $\mathcal{S}^{ij}(t) \neq \mathcal{S}^{ji}(t)$ and $WR^{ij} \neq WR^{ji}$. The parameter $\beta = 1/\Lambda$ is a control parameter (valid for the whole population) related to the training error of the replicator [12].

Hence, for large β the individual tends to adopt C because the whole population reduces its fluctuations and a bandwagon effect appears. If $\beta \to 0$ then the individual must choose in a set of mixed strategies. Indeed, in this heuristics the imitation of actions depends on the fluctuations of actions of the whole population.

2.2 Minimal Neuronal Network

According to this schema the learner try to find some patron in the behavior of their opponents. Hence, this heuristics requires a kind of individual's mind, which is modeled using a simple neuronal network. Imitation heuristics is based on the pay-off of the individual, with a rule based on a linkage function that depends on the individual's utility.

The function $\tilde{\mathcal{S}}^{ij}(t)$ for the learner is defined as

$$\tilde{\mathcal{S}}^{ij}(t) = \sum_{l=1}^{m_i} \tilde{J}^{ij}\sigma^j(t-l), \quad (2)$$

where $\tilde{J}_{ij}$ is the linkage parameter defined according to the following learning rule: if $\sigma^i(t-l) = 1$ and $\sigma^j(t-l) = 1$ then $\tilde{J}_{ij} = 1$; if $\sigma^i(t-l) = 1$ and $\sigma^j(t-l) = -1$ then $\tilde{J}_{ij} = 1$ (i.e. it is better to imitate the opponents actions); if $\sigma^i(t-l) = -1$ and $\sigma^j(t-l) = 1$ then $\tilde{J}_{ij} = 1$ (i.e. the individual transforms a non-cooperative attitude into a cooperative attitude); if $\sigma^i(t-l) = -1$ and $\sigma^j(t-l) = -1$ then $\tilde{J}_{ij} = 1$ (i.e. it is better to imitate the opponents actions). This definition corresponds to a strategy of the kind $((1,1),(-1,1))$. Nevertheless an additional analysis with a strategy of the form $((1,1),(-1,-1))$ (when $\sigma^j(t-l) = -1$ then $\tilde{J}_{ij} = 1$) will also be made in this investigation.

A simple example of the typical moves for a learner with $M = 6$ is presented in table 1. In this example the opponent present to the learner two different patrons that it should recognize. This response strongly depends on the initial conditions.

Table 1. An example of the learning heuristcs of a learner with $M = 6$. The elements in the discrete table represent the first component of the output σ^i, where i is for the reference individual and j its opponent. This table presents the learning process (negative time t) and the actions in the first six time steps.

t	$\hat{\sigma}^j$	$\hat{\sigma}^i$	$\tilde{J}_{ij}$	$\tilde{\mathcal{S}}^{ij}$	t	$\hat{\sigma}^j$	$\hat{\sigma}^i$	$\tilde{J}_{ij}$	$\tilde{\mathcal{S}}^{ij}$	t	$\hat{\sigma}^j$	$\hat{\sigma}^i$	$\tilde{J}_{ij}$	$\tilde{\mathcal{S}}^{ij}$	t	$\hat{\sigma}^j$	$\hat{\sigma}^i$	$\tilde{J}_{ij}$	$\tilde{\mathcal{S}}^{ij}$
-6	-1	1	1	-	-6	-1	-1	1	-	-6	-1	1	1	-	-6	-1	-1	1	-
-5	1	1	1	-	-5	1	-1	-1	-	-5	1	1	1	-	-5	1	-1	-1	-
-4	1	1	1	-	-4	1	-1	-1	-	-4	-1	1	1	-	-4	-1	-1	1	-
-3	1	1	1	-	-3	1	-1	-1	-	-3	1	1	1	-	-3	1	-1	-1	-
-2	-1	1	1	-	-2	-1	-1	1	-	-2	-1	1	1	-	-2	-1	-1	1	-
-1	-1	1	1	-	-1	-1	-1	1	-	-1	1	1	1	-	-1	1	-1	-1	-
0	-1	(-1,1)	-	0	0	-1	-1	-	-6	0	-1	(0,1)	-	0	0	-1	-1	-	-6
1	1	(-1,1)	-	0	1	1	-1	-	-2	1	1	(0,1)	-	0	1	1	1	-	6
2	1	(-1,1)	-	0	2	1	1	-	2	2	-1	(0,1)	-	0	2	-1	-1	-	-6
3	1	(-1,1)	-	0	3	1	1	-	6	3	1	(0,1)	-	0	3	1	1	-	6
4	-1	(-1,1)	-	0	4	-1	1	-	2	4	-1	(0,1)	-	0	4	-1	-1	-	-6
5	-1	(-1,1)	-	0	5	-1	-1	-	-2	5	1	(0,1)	-	0	5	1	1	-	6

In the present simulation this learning process does not only take place at the beginning of the process but also could take again place after some random period of time. The transition probability for σ^i is in this case given by the following function [25]

$$WP^{ij} = \begin{cases} \text{C} & \text{if } \tilde{\mathcal{S}}^{ij} > 0; \\ \text{(C,D)} & \text{if } \tilde{\mathcal{S}}^{ij} = 0; \\ \text{D} & \text{if } \tilde{\mathcal{S}}^{ij} < 0 \end{cases} \tag{3}$$

This definition does not depends on any noise source, but on changes of $\tilde{J}_{ij}$ according to the individual's learning rules. The mathematical meaning of C and D will be given in the next section.

This model for a learner is equivalent to similar definitions of individuals owning a memory and that react according to the stored information and a fixed strategy [21]. However, instead of a sigmoid function, the transition probability is given by a delta function $\delta(\tilde{\mathcal{S}}^{ij} - S_0)$, where S_0 is the restriction imposed by the strategy. Hence, such kind of individuals does not adapt to their environment (as the learner), but own a strategy that is more or less fit to the given environment.

2.3 Co-evolutive Dynamics

The action of individual i is represented by the action σ^i, that can be $\sigma^i = 1$ for C (Cooperate) or $\sigma^i = -1$ for D (Defect). The pay-off of individual i relative to individual j, given by U^{ij}, and individual j relative to i, given by U^{ij}, are defined according to the matrix defined in table 2 [26], with $W > R > P > S$, where W is for temptation (or winner), R for reward, P for punishment and S

Table 2. Definition of the pay off of individuals i and j in the prisoner's dilemma game. The first horizontal line corresponds to individual i; the first column to individual j. D represents defect and C represents cooperate. W is for winner, R for reward, S for sucker and P for punishment, such that $W > R > P > S$ [23,17].

-	C	D
C	R	W
D	S	P

for sucker (please do not confuse S with $\mathcal{S}^{ij}$, the history of the signals for the Bayes rule). The values of the matrix are defined as $R > \frac{1}{2}(W + S)$, such that for an individual is better to switch from cooperate to non-cooperate, but all the other individuals will profit if a single individual switches from defection to cooperation. Setting $W = 5$, $R = 3$, $P = 2$ and $S = 0$ this rule approaches the game to the pay-off matrix introduced by Axelrod (1984) [23,17].

The total outcome for the individual i respect to its opponents is $f^i = \sum_{j=1}^{K} U^{ji}$ and the total outcome of these opponents respect to i is given by $f'^i = \sum_{j=1}^{K} U^{ij}$, where K is the number of neighbors. The utility is a fundamental quantity that should determine the co-evolutionary process. The structure of the pay-off matrix is in general non-commutative; therefore, $f'^i \neq f^i$.

Suppose an individual in the lattice, that has a given heuristics, is selected and plays simultaneously with its four neighbors. Also suppose that i is a replicator. In this example the following actions were obtained: C^{i1} vs. C^{1i}, D^{i2} vs. C^{2i}, D^{i3} vs. D^{3i} and D^{i4} vs. D^{4i}. Hence $f^i = 3+5+2+2 = 12$, whereas $f'^i = 3+0+2+2 = 7$; hence, in this case $f^i > f'^i$ and, therefore, the agent can preserve its learning heuristics. Otherwise this heuristics is replaced by its complementary heuristics.

2.4 Simulation

The results were obtained from computer simulations of this model. The population has 2500 individuals placed on places of a two dimensional square lattice with periodic boundary conditions. Each individual has a memory size $M = 18$ and interacts with its four neighbors randomly selected inside a circular radius $R = 2$. The simulations were started introducing an initial random distribution of actions in an initial period of time, equivalent to the memory size of the individuals, in order to compute the initial learning heuristics of the learner and the initial action of the replicator. The final results do not contain the information of the initial period of time.

3 Results

In a first analysis the reaction of two learners is shown. If both individuals have a small memory size, the willingness to cooperate is relative high. But when one of both individuals increases its memory, the frequency of cooperation decreases. One suspect that the frequency of cooperation depends on the memory size,

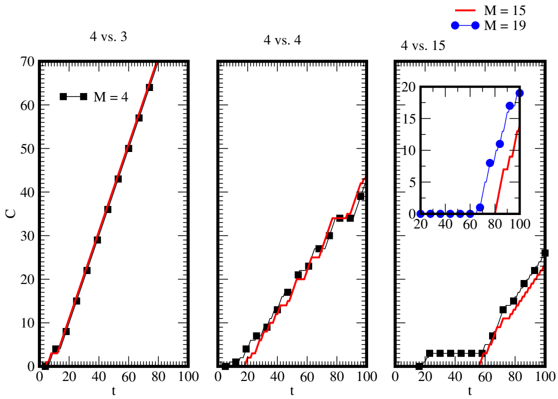

Fig. 1. Cumulative cooperation frequency of two learners with different memory (information storage) size as a function of the time. The strategy in this example is ((1,1),(-1,1)).

in particular those larger memories have a smaller cooperation rate. However, the interaction of two learners with $M > 10$ show that the individual with small memory size has a lower cooperation frequency. In general is possible to conclude that individuals with $M > 10$ are more 'cautious'.

The analysis of the behavior of the individuals is extended to learners vs. replicators. Given that the behavior of the replicators depends on the fluctuations of the environment, the cooperation frequency also depends on the fluctuation sizes, given by the parameter β. Low values of β imply large fluctuations in the system. For low β the learner cannot imitate the replicator, because the fluctuations in the behavior of the replicator does not help the individual in its learning process. On the other side, the larger the value of β, the larger is the cooperation frequency, because the learner can imitate the behavior of its opponent. In this sense we suspect that the fluctuations of the environment affects the form that a class of individuals can invade a given population.

The previous results were obtained for fixed memory sizes. However, there is no clear criteria for the selection of the memory size of the individuals of the population. One plausible starting point is to assume that the memory of the individuals also co-evolve with the population. This option implies not only an ensemble of imitators but also, additionally, an ensemble of memories assigned to this population of imitators. The combination of both ensembles could represent a more realistic system, but this assumption do not helps to understand the specific role that the imitation rules have in the co-evolution of the population. For this reason the memory size of the individuals will remain fixed in order to restrict the dynamics of the population to the effects induced by the imitation rules.

In order to analyze such a system it is necessary to find a criterion to fix the memory size (storage size) of individuals. For the replicators, previous investigations shown that relative memory sizes are associated to larger individual fitness.

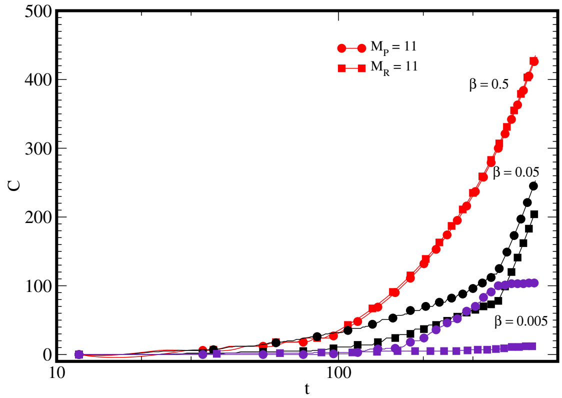

Fig. 2. Cumulative cooperation frequency C (i.e. the number of times that anindividual selects C) of a learner vs. a replicator as a function of the time. Different cooperation frequencies were computed as a function of the fluctuations of the environment. The learner's strategy is ((1,1),(-1,1)).

Nevertheless, this result depends on β [27]; but we can assume in general that this kind of individual's large memory size represents an advantage in evolution. In general it is reasonable to assume that both imitators share the same relative large memory size. In the present investigation the individual memory size were fixed to $M = 18$ (i.e. the individual can store 18 individual bits).

The initial configuration considers more replicators in order to analyze if the learners can invade the initial population. If the control parameter β is small, then the chance that a population of learners invades the population of replicators increases. However, this final population of learners does not extinguish the population of replicators, i.e. there is a coexistence of both groups of individuals. If β increases then the initial population of learners is almost extinguished; this result is logic because the learner has a very poor performance while the replicator respnses to the noise of the environment (fig 3). For this analysis the population of learners grows as a function of the time until it reaches an equilibrium state.

The dynamics of the population depends on the probability that a given imitator is replaced by another imitator. This probability depends on the imitator's fitness. This transition has not only effect in the population of imitators, but also in the number of individuals with a cooperative (or non-cooperative) behavior. This process is similar to remove a given individual with a probability given by W_p. Of course, this removal is preferential, depending on the individual's fitness, which also depends on β. Hence, the parameter β determines the probability that a given class of individual will be replaced or not. Therefore, this is the order parameter to be used in the subsequent analysis.

The strategy matrix for the learner allows the representation of different individual behaviors. In particular, if the strategy is ((1,1),(1,1)) the individual simply repeats the same actions as its neighbors, i.e. the individual behaves using

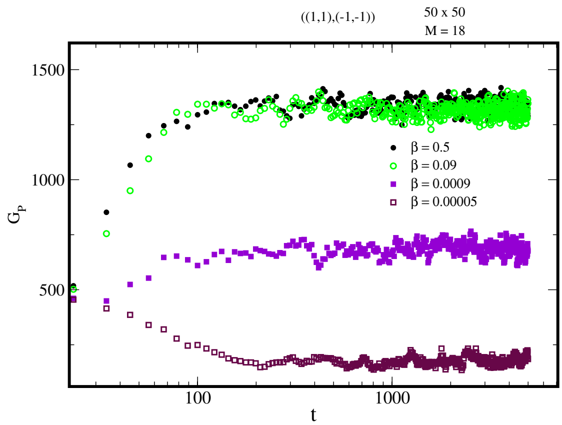

Fig. 3. Average number of learners G_P as a function of the time for different parameters β

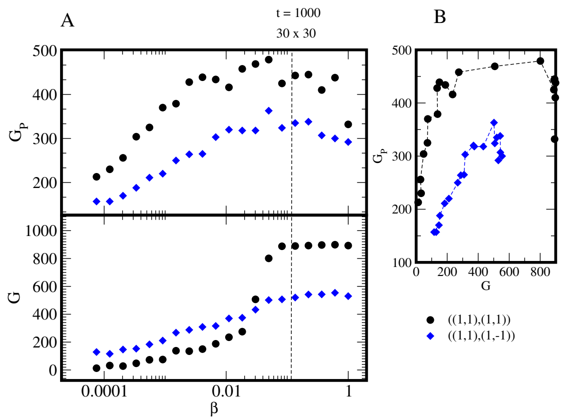

Fig. 4. Comparison of Tit for Tat ((1,1),(1,1)) against a ((1,1),(-1,1)) strategy. The frequency of coopeators (mean number of cooperators represented by G) as well as the population of learners (mean number of learers, represented by G_P) as a function of β is shown (part **A**). In **B** the Population of learners as a function of the frequency of cooperators (G_P vs. G) is shown.

a kind of Tit for Tat strategy (TFT). In several experiments and computer tournaments it has been shown that this strategy is very successful [1,23]. In the present work we also found that individuals with a large information endowment are also successful if it adopts a TFT strategy against the replicators (See Fig. 4, part **A** and **B**). In this simulation the frequency of cooperators G with TFT shows a behavior similar to a ferromagnetic material, i.e. close to the critical parameter β_C there is a spontaneous change of non-cooperative to cooperative actions; this behavior is logic because the learners simply reproduce the behavior of the replicators, which essentially are a kind of Ising model. In contrast to this

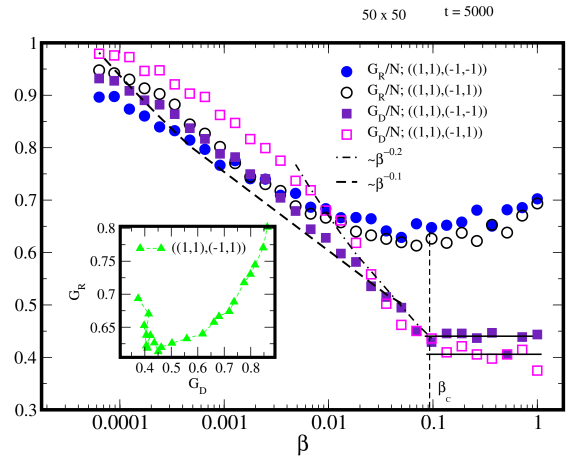

Fig. 5. Averaged number of defectors G_D (i.e. individuals with actions of type D) and replicators G_R (i.e. individuals with a replicate heuristics) as a function of the parameter β. The results are averaged and the error bars are smaller than the size of the symbols. Two strategies assigned to the learners were considered. In the inset, the number of replicators depends on the number of defectors in the population.

result, the behavior of ((1,1),(-1,1)) shows a kind of cross over, with a constant exponent $\gamma << 0.5$ for the whole variation of the parameter β. In resume, in this system there is a clear difference between TFT and other strategies, namely that a population with strategies different to TFT gradually changes its frequency of cooperation below a critical parameter β_C, whereas individuals with TFT shows a phase transition from defect to cooperate.

The dependence on β is a reminiscence of a kind of an Ising model. However, in the present system the replacement of individuals avoid the appearance of domains of cooperators or defectors. The replacement of individuals may imply that this process is similar to a percolation process. In the fig. 5, the average of the number of defectors and the average of the number of replicators is shown.

In the first case the increase of the β parameter suggest a kind of inverse percolation process in the number of defectors. This result is equivalent to a kind of net magnetization of the system. However, the critical parameter β_c (equivalent to a critical temperature) is $\beta \sim 0.09$, which is much smaller than the critical temperature of a common two-dimensional Ising model. Above this parameter the population of defectors does not get totally extinguished. The critical exponent is $\gamma \sim 0.1$. This result shows a slight similitude to the random node removal of scale-free networks [28], where β is equivalent to the fraction of nodes to be removed.

In the second case there is also a decrease in the number of replicators. However, above the critical parameter β_C the number of replicators increases again. Contrary to the actions, the population does not clearly show a kind of reverse percolation process. The phase diagram of number of defectors against the number of replicators shows that there is a critical number of defectors where the population is almost invaded by learners, at $G_D \sim 0.45$; below this value there is again an increase in the number of replicators.

The present was not only restricted to a single strategy for the learners. A test with a second strategy was also performed. For ((1,1)(-1,-1)) the critical exponent is $\gamma \sim 0.1$, which is much lower than the critical exponent for the original strategy. Additionally, the number of learners above the critical value is much slower than the original strategy. Hence, a change in the strategy introduces changes in the whole population and in the critical exponents.

4 Discussion

The learners can reproduce some behavioral patron when the number of errors in the training of the replicators is low. From an intuitive point of view this result is reasonable because an efficient learning rule (as the rule used by learners) requires low corruption of information by noise. However, this fact does not exclude the chance that a set of learners cannot invade a population of replicators when the number of errors in the imitation process is large. Even with $\beta \sim 0.0009$ (i.e. the replicators change frequently of actions) a set of learners can also invade a population of replicators. Only for very low values of β there is an extinction process of learners. Hence, a learning heuristics can invade a simple replicator heuristics if the individuals can make use of the informational stability available from its environment. Naturally, trying to reproduce a patron is less effective than doing a replication of the opponents actions; the present computation shows that a population of learners with a TFT strategy (i.e. the heuristics for a learner but without learning) is larger than a population of infividuals with learning.

This result is based on two representative heuristics, which are at the same time a representative example within other several specific imitation heuristics. The reader could have the opinion that this model is defined in an ad-hoc way restricted to only two behavioral rules. Furthermore, the system is a population constrained in a 2-Dimensional lattice with periodic boundary conditions. However, the construction and the results computed with this model could have potential implications in the use of tools coming from the statistical mechanics in artificial intelligence to describe populations of individuals trying to define some trend in the memetic heuristics, when errors in the imitation process (for instance induced by the environment) are present.

5 Conclusion

In a population with two kinds of heuristics the control parameter β, related to the training error of the replicator, has not only influence in the individual's actions, but also in the size of the population of individuals owning a particular heuristics. At the same time this behavior has influence in the frequency of actions within the population, i.e. the willingness to cooperate or not with its neighbors. Above a critical parameter β_C the cooperative attitude of the individuals do not depends in this control parameter. Above this critical value β_C

the population of learners reaches also an optimal value. In general it has been shown that the penetration process of learners in a population of replicators is similar to a percolation process, and that this processis robust against changes in the individual's learning rule.

In this frame the following question could be made: is preferable to restrict the actions to the information available after some decision process in the neighbor or is better to try to find some reaction patron? In this case it is not clear if learning or imitation is the basis in the formation of attitudes, in particular in the consideration of social dilemmas and collective behavior of heterogeneous individuals [29,30]. In the formulation of individual actions there is not only imitation but also learning rules that influence individual attitudes: the combined effect of both (and not simply imitation, as is usually assumed) is relevant when an individual takes some decision.

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