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Escaping the tragedy of the commons via directed 1 investments 2

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16

Abstract

17 Cooperation is ubiquitous in the world surrounding us, from bacteria to Human 18 interactions. In Humans, cooperation is often associated with various group decisions, 19 resulting from their complex web of interrelated interests, associations or preferences. 20 The existence of such social structures not only opens the opportunity of having diverse 21 behaviors depending on the individuals' social position, but also for a dynamical allocation of contributions depending on the returns obtained from each group. Here, we 22 23 address these issues by studying the evolution of cooperation under Public Goods Games 24 in the framework of Evolutionary Game Theory where cooperative players are able to 25 distribute their donations to their liking. As a result, cooperation is greatly enhanced when the community structure is described by homogeneous graphs, as cooperators 26 27 become able to support cooperative groups and retaliate against those with poor achievements by withdrawing donations from them. Whenever the underlying network 28 29 becomes complex enough to add diversity to the distribution of group sizes, directed 30 investments do not optimize the emergence of cooperation, but they do enhance its 31 robustness against the invasion of a minority of free-riders. We define a robustness index 32 and show that directed investments expand the robustness of cooperation by about 50%.

33 Keywords: evolutionary game theory; public goods game; structured populations;
34 evolution of cooperation; complex networks.

36 **1 Introduction**

37 Cooperation is a key feature of self-organized systems, occurring at all scales and levels 38 of complexity (Hardin, 1968; Taylor, 1982; Axelrod, 1984; Trivers, 1985; Mavnard-39 Smith and Szathmáry, 1995; Sigmund, 1995; Barrett, 2007; Sigmund, 2010). Despite 40 this, the reasons behind its ubiquity remain an open, and challenging, quest in several 41 areas of science. To address this issue, different models were built in the framework of 42 evolutionary game theory (Maynard-Smith, 1982; Sigmund, 2010) to try to reproduce the 43 emergence of cooperation amongst selfish individuals, using different mechanisms to 44 achieve this goal. In this quest, the role of higher levels of individual cognition has remained elusive. In the present paper, we show that an additional layer of individual 45 complexity may provide a major contribution to the emergence and robustness of 46 47 cooperation and investigate how the evolutionary advantage of such complexity is tightly 48 connected with the way in which the population is structured.

49 For this purpose, we study the N-person Prisoner's Dilemma, better known as a Public 50 Goods Game (PGG) of cooperation (Hardin, 1968; Kollock, 1998; Barrett, 2007; 51 Sigmund, 2010). PGGs constitute the primary tool in evolutionary game theory to investigate the emergence of cooperation in group interactions. In this game, N52 53 participants can decide to donate or not an amount to the public good. An individual is 54 considered to be a cooperator (C), if she donates; otherwise she is a defector (D). The 55 donations are collected in a common pot and multiplied by a factor r(r>1). The resulting 56 sum is subsequently shared equally among the members of the group independently of 57 their contribution. Hence, in a mixed group of N individuals, refusing to contribute to a

58 common good assures the highest individual payoff. Thus, if all participants are rational,

59 individuals refuse to donate, falling into the Tragedy of the Commons (Hardin, 1968).

60 Among the many mechanisms (Nowak, 2006; West et al., 2007) suggested to avoid this 61 negative outcome, such as repeated interactions (Trivers, 1971), reward and punishment 62 mechanisms (Sigmund et al., 2001; Fehr and Gachter, 2002; de Quervain et al., 2004; 63 Sigmund et al., 2010; Szolnoki and Perc, 2010), reputation systems (Nowak and 64 Sigmund, 2005; Ohtsuki and Iwasa, 2006), voluntary participation (Brandt et al., 2006), 65 etc., most assume large populations and a well-mixed interaction pattern in which every player interacts equally likely with everyone else. While the well-mixed limit may be 66 67 valid for small populations, spatial constraints or complex networks of contacts often shape the interactions within large-scale societies. This feature has been initially 68 69 addressed by means of regular lattices and graphs, exploring the role of space in the emergence of collective behaviors (Nowak and May, 1992; Nowak et al., 1994; Szabó 70 71 and Hauert, 2002; Szabó et al., 2005; Ohtsuki et al., 2006; Szabó and Fáth, 2007; Taylor 72 et al., 2007). More recently, our increasing understanding of real interactions structures 73 (Doreian and Stokman, 1997; Barabási and Albert, 1999; Watts, 1999; Amaral et al., 74 2000; Dorogotsev and Mendes, 2003; Newman, 2003) has led to a general analysis of 75 evolutionary dynamics in a broad range of topologies (Santos and Pacheco, 2005; Vukov 76 and Szabó, 2005; Santos et al., 2006; Gómez-Gardeñes et al., 2007; Szabó and Fáth, 77 2007; Santos et al., 2008).

In a networked population, nodes represent individuals, whereas links represent shared
goals, investments or exchanges. In an N-person interaction setting, neighborhoods define
a network of overlapping groups (Szabó and Hauert, 2002; Santos et al., 2008), defining

81 not only who interacts with whom, but also the universe of possible role models of each 82 individual. With the help of this powerful and general population structure metaphor, 83 many different communities can be modeled and the outcome of the strategies' evolution 84 is highly dependent on the underlying topology. During the evolutionary process, every 85 player is involved in (k+1) game-interactions, where k is the number of acquaintances 86 (neighbors) of the given player. The group interactions take place in the (k+1) groups 87 centered on the neighbors and on the focal player (see Figure 1A). The total payoff of a 88 player is gained from these (k+1) games (Szabó and Hauert, 2002; Santos et al., 2008).

89 In the simplest setting (Santos et al., 2008), cooperators donate a fixed cost c to every PGG they participated. However this assumption may be unrealistic in situations where 90 91 players participate in a large number of interactions, as it is very unlikely that players 92 have such a huge amount of resources at their disposal at any time. Limited resources may add the limitation that all players have the same amount to invest, which will be 93 94 equally shared amongst all the groups (Santos et al., 2008; Pacheco et al., 2009). This 95 means that cooperators donate c/(k+1) to every group. This modification has a big impact 96 when the interaction graph is heterogeneous, as we will discuss later. However for regular 97 networks where the number of neighbors is the same for every node, this principle is equivalent to the traditional case with a rescaling of the cost c by a factor of 1/(k+1). 98 99 Nevertheless fixing the available resources for the players raises new opportunities: what 100 if cooperators could decide themselves how to distribute their donations amongst the 101 groups they interact with?

Such a cooperator opens up a whole avenue of new strategies, from random ones wherecooperators just randomly contribute to the different groups, to strategies where

104 cooperators can take past events, decisions or incomes into account before deciding about 105 the amount to contribute to each collective endeavor. Using this idea, we shall address the 106 role played by this additional speck of complexity, and consider cooperators that donate 107 to different groups proportionally to the income previously received from each given 108 group (see Figure 1B). Individuals assess how large is the share they obtained from each 109 group and, in the next generation, they donate the corresponding fraction of c to this 110 group. As detailed in Section 2, this strategy is reactive and inherently assumes that 111 players can keep track of their payoffs from immediate past events, i.e., they have some 112 kind of short-term memory. As group profits are generated solely from donations of 113 cooperators, this strategy rewards groups with higher cooperative standards. From this 114 point of view, this strategy can be seen as a form of direct reciprocity (Trivers, 1971) in 115 group interactions. For this reason, we shall refer to this type of behavior as reactive 116 strategies. ted

2 Methods 117

118 To have a clearer understanding of the results, here we give a more thorough description 119 of the model details. Players are located on the nodes of a graph. The edges of the graph 120 define who interacts with whom and who can imitate whom. Each individual engages in 121 k+1 PGG games where k is the number of her neighbors. The PGG groups are defined 122 by the central player and her neighbors, i.e., a given player is member of his own and his 123 neighbors' group (Figure 1A). Players gain their accumulated payoff from these 124 interactions in each generation. There are two available strategies: defectors (D) do not 125 donate to the public good, while cooperators (C) donate the cost c. For the different

126 simulation scenarios, cooperators use slightly different strategies. In the unconditional, 127 unconstrained case (UUC), they donate the cost c to every group they participate in. In 128 the unconditional, constrained case (UCC), when the amount of donation per player is 129 fixed to c, they donate to all their groups equally, i.e., all groups' pot receive c/(k+1). In 130 the conditional, reactive case (CRC), cooperators are allowed to redistribute their 131 donations, and they donate proportional to the payoffs they received from the given group 132 in the previous simulation step. Hence, if a cooperator received payoff p_i from his *i*th group at a given time (see Introduction and Fig. 1) then she will donate $(c \cdot p_i)/P$ in the 133 next round, where $P = \sum_{j=1}^{k+1} p_j$. In the first round of the simulation, cooperators donate 134

equally to the groups. The same happens if a defector imitates a cooperator and she had zero total payoff (P=0) in the previous round.

137 Simulations start from a random initial condition where the concentration of cooperators 138 and defectors is equal. Having different initial conditions (e.g. fewer cooperators at the 139 start) does not really influence the stationary distributions. The average values are 140 decreased slightly because of the cases when cooperator clusters cannot form and 141 cooperation vanishes at the initial transitional period due to the low initial cooperator 142 frequency. We use synchronous update: In each simulation time step, we update the payoff for every player, and then randomly pick a neighbor (y) for every player (x). 143 144 Player x can adopt the strategy of player y with a probability given by the so called pair-

145 wise comparison rule:
$$W(x \leftarrow y) = \frac{1}{1 + e^{(P_x - P_y)/K}}$$
, where P_x and P_y are the total payoff of

146 players x and y while K is characterizing the amount of errors in decision making. After 147 calculating the possible strategy imitations, we update the strategy of every player at the

same time.

149 The final outcome of evolution and cooperation is obtained from extensive computer 150 simulations performed on the following network topologies: We consider paradigmatic 151 examples of homogeneous and heterogeneous network structures. For the former class we 152 consider a square lattice with von Neumann neighborhood structure and periodic 153 boundary conditions. For the latter class, we explore the effects of topological 154 heterogeneity using Barabási-Albert scale-free networks (Barabási and Albert, 1999), 155 generated by the combination of growth and linear preferential attachment. This leads to 156 distributions of group sizes and number of games played by each player that follows the 157 degree distribution of the network, i.e., a power-law. After 2000 initial generations, we 158 average the strategy concentrations over the population during 10000 generations. Each 159 result is obtained from 100 runs from different random initial conditions and in the case of heterogeneous networks, from 10 different network realizations. We investigated the 160 161 strong selection regime and used K=0.04. The qualitative behavior of the system is the 162 same for higher K values (we tested it up to K=1.0), the ranking among the different 163 strategies remains the same so the conclusions are valid for those parameter values too. In 164 the case of the homogeneous networks, higher K shifts the threshold above which cooperation can be maintained to higher multiplication values as among these conditions 165 166 defectors can break in to the cooperator cluster more easily due to the higher noise. For 167 heterogeneous networks, the thresholds are about the same but the transition from the full 168 defector state to full cooperation is sharper, isolated, small islands of the minority 169 strategy are consumed due to the higher noise.

170 **3 Results and Discussion**

171 Figure 2 shows the results for the unconditional cooperative strategy (UUC) and the reactive cooperative strategy (CRC) on the square lattice (see Fig. 1A) as a homogeneous 172 173 interaction network (note that, in this case, UUC and UCC lead to the same results). The 174 fraction of cooperators is plotted as a function of the normalized multiplicative factor 175 $\eta = r/(k+1)$, where k=4 for the square lattice with von Neumann-neighborhood. In infinite, well-mixed populations, full defection is replaced by full cooperation at $n \ge l$, as in this 176 177 case, a single cooperator can provide positive payoff for the whole group. Under spatial 178 reciprocity, the threshold happens for significantly lower values of η . There is also formally a lower threshold at $\eta \le l/(k+1)$, in which case even full cooperation results in 179 180 negative payoffs, that is, cooperation becomes impossible among these conditions.

The results in Fig. 2 show that reactive cooperative strategy (CRC, red circles) 181 182 successfully outcompetes defectors for a wide range of parameters when compared with 183 unconditional cooperators (blue squares), while managing to achieve mixed, dynamical 184 coexistence with them under rather unfavorable conditions. By dividing their donations 185 among successful groups, cooperators are able to support the emergence of cooperative clusters by "directed" contributions to fellow cooperator groups. Moreover, these 186 187 individuals are able to withdraw help from the most defective groups, located at the edges 188 of the cooperative clusters. So the reactive cooperative strategy could be considered as a 189 mix of two mechanisms: reciprocity towards good, generous neighbors/groups and 190 punishment with the withdrawal of donations from defective neighbors. As a result, 191 whenever the conditions are not too adverse, the cooperative clusters can grow and they 192 will almost always take over the whole community. In the coexistence region, due to the

193 lower multiplication factor, cooperator clusters gain and loose territories dynamically 194 while the strategy concentrations slightly fluctuate around the average. We have 195 investigated other regular networks, such as the kagome-lattice (Svôzi, 1951) and the 196 one-dimensional ring-graph (Watts, 1999) to filter out possible "square lattice"-specific 197 features but the results were qualitatively the same on all of them: the overall level of 198 cooperation was very significantly increased with the introduction of a small level of 199 complexity (CRC). Similar qualitative results are also obtained for other values of the 200 intensity of selection, here associated with the parameter K.

201 The picture is different when the interaction graph is described by a heterogeneous 202 network. In this case different players will have, in general, different number of 203 neighbors. Consequently, fixing the maximum amount of contribution for unconditional cooperators is no longer a mere rescaling issue — in fact, it has a huge impact on the final 204 outcome of evolution (Santos et al., 2008; Pacheco et al., 2009). Blue squares in Figure 3 205 206 show the results on a scale-free network when cooperators donate c to every group they 207 are part of (UUC). Cooperation becomes viable in a considerably wide range even if 208 cooperators in a central role have to invest a big amount. The key of the success of 209 cooperation is that the complex interaction network made the payoff distribution 210 heterogeneous and this gave an opportunity for cooperators to outplay defectors: central 211 cooperators can collect a high income due to the many groups they are part of and can 212 turn most of their neighbors to cooperators while if a defector ends up in a central role, 213 she will turn her followers to defectors, decreasing her own payoff and after a while 214 loosing the "leading" position. However for lower η , the establishment of cooperation is 215 hindered by the fact that highly connected individuals (hubs) have to invest a huge

amount which can be non-remunerative in a partly defective environment. Fixing the total amount of donation of each individual (UCC) can be of assistance to this problem, as shown with the green triangles. Indeed, in (Santos et al., 2008; Pacheco et al., 2009) it has been argued that it is not the amount given what is important but the act of giving.

Unlike the situation observed in homogeneous networks, the introduction of reactive cooperators (CRC) does not boost cooperation further (red circles in Fig. 3). Apparently, the additional complexity in the strategy does not add up to the effects already induced by the scale-free interaction network, associated with the heterogeneous payoff distribution In other words, the network structure may by itself dispense the need to develop highly cognitive capabilities. Differently, a heterogeneous allocation of donations may open a window to smarter ways of cheating in a heterogeneous network context.

227 On the other hand one expects that additional skills may enhance the aptitude of Cooperators to protect themselves against Defectors, which may play a different role 228 229 depending on the composition of the population. Up to now we have been discussing the viability of cooperation to emerge from an equal distribution of cooperators and 230 231 defectors. But how stable is cooperation once established? In the following we investigate 232 the robustness of the cooperative community against defector invasion attempts. To this 233 end, and after an initial transient period, in every generation we replace a given amount of 234 the population by defectors. It turns out that reactive cooperators can withstand defector 235 attacks far more successfully. Figure 4 shows that even for extreme defector inflow 236 values as high as 10% of the population in every generation, cooperation survives with 237 the help of this more sophisticated strategy. We can define a numerical index to compare 238 the robustness of cooperation in different scenarios by calculating the integral below the

surfaces in Fig. 4. The ratio of the integrals $\Omega_{CRC}/\Omega_{UCC}=1.46$ shows that the reactive cooperative strategy (CRC) is almost 1.5 times more successful in defending itself than the unconditionally equal cooperators (UCC).

242 Finally, it is also noteworthy that different cognitive skills and levels of complexity can 243 have an impact in several emerging features of the population beyond the levels of 244 cooperation. In Fig. 5 we portray the wealth (here understood as fitness) distribution of the population in a fully cooperative community, that is, we compute how the total 245 income is divided among the individuals. It is known (Santos et al., 2008) that donating a 246 247 fixed cost per individual results in less poor and more rich people than in the case of 248 donating a fixed cost per game. With the advent of reactive cooperators, society becomes 249 more "fair", individuals are shifted from the poor regions to the "middle class". This can 250 be also shown by the Gini coefficient G (Gini, 1912), which measures inequality of a 251 distribution (G=0 for maximum equality and G=1 for total inequality): G is 0.30 for the 252 reactive cooperators (CRC) and 0.38 for the UCC. The few, very poor individuals are 253 victims of the randomly built scale-free interaction network: they belong to an 254 unfortunate neighborhood that condemns them to lower payoffs.

255 **4 Conclusions**

We investigated the emergence of cooperation in Public Goods Games from the point of view of individual complexity. We found that increasing the complexity of the cooperator strategy can help to establish and maintain cooperation in different environments. When the interaction network is homogeneous, described by regular graphs, the introduction of a more complex, reactive cooperator strategy (CRC) helped to improve the performance

- 261 of cooperators to a great extent. However if the interaction network itself is complex and
- heterogeneous, as in the case of a scale-free graph, then the additional complexity in
- 263 strategy (CRC) does not positively take effect on the spreading range but renders
- 264 established cooperation more robust against defector invasion.

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346 Figure legends

Figure 1. Public Goods Game on graphs. A. Players are participating in (k+1) games in every generation. Colored bubbles show the PGG groups in which the central (orange) player is participating while the p_i values show the payoff she gains from the corresponding groups. B. Reactive behavior of CRC cooperators: colored bars show the orange player's payoff-share gained from each group (with a given color) compared to the player's total payoff. In the next generation, cooperators divide their contribution to the public good according to their previous income.

Figure 2. Results of additional cooperator complexity on the square lattice: the 354 355 fraction of cooperators as a function of the normalized multiplicative factor (η) for the 356 different cooperator strategies. The incipient cognitive abilities of CRC cooperators make 357 it possible to prevail under much worse conditions. Red circles show the concentration of 358 CRC cooperators when the donations are given proportional to the payoff from the 359 groups, while blue squares show the results of the traditional case (UUC or, equivalently, 360 UCC), where the donations are shared equally. We used a square lattice of size 361 Z=100x100 as an example of a homogeneous interaction structure, with nearest neighbor 362 (von Neumann) interactions (k=4) and with periodic boundary conditions.

364 Figure 3. Cooperation level with scale-free networks as interaction structures. The 365 different symbols show the fraction of cooperators with different model setups as a 366 function of the normalized multiplicative factor (η) . For heterogeneous, scale-free 367 networks, η is calculated using the average connectivity ($\langle k \rangle = 4$) of the graph. Blue 368 squares stand for the UUC cooperators, green triangles for the UCC cooperators, while 369 red circles indicate the CRC cooperators. The definition of the strategies is given in the Methods. Scale-free networks (size of Z=1000 and average degree of $\langle k \rangle = 4$) were 370 generated using the Barabási-Albert algorithm (Barabási and Albert, 1999). 371

372 Figure 4. Robustness against defector inflow on scale-free networks. Color codes 373 show the cooperator concentration for different defector inflow rates as a function of η . 374 After a transient period, a given amount of players were randomly replaced by defectors 375 in every generation and the concentration values were calculated during the subsequent 10⁴ generations under continuous defector inflow. The left panel (4A) displays the results 376 377 for the case when cooperators share their donations equally (UCC), while the right panel 378 (4B) shows them for the more complex, reactive cooperator strategy (CRC). CRCs are 379 more robust against the invasion of a minority of free-riders, specially for large η and 380 defectors inflow rates.

381 Figure 5. Wealth distribution in fully cooperative populations for the different

cooperative strategies. Red bars stand for the cognitive cooperator strategy (CRC) while striped bars show the distribution for the "equal" cooperators (UCC). CRC cooperators lead to less poor and more rich individuals. Both distributions were obtained from an average over 10 different network realizations with a size of $Z=10^3$.

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387 388 389 390	Highlights:	
	•	We study the evolution of cooperation in the framework of Public Goods Games.
391	•	Cooperative players are able to distribute their donations to their liking.
392	•	Directed investments greatly enhance cooperation on homogeneous graphs.
393	•	Established cooperation is robust against the invasion of free-riders.
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398 Fig. 2 1.0 concentration of cooperators 0.8 0.6 ບບົດ ບົດດ CRC decepted manufactures of the second s 0.4 399 400





