Exploring the cooperative regimes in a model of agents without memory or "tags": indirect reciprocity vs. selfish incentives

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The self-organization in cooperative regimes in a simple mean-field version of a model based on "selfish" agents which play the Prisoner’s Dilemma (PD) game is studied. The agents have no memory and use strategies not based on direct reciprocity nor 'tags'. Two variables are assigned to each agent $i$ at time $t$, measuring its capital $C(i;t)$ and its probability of cooperation $p(i;t)$. At each time step $t$ a pair of agents interact by playing the PD game. These 2 agents update their probability of cooperation $p(i)$ as follows: they compare the profits they made in this interaction $\delta C(i;t)$ with an estimator $\epsilon(i;t)$ and, if $\delta C(i;t) \geq \epsilon(i;t)$, agent $i$ increases its $p(i;t)$ while if $\delta C(i;t) < \epsilon(i;t)$ the agent decreases $p(i;t)$. The 4! = 24 different cases produced by permuting the four Prisoner’s Dilemma canonical payoffs 3, 0, 1, and 5 - corresponding, respectively, to $R$ (reward), $S$ (sucker’s payoff), $T$ (temptation to defect) and $P$ (punishment) - are analyzed. It turns out that for all these 24 possibilities, after a transient, the system self-organizes into a stationary state with average equilibrium probability of cooperation $\bar{p}_\infty = \text{constant} > 0$. Depending on the payoff matrix, there are different equilibrium states characterized by their average probability of cooperation and average equilibrium per-capita-income ($\bar{p}_\infty, \bar{\delta C}_\infty$).

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I. INTRODUCTION

A common approach to the problem of how cooperation emerges in societies of "selfish" individuals - individuals which pursue exclusively their own self-benefit - is based on game theory, and specifically on the Prisoner’s Dilemma (PD) of the early fifties. In a series of works Robert Axelrod and co-workers [1] used this kind of computer games to examine the basis of cooperation between selfish agents in a wide variety of contexts. Mechanisms of cooperation based on the PD have shown their usefulness in economy [2] - [8], political science [9] - [11], international relations theory [12] - [15], theoretical biology [16] - [18], ecosystems [19] - [20], etc.

The beauty of the PD game relies on the fact that it embodies the central ingredients of the cooperation problem in a very simple and intuitive way. There are two players, each confronting two choices: cooperate (C) or defect (D) and each makes its choice without knowing what the other will do. Independently of what the other player does, defection D yields a higher payoff than cooperation and is the dominant strategy. In other words, the outcome (D,D) of both players is the Nash equilibrium [21]. The dilemma is that if both defect, both do worse than if both had cooperated.

The emergence of cooperation in prisoner’s dilemma (PD) games is generally assumed to require repeated play (and strategies such as Tit for Tat (TFT) [1], involving memory of previous interactions) or features ("tags") permitting cooperators and defectors to distinguish one another [22].

In this work, I consider a simple model of selfish agents playing PD, possessing neither memory nor tags, to study the self-organized cooperative states which emerge for different payoff matrices. The model consists of $N_{ag}$ agents, with two variables assigned to each agent at the site or cell $i$ and at time $t$: its probability of cooperation $p(i;t)$ and its capital $C(i;t)$. Pairs of agents, 1 and 2, interact by playing the PD game at each time step $t$. That is, there are 4 possible outcomes for the interaction of agent $i$ with
agent \( j \): 1) they can both cooperate (C,C) 2) both defect (D,D), 3) \( i \) cooperates and \( j \) defects (C,D) and 4) \( i \) defects and \( j \) cooperates (D,C). Depending on the situation 1)-4), the agent \( i \) (\( j \)) gets respectively: the "reward" \( R(R) \), the "punishment" \( P(P) \), the "sucker’s payoff" \( S(\text{"temptation to defect" } T) \) or \( T(S) \), i.e. the payoff matrix \( M^{RSTP} \) is

\[
M^{RSTP} = \begin{pmatrix}
(R, R) & (S, T) \\
(T, S) & (P, P)
\end{pmatrix}
\]

The payoff matrix gives the payoffs for ROW actions when confronting with COLUMN actions.

After playing the PD the agents update their probability of cooperation \( p(i; t) \) and \( p(j; t) \) according to the same definite "measure of success" which does not vary with time. Thus all agents follow a universal and invariant strategy defined by a measure of success plus an updating rule to transform \( p(1; t) \) and \( p(2; t) \) into \( p(1; t + 1) \) and \( p(2; t + 1) \).

The 4!=24 different payoff matrices produced by permutation of the four Prisoner’s Dilemma canonical payoffs -3, 0, 1, and 5- are analyzed by means of a Mean Field (MF) approach, in which all the spatial correlations in the system are neglected. It turns out that for all these 24 possibilities, after a transient, the system self-organizes into a state of equilibrium characterized by the average probability of cooperation and average per-capita-income \( \bar{p}_\infty, \bar{C}_\infty \), always with \( \bar{p}_\infty > 0 \). Furthermore, in the majority of cases \( \bar{p}_\infty \simeq 0.5 \).

Payoff matrices can be classified into sub-categories according to their dominant strategy. Let us call \( M_D \) the class of those matrices such that:

\[
T > R, \text{ and } P > S,
\]

for which the dominant strategy is D. This class comprises six matrices: \( M^{3051}, M^{1053}, M^{1035}, M^{0315}, M^{0153} \) and \( M^{0135} \). A second class \( M_C \) corresponds to

\[
R > T, \text{ and } S > P,
\]

for which the dominant strategy is C and comprises the following six matrices: \( M^{5310}, M^{5301}, M^{5130}, M^{5510}, M^{5501} \) and \( M^{1503} \). The remaining twelve matrices do not comply with equation (1) or (2) and produce situations not dominated by (D,D) or (C,C).

The only payoff matrix that implies a dilemma, in the sense explained above, is the canonical one with \( R = 3, S = 0, T = 5 \) and \( P = 1 \) which belongs to class \( M_D \) and comply with the condition (1) plus condition \( R > P \), or equivalently the chain of inequalities: \( T > R > P > S \). However, some matrices exhibit a tension between C and D and give rise to \( \bar{p} \approx \frac{1}{2} \). The matrices which do not embody such trade-off produce the situations which depart from \( \bar{p}_\infty \approx \frac{1}{2} \). Clearly, these payoff matrices are unrealistic in order to model the social behavior of the majority of individuals. So, why bother to study matrices which imply no dilemma? Well, one reason is that they could be of importance in other contexts. One might envisage situations in which a definite value of \( \bar{p}_\infty \) is required in the design of a system or is the one which optimizes the functioning of a particular mechanism, etc. Another motivation is that this "unreasonable" payoff matrices can be used by minorities of individuals which depart from the "normal" ones (assumed to be neutral) for instance, D-inclined "free riders" or C-inclined "altruistic" individuals. Finally, we will show results for these payoff matrices which, at first glance, defy our intuition. For example, payoff matrices which, at least in principle, one would bet that favor cooperation and indeed produce a very low degree of cooperation.

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1In fact there is an "anti-dilemma" posed by matrix \( M^{1503} \) for which \( T < R < P < S \) and although the dominant strategy is C both players would prefer the punishment P associated with (D,D).
II. THE MODEL

The pairs of interacting partners, by virtue of the MF treatment, are chosen randomly instead of being restricted to some neighborhood. The implicit assumptions are that the population is sufficiently large and the system connectivity is high i.e., the agents display high mobility or they experiment interaction at a distance (for instance electronic transactions). In this work the population of agents will be fixed to $N_{ag} = 1000$ and the number of time steps will be of order $t_f = 10^5 - 10^6$ in such a way that both assumptions be also consistent with the fact that agents have no memory.

Starting from an initial state at $t = 0$ taken as $p(i;0)$ chosen at random (in the interval $[0,1]$) and $C(i,0) = 0$ for each cell $i$, the system evolves by iteration during $t_f$ time steps following these stages in this order:

1. **Selection of players:** At each time step $t$ two agents, located at random positions $i$ and $j$, are selected to interact i.e. for playing the PD game.

2. **Playing pairwise PD:** The action, C or D, of each interacting agent $k$ ( $k=i$ or $k=j$ ) is decided generating a random number $r$ and if $p(k;t) > r$ then it cooperates and, conversely, if $p(k;t) < r$ it defects.

3. **Capital update:** As a result of the interaction the capital of each interacting agent $k$ is updated as $C(k;t) \rightarrow C(k;t) + \delta C(k;t)$, being the profit of agent $k$, $\delta C(k;t)$ one of the four PD payoffs: $R$, $S$, $T$ or $P$.

4. **Assessment of success:** Each of the two agent who have just interacted compares its profit $\delta C(k;t)$ with an estimate $\epsilon(k;t)$ of the expected utilities. If $\delta C(k;t) \geq \epsilon(k;t)$ ($\delta C(k;t) < \epsilon(k;t)$ ) the agent assumes it is doing well (badly) and therefore its level of cooperation is adequate (inadequate).

5. **Probability of cooperation update:** Pursuing to increase their utilities in future PD games the agents that just interacted update their $p(k;t)$. If agent $k$ is doing well it increases its probability of cooperation $p(k;t)$ choosing an uniformly distributed value between $p(k;t)$ and 1. On the other hand, if agent $k$ is doing badly it decreases its probability of cooperation $p(k;t)$ choosing an uniformly distributed value between 0 and $p(k;t)$ (see below for a discusson of this update rule).

Let us see how the estimate $\epsilon(k;t)$ emerges naturally. If the interacting agents $i$ and $j$ cooperate with probabilities $p_i$ and $p_j$ respectively (and defect with probabilities $1 - p_i$ and $1 - p_j$ ), then the expected value of the payoff to $i$, $\delta C^{RSTP}_i$ is given by:

$$\delta C^{RSTP}_i = Rp_i p_j + Sp_i (1 - p_j) + T(1 - p_i) p_j + P(1 - p_i)(1 - p_j).$$  \hspace*{1cm} (3)

Hence I consider an estimate $\epsilon(k;t)$, which only involves the probability of cooperation $p(k;t)$ of the agent $k$ who uses the estimate, obtained by replacing in equation (3) $p_i$ and $p_j$ by $p(k;t)$:

$$\epsilon^{RSTP}(k;t) = (R - S - T + P)p(k;t)^2 + (S + T - 2P)p(k;t) + P. \hspace*{1cm} (4)$$

While the measure of success seems natural, the updating rule for the probability of cooperation is quite arbitrary. For instance, for the case of the canonical payoff matrix, the update rule for the probability of cooperation implies the following: if your partner cooperated, increase your level of cooperation; else lower it (of course, with boundaries at 0 and 1). A priori, it is not obvious if this is a good update rule in order to maximize your utilities. After all, the other player might be a sucker. In that case perhaps you should defect more. However, as we will see in the next section, this update rule basically works by tuning the agent’s cooperation in order to accomplish some sort of “indirect reciprocity” which in turn
produces cooperative equilibrium states. Furthermore, modifying the strategy of each agent so that it defects more often, when it is doing well, pursuing to exploit an assumed high percentage of suckers, ends by spoiling cooperation. A natural implementation of this change of strategy would be: if you are doing well decrease your probability of cooperation $p$ with probability proportional to $1 - p$ and increase it with probability proportional to $p$. But this is equivalent to the replicator dynamics [24] - [26] for which, in ordinary situations, it is known that the cooperation becomes extinct.

General remarks on the model.

I. Among the weaknesses of major approaches that have been considered to answer the question about the emergence of cooperation two are often remarked.

I.A The first criticism is about the generally assumed "binary" probability of cooperation i.e. agents either always cooperate (C) or always defect (D). Clearly, this is no very realistic. Indeed the levels of cooperation of the individuals are continuous. Hence a real $p(i; t)$ (in the interval $[0,1]$) is used, reflecting existence of a "gray scale" of levels of cooperation instead of just "black" and "white".

I.B The second objection is concerning the deterministic nature of the algorithms which seem to fail to incorporate the stochasticity of agent behavior. The used algorithm is non deterministic. Comparison with the random number $r$ reflects a stochastic component of agents behavior.

II. All the agents follow the same universal strategy which does not evolve over time. However, the system is adaptive in the sense that the probabilities of cooperation of the agents do evolve.

III. RESULTS

For all the 24 payoff matrices the system self-organizes, after a transient, in equilibrium states with six values of $\bar{p}_\infty > 0$: 1, 0.56±0.003, 0.5±0.02, 0.42±0.006, 0.22±0.002 and 0.115±0.005. The 24 measures are performed over 100 simulations of $10^6$ time steps each. Fig. 1 show the average probability of cooperation for different payoff matrices vs. time for the 200,000 first time steps.

Roughly, the equilibrium asymptotic states can be classified in 3 classes: highly cooperative ($\bar{p}_\infty > 0.5$), moderately cooperative ($\bar{p}_\infty \approx 0.5$) and of low cooperation ($\bar{p}_\infty < 0.5$). In the second column of Table 1 are listed the values of $\bar{p}_\infty$ for the 24 payoff matrices.
FIG. 1. Curves of $\bar{p}$ vs. time, corresponding to the 24 choices of payoff matrix $M^{RSTP}$. The system self-organizes in 6 different cooperative states with: $\bar{p}_\infty = 1$ (filled lines), $\bar{p}_\infty \simeq 0.56$ (dotted lines), $\bar{p}_\infty \simeq 0.5$ (dashed lines), $\bar{p}_\infty \simeq 0.42$ (dot-dashed lines), $\bar{p}_\infty \simeq 0.22$ (‘s) and $\bar{p}_\infty \simeq 0.115$ (‘s).

| $RSTP$ | $\bar{p}_\infty$ | $\delta C_\infty$ |
|--------|-----------------|------------------|
| 5 3 1 0 (C) | 0.425 | 1.87 |
| 5 3 0 1 (C) | 0.113 | 1.15 |
| 5 1 3 0 (C) | 0.42 | 1.81 |
| 5 1 0 3 | 0.49 | 2.16 |
| 5 0 3 1 | 0.22 | 1.35 |
| 5 0 1 3 | 0.49 | 2.16 |
| 3 5 1 0 (C) | 1.0 | 3.0 |
| 3 5 0 1 (C) | 1.0 | 3.0 |
| 3 1 5 0 | 1.0 | 3.0 |
| 3 1 0 5 | 0.485 | 2.28 |
| 3 0 5 1 (D) | 0.5 | 2.25 |
| 3 0 1 5 | 0.485 | 2.28 |
| 1 5 3 0 | 0.51 | 2.22 |
| 1 5 0 3 (C) | 0.5 | 2.25 |
| 1 3 5 0 | 0.51 | 2.22 |
| 1 3 0 5 | 0.495 | 2.27 |
| 1 0 5 3 (D) | 0.5 | 2.25 |
| 1 0 3 5 (D) | 0.42 | 2.6 |
| 0 5 3 1 | 0.5 | 2.22 |
| 0 5 1 3 (D) | 0.5 | 2.23 |
| 0 3 5 1 (D) | 0.51 | 2.22 |
| 0 3 1 5 (D) | 0.495 | 2.25 |
| 0 1 5 3 | 0.56 | 2.1 |
| 0 1 3 5 | 0.48 | 2.37 |

Table 1. Equilibrium values of probability of cooperation $\bar{p}_\infty^{RSTP}$ & income-per-agent $\delta C_\infty^{RSTP}$ for the 24 possible payoff sets $\{RSTP\}$. (C) or (D) in first column indicate if the dominant strategy is C or D.
Let us now analyze the average equilibrium income-per-agent $\delta C_{\infty}$ for the different payoff matrices. The curves of per-capita-income $\delta C_{\text{RSTP}}$ as a function of the average probability of cooperation $p$ are the parabolas obtained by replacing in equation (3) $p_i$ and $p_j$ by $p$ i.e.

$$\delta C_{\text{RSTP}}(p) = (R - S - T + P)p^2 + (S + T - 2P)p + P.$$  

(5)

These curves are invariant under the interchange of the sucker’s payoff $S$ and the temptation $T$, i.e.

$$\delta C_{\text{RSTP}}(p) = \delta C_{\text{RTSP}}(p),$$

(6)
i.e. the 24 payoff matrices give rise to the 12 different parabolas depicted in Fig. 2. In each subplot, the values of $\{\text{RSTP}\}$ and $\{\text{RTSP}\}$ and the equation (5) for the corresponding parabola is indicated. For example, we have in the first box: $\delta C_{5310}(p) & \delta C_{5130}(p) \equiv p^2 + 4p$. In all the subplots the equilibrium points $(p_\infty, \delta C_{\infty})$ for the payoff matrix with $S > T$ and $S < T$ are denoted, respectively, by circles and the '+'s. Note that by virtue that

$$\delta C_{\text{RSTP}}\left(\frac{1}{2}\right) = \frac{R + S + T + P}{4} = \frac{9}{4},$$

all the parabolas $\delta C_{\text{RSTP}}(p)$ pass through the point $[1/2, 9/4]$. The values of $\delta C_{\infty}$ are listed in the third column of Table 1 for the 24 payoff matrices.

FIG. 2. The 12 curves of per-capita-income $\delta C_{\text{RSTP}}(p)$ corresponding to the 24 choices of payoffs R,S,T and P in equation (5). The payoff matrices $M_{\text{RSTP}}$ and $M_{\text{RTSP}}$ produce the same parabola. In each box is indicated the equation for the parabola and the corresponding pair of payoffs which produce it between parenthesis (RSTP & RTSP). The equilibrium points $(p_\infty, \delta C_{\infty})$, listed in Table 1, are marked with circles over the curves for the case $S > T$ and with '+'s for the case $S < T$. 

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Let us analyze the distributions of probabilities of cooperation and their corresponding average capitals and average income-per-agent. Fig. 3, Fig.4 and Fig.5 illustrate, respectively, the cases of payoff matrices giving rise to equilibrium states with $\bar{p}_\infty > 0.5$, $\bar{p}_\infty \simeq 0.5$ and $\bar{p}_\infty < 0.5$. Measures are performed over 100 simulations of 50,000 time steps each, after the equilibrium state was reached i.e. typically discarding the first 200,000 configurations $^2$. The upper plots are distributions for the probabilities of cooperation $p$ using 100-bin histograms. The frequencies $\nu(p)$ are normalized in such a way that the total area is equal to 1. The middle (lower) plots present the corresponding average capitals $\bar{C}(p)$ (average income-per-agent $\bar{\delta C}(p)$) obtained by taking the quotients between the histograms for the capitals (income-per-agent) and the frequencies histograms. Fig.3 corresponds to 2 payoff matrices giving rise to high cooperation: $M^{3150}$ and $M^{0153}$, with $\bar{p}_{\infty}^{3150} = 1$ and $\bar{p}_{\infty}^{0153} \simeq 0.56$. The histograms of frequencies $\nu(p)$ exhibit a peak at $p = 1$ (in the case of $M^{3150}$ the 3 histograms are non null only for $p = 1$). Fig. 4 illustrates two cases of moderate cooperation produced by payoff matrices $M^{3051}$ (the canonical one) and $M^{5310}$, with $\bar{p}_{\infty}^{3051} = 0.5$ and $\bar{p}_{\infty}^{0153} \simeq 0.42$. Both histograms exhibit two peaks, one at $p = 0$ and one at $p = 1$.

$^2$The particular case of matrix $M^{3150}$ approach to $\bar{p}_{\infty} = 1$ more slowly and after 200,000 iterations the system has not reached equilibrium yet as can be seen from Fig.1. In that case 450,000 iterations were discarded before measuring.
FIG. 4. 100-bin histograms for moderately cooperative payoff matrices $M_{3051}$ (thin line) and $M_{5310}$ (thick line). Above: Distribution of probabilities of cooperation $p$. Middle: the corresponding average capitals $\bar{C}$ vs. $p$. Below: the corresponding average income-per-agent $\bar{\delta C}$ vs. $p$.

In Fig. 5 are shown two cases of low cooperation, produced by $M_{5301}$ and $M_{5031}$, with $p_{5301}^\infty \simeq 0.113$ and $p_{5031}^\infty \simeq 0.22$. Both histograms of frequencies exhibit a peak at $p = 0$.

FIG. 5. 100-bin histograms for low cooperative payoff matrices $M_{5301}$ (thin line) and $M_{5031}$ (thick line). Above: Distribution of probabilities of cooperation $p$. The inset is a zoom showing the smaller peak at $p = 0$ for $M_{5031}$. Middle: the corresponding average capitals $i.e. \bar{C}$ vs. $p$. Below: the corresponding average income-per-agent $i.e. \bar{\delta C}$ vs. $p$. 

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Let us summarize the main results which emerge from the data:

- The state of complete cooperation $\bar{p}_\infty = 1$ is reached for payoff matrices with $R = 3$: $M^{3510}$, $M^{3501}$, and $M^{3150}$. produce the highest possible average cooperation $\bar{p}_\infty = 1$.

- The payoff matrices with the highest possible reward $R=5$, contrary to one might think, do not produce the higher $\bar{p}_\infty$. Moreover, the states of lower average cooperation is produced by a payoff matrix with $R = 5$ : $\bar{p}_\infty = 0.115$ occurs for $M^{5301}$ and $\bar{p}_\infty = 0.22$ for $M^{5031}$. The explanation of this fact relies on the adopted measure of success based on the estimate $\epsilon(i; t)$: From equation (4) and from Fig.2 note that for $R = 5$ the estimates, for high values of $p$, are $\epsilon > 3$ (i.e. they are greater than all the payoffs except the reward), making agents excessively exigent. In other words: too much rewarding makes the expectation of utilities by the agents to be so high that spoils cooperation.

- From the two above results it is obvious that there is no completely clear connection between the dominant strategy and the equilibrium state. For instance, matrices belonging to class $M_C$ produce both the highest and lowest values of $\bar{p}_\infty$.

- The highest $\delta C_\infty$ is obtained from payoff matrices which produce the highest $\bar{p}_\infty$, namely $\delta C^{3510} = \delta C^{3501} = \delta C^{3150} = 3$. On the other hand, the lowest $\delta C_\infty$ is obtained from payoff matrix which produce the lowest $\bar{p}_\infty$, namely $\delta C^{5301} \simeq 1.15$.

- The distributions for the probability of cooperation are clearly non uniform showing peaks at $p = 0$ or/and at $p = 1$.

- The strategy used by the agents is robust enough to lead for all the payoff matrices to $\bar{p}_\infty > 0$. Furthermore, for the majority of the 24 payoff matrices $\bar{p}_\infty \gtrsim 0.5$. This robustness relies on the strategy combining the proposed measure of success and update rule for the probability of cooperation. Basically it works by tuning the agent’s cooperation guided by a trade-off between efficiency (increase of utilities) and equity (indirect reciprocity). If the agent is doing well it behaves nicely and increases its probability of cooperation. Nevertheless, in future interactions, if its probability of cooperation is inadequate (too high) and it does badly (it is exploited) then it reacts by decreasing its cooperation till it starts doing well again.

- The equilibrium states are such that, although the average income-per-agent depends on the value of the probability of cooperation $p$ i.e. $\delta C^{RSTP} = \delta C^{RSTP}(p)$, the distribution of average capitals is almost uniform and does not depend on $p$ (as can be observed from Fig.3 to Fig.5). This is consistent with the fact that agents constantly adapt their probability of cooperation in such a way to improve utilities. Hence, for a given value of $\bar{p}$, the utilities of each agent, with probability of cooperation $p$, oscillates around $\epsilon(\bar{p})$ in such a way that their accumulated capital at a given time (in equilibrium) is independent of $p$.

IV. CONCLUSIONS AND FINAL REMARKS

The first general conclusion is concerning the robustness of the cooperative asymptotic state, which indicates that, in this model, cooperation seems based more in a sort of indirect reciprocity than in selfish incentives. For example, the permutation of the canonical values of $R$ and $T$ has the dramatic effect of transforming a society with an intermediate level of cooperation into one dominated by defection,
as it arises from comparing the results for payoff matrices $M^{3051}$ and $M^{5031}$. On the other hand, the permutation of the canonical values of $S$ and $P$ has also a dramatic effect: it transforms a society with an intermediate level of cooperation into a completely cooperative one, as one can see from comparing the results for payoff matrices $M^{3051}$ and $M^{3150}$.

An interesting extension of the model would be to allow competition of different strategies to promote their evolution i.e. players which imitate the best-performing ones in such a way that lower scoring strategies decrease in number and the higher scoring increase. In particular, a possibility would be to associate different strategies with the use of distinct payoff matrices. For instance, individuals inclined to cooperate (defect) might be represented by agents using the payoff matrix $M^{3150}$ ($M^{5301}$) while "neutral" agents by agents using the canonical payoff matrix $M^{3051}$. This would make possible to study if mutants inclined to D can invade a group of neutral individuals or individuals inclined to C and drive out all cooperation. However, a previous necessary step was the knowledge of the effect of changing the payoff matrix on the system self-organization and in particular on the equilibrium point $(\bar{p}_R^{\infty}, \bar{\delta}_C^{\infty})$. So in this work we considered each of these 24 payoff matrices by separate.

This model can be extended in other ways in order to make it more realistic. For instance, here I considered a MF approximation which neglects all the spatial correlations. One virtue of this simplification is that it shows the model does not require that agents interact only with those within some geographical proximity in order to sustain cooperation. Playing with fixed neighbors is sometimes considered as an important ingredient to successfully maintain the cooperative regime [27], [28]. However, the quality of this MF approximation depends on the nature of the system one desires to model (people, cultures of bacteria, market of providers of different services or products, etc.). Therefore, in order to apply the model to situations in which the effect of geographic closeness cannot be neglected an interesting extension of the model would be: to transform the entirely random PD game into a spatial PD game, in which individuals interact only (or mainly) with those within some geographical proximity.

To conclude, this work is based on the canonical assumption that individuals are entirely self-interested. However, recent investigations, performed in twelve countries on four continents, have uncovered systematic deviations from the material payoff-maximizing dogma [29]. In addition to their own material payoffs, many experimental subjects appear to prefer to share resources and undertake costly reciprocal actions in anonymous one-shot interactions. Therefore, an open issue is how to incorporate this fact in a more realistic model.

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