



Evolution of cooperation in a one-shot Prisoner's Dilemma based on recognition of trustworthy and untrustworthy agents

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Abstract

This article explores the conditions under which agents will cooperate in one-shot two-player Prisoner's Dilemma games if they are able to withdraw from playing the game and can learn to recognize the trustworthiness of their opponents. When the agents display a number of symbols and they learn which symbols are important to estimate the trustworthiness of others, agents will evolve who cooperate in games in line with experimental observations. These results are robust to significant levels of mutations and errors made by the players.

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1. Introduction

Several theories have been proposed to explain the evolution of human cooperation. The theory of kin selection focuses on cooperation among individuals who are closely related genetically (Hamilton, 1964), whereas theories of direct reciprocity focus on the selfish incentives for cooperation in repeated interactions (Trivers, 1971; Axelrod, 1984). The theories of indirect reciprocity and costly signaling show how cooperation in larger groups can emerge when the cooperators can build a reputation (Alexander, 1987; Nowak and Sigmund, 1998; Lotem et al.,

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27 1999; Wedekind and Milinski, 2000; Leimar and Hammerstein, 2001; Zahavi, 1977; Gintis et al.,
28 2001).

29 Cooperation in repeated settings is well explained, but as Field (2001) points out, cooperation
30 in one-shot Prisoner Dilemma games is an important finding of experimental research that needs
31 to be understood to improve insight to the evolution of human behavior. Altruistic punishment
32 is proposed as an explanation of why cooperation is found frequent among genetically unrelated
33 people, in non-repeated interactions, when gains from reputation are small or absent (Fehr and
34 Gächter, 2002). In this article I propose an alternative explanation, namely the ability to recognize
35 untrustworthy opponents. Trusting behavior can explain cooperation in experimental one-shot
36 games (Ostrom and Walker, 2003). Recognition of trustworthiness of others has been found to be
37 an important factor in experimental studies (Frank et al., 1993; Mealey et al., 1996; Oda, 1997).
38 Humans especially have an ability to recognize defectors (see also Cosmides, 1989).

39 Through the use of simulation experiments with artificial agents, I will show that evolution
40 of cooperation in non-repeated interactions between unrelated agents might be possible when
41 the agents have the ability to learn to recognize the trustworthiness of other agents. Also, the
42 agents have different tendencies to cooperate and will learn to recognize these agent types.
43 An analytical model of one-shot games in relation to honest and dishonest players has been
44 developed by Frank (1987). He analyzed equilibria for different assumptions of the information
45 from signals and costs of adapting the signals. The difference between this study and Frank's
46 study is the ability not to play a game and the explicit learning process of the agents. Costs
47 of detecting the types of players, constant in Frank, is a function of learning abilities as I will
48 discuss later in this article. The model also relates to the indirect evolutionary approach (Güth
49 and Kliemt, 1998; Berninghaus et al., 2003) in which subjective and objective payoffs explic-
50 itly different play a role. A subjective pay-off function and an objective pay-off function apply
51 simultaneously. The former is driving choice, the latter selection. Güth and colleagues use evolu-
52 tionary game theory and do not distinguish interactions between individuals but apply fractions
53 of agent types. They show that a mixed equilibrium of trustworthy and untrustworthy agents can
54 evolve.

55 The model builds on the literature of partner selection and the use of symbols in Prisoner's
56 Dilemma games to recognize types of agents and show that cooperation occurs when agents
57 cooperate only with agents with the same symbols (Hales, 2001; Lindgren and Nordahl, 1994;
58 Riolo, 1997; Riolo et al., 2001). Macy and Skvoretz (1998) use symbols related to the types of
59 players' behavior.

60 Besides providing the decision to cooperate or defect in a Prisoner's Dilemma, various scholars
61 have included the option of not playing the game, in experimental tests as well as modeling
62 exercises. Orbell et al. (1984), Orbell and Dawes (1991) and Hauk and Nagel (2001) argue that
63 players with the intention to defect have a higher level of not playing the game compared with
64 players who have an intention to cooperate. In model analyses of Schluessler (1989) and Vanberg
65 and Congelton (1992), agents with successful strategies are those who exit when the opponent
66 defected in the previous game. In fact, these strategies do not tolerate errors. Stanley et al. (1994)
67 and Ashlock et al. (1996) allowed players to chose partners, and their chosen partners to refuse
68 offers, based on the known history of interactions with other players.

69 In the next section I will present my model that combines ideas from partner selection and
70 the use of tags in order to study whether agents learn to recognize trustworthiness of strangers in
71 playing one-shot Prisoner's Dilemma games. In Section 3, I will discuss the experimental set-up,
72 the basic results are presented in Section 4, and a sensitivity analysis in Section 5. The conclusions
are presented in Section 6.

73 **2. The model**

74 The model consists of a population of n players who randomly play one-shot two-person
 75 Prisoner’s Dilemma games. I define the game they play, which strategy the players use, what
 76 types of symbols the players display, and how they learn to recognize the trustworthiness of these
 77 symbols. Finally, I discuss how the composition of players evolves when the game is played for
 78 a number of generations.

79 *2.1. The game*

80 Each individual has three possible actions: cooperate (C), defect (D), or withdraw (W). If both
 81 players cooperate, they each get a payoff of R (reward for cooperation). If both players defect, they
 82 each get a payoff of P (punishment for defecting). If player A defects and B cooperates, A gets
 83 a payoff of T (temptation to defect), and B gets S (sucker’s payoff). If at least one of the players
 84 withdraws from the game, both players get a payoff of E (exit payoff). The resulting payoffs are
 85 given in Table 1.

86 In line with Tullock (1985) and Vanberg and Congelton (1992), I assume that the costs and
 87 benefits of exit are such that the expected payoffs from choosing not to play are higher than those
 88 resulting from mutual defection, but lower than those expected from mutual cooperation. The
 89 Prisoner’s Dilemma is defined when $T > R > E > P > S$ and $2R > T + S$. In this situation the best
 90 option for any one move is to withdraw from the game. If one expects that the other agent will
 91 cooperate, the best option is to defect. If one expects that the other agent will defect, the best
 92 option is to withdraw. Since the game is symmetrical, each player comes to the same conclusion,
 93 so they both withdraw and end up with payoffs that are much lower than if they both trust that the
 94 other will cooperate. The pay-off matrix for the game in this article is defined using $T = 2$, $R = 1$,
 95 $E = 0$, $P = -1$, and $S = -2$, which is in line with Tullock.

96 Experimental research has shown that the material payoff does not have to equal the utility pay-
 97 off experienced by the players (see, for example, Ahn et al., 2001, 2003). Not every subject shows
 98 selfish behavior. In fact, the majority of non-selfish players seem to be conditionally cooperative
 99 and cooperate only when they know that the other will probably cooperate. I will use the notion
 100 of social-welfare preferences to formulate the utility of agents (e.g. Andreoni and Miller, 2002).
 101 With these social-welfare preferences, subjects always prefer more for themselves and the other
 102 person, but are more in favor of getting payoffs for themselves when they are behind than when
 103 they are ahead. The strength of such preferences is increasing in the magnitudes of parameters α
 104 and β . The utility can then be formulated as:

$$u_i = \pi_i - \alpha_i \max(\pi_i - \pi_j, 0) + \beta_i \max(\pi_j - \pi_i, 0) \tag{1}$$

Table 1
 Pay-off table of the Prisoner’s Dilemma with the option to withdraw from the game

		Player B		
		Cooperate	Defect	Withdraw
Player A	Cooperate	R, R	S, T	E, E
	Defect	T, S	P, P	E, E
	Withdraw	E, E	E, E	E, E

Table 2
 Utility pay-off table of the Prisoner’s Dilemma with the option to withdraw from the game

	Player B		
	Cooperate	Defect	Withdraw
Player A			
Cooperate	R, R	$S + \beta_A(T - S), T - \alpha_B(T - S)$	E, E
Defect	$T - \alpha_A(T - S), S + \beta_B(T - S)$	P, P	E, E
Withdraw	E, E	E, E	E, E

106 where u_i is utility of agent i , and π_i the monetary income of agent i . We define $\beta_i \leq \alpha_i$ and
 107 $0 \leq \beta \leq 1$. The α value can be regarded as the strength of an individual’s aversion to exploiting
 108 others, and β can be regarded as an individual’s degree of altruistic tendency. These α and β values
 109 determine the strategies of the agents to cooperate or not. Furthermore, the simulated evolution-
 110 ary process may affect the α and β values of the agents. Both aspects will be explained below in
 111 more detail. Although there are other competing utility models of other regarding preferences,
 112 Charness and Rabin (2002) find that social-welfare preferences explain the data best for a com-
 113 prehensive set of experimental data. The experimental estimates for α and β vary around 0.4 and
 114 0.1.

115 To include the heterogeneity of motivations, I formulate the utility function in Table 2, where
 116 the material payoffs can be adjusted by individual motivations.

117 An agent has three elements: (1) the set of symbols that it displays, (2) the strategy that it uses
 118 to decide whether to trust or not another agent, and (3) the strategy it uses in Prisoner’s Dilemma
 119 games.

120 The symbols are represented in the following way. Each agent has s symbols that can have
 121 value 0 or 1, where 0 means no display of the symbol and 1 means display of the symbol. The
 122 other two elements require more discussion.

123 2.2. Trust

124 The rule an agent uses to decide to trust the other agent, and thus be willing to play a Prisoner’s
 125 Dilemma game, is represented as a single-layer neural network (Janssen and Ostrom, 2006).
 126 Such a basic neural network model is a simple but effective model to represent human learning
 127 processes of pattern recognition (Mehrota et al., 1997). A neural network has s inputs, which are
 128 the values 0 and 1 of the other agent’s symbols. A weighted sum M of these inputs is calculated
 129 using the following equation:

130
$$M = w_0 + \sum_{i=1}^s w_i x_i, \tag{2}$$

131 where w_0 is the bias, w_i the weight of the i th input, and x_i the i th input. Initially, all weights
 132 are zero, but during the simulation the network is trained, when new information is derived, by
 133 updating the weights as described below in Eq. (4).

134 Neural networks use a so-called threshold function to translate the inputs into one output. The
 135 standard threshold function used for neural networks is a sigmoid function, and it determines trust

136 defined as the probability $\Pr[\text{Tr}]$ that the agent will cooperate with its prospective partner:

$$137 \quad \Pr[\text{Tr}] = \frac{1}{1 + e^{-M}}. \quad (3)$$

138 The higher the value of M , the higher the probability will be. The probability of not trusting the
139 other agent is $1 - \Pr[\text{Tr}]$. Since the initial weights are assumed to be zero, the initial value of
140 $\Pr[\text{Tr}]$ is 0.5.

141 If a game is played, each agent receives feedback, F , on the experience. This feedback is
142 simply whether the partner cooperated or not. If the partner cooperated ($F = 1$), the agent adjusts
143 the weights associated with the other agent's symbols upward, so that it will be more likely to
144 trust that agent, and others displaying similar symbols, in the future. On the other hand, if the
145 partner defected ($F = 0$), the agent will adjust the same weights downward, so that it will be less
146 likely to trust that agent and others with similar symbols. The equation to adjust the weights is as
147 follows:

$$148 \quad \Delta w_i = \lambda(F - \Pr[\text{Tr}])x_i, \quad (4)$$

149 where Δw_i is the adjustment to the i th weight, λ the learning rate, F the feedback, $F - \Pr[\text{Tr}]$ the
150 difference between the agent's level of trust in the other agent and the observed trustworthiness
151 of the other agent, and x_i the other agent's i th symbol. In effect, if the other agent displays the i th
152 symbol, the corresponding weight is updated by an amount proportional to the difference between
153 the observed trustworthiness of an agent and the trust placed in that agent. The weights of symbols
154 associated with positive experiences increase, while the weights of those associated with negative
155 experiences decrease, reducing discrepancies between the amount of trust placed in an agent and
156 that agent's trustworthiness.

157 The initial values of α are drawn from a uniform distribution between 0 and 1, and for β
158 between 0 and 1, by which only initial conditions are accepted where $\beta \leq \alpha$. The initial values of
159 the symbol x_i , 0 or 1 for each, are chosen randomly, and all initial weights w_i are set to 0.

160 2.3. Strategies

161 When neither agent withdraws from playing a game, they have to decide to cooperate or to
162 defect. The agents are assumed conditionally to cooperate. In Vanberg and Congelton (1992),
163 conditional cooperation was deterministic; as soon as the other player defects, the agent will
164 withdraw from playing the game. Since in my case the players play one-shot games, such a
165 strategy will not work. I assume that the players will estimate the expected utility for cooperation,
166 $E[U(C)]$, or defection, $E[U(D)]$. The expected utility is determined by assuming that the level
167 of expected trust of an agent in its opponent, defined in (3), represents the probability that the
168 opponent will cooperate:

$$169 \quad E[U(C)] = \Pr[\text{Tr}]R + (1 - \Pr[\text{Tr}])S + \beta_i(T - S) \quad (5)$$

170 or

$$171 \quad E[U(D)] = \Pr[\text{Tr}](T - \alpha_i(T - S)) + (1 - \Pr[\text{Tr}])P. \quad (6)$$

172 Given the two estimates of expected utility, the player is confronted with a discrete choice problem,
173 which I address with a logit function. The probability to cooperate, $\Pr[C]$, depends on the expected
174 utilities and the parameter γ , which represents how sensitive the player is to differences in the

175 estimates. The higher the value of γ , the more sensitive the probability to cooperate is to differences
 176 between the estimated utilities:

$$177 \quad \Pr[C] = \frac{e^{\gamma E[U(C)]}}{e^{\gamma E[U(C)]} + e^{\gamma E[U(D)]}}. \quad (7)$$

178 Logit models are used by other scholars to explain observed behavior in one-shot games such as
 179 the logit equilibrium approach by Anderson et al., in press (forthcoming). Although the functional
 180 relation is similar, their approach differs from mine since they assume an equilibrium and perfect
 181 information of the actions and motivations of other players. Moreover, in my games agents do
 182 not play anonymously but can observe symbols of others in order to estimate the behavior of the
 183 opponent.

184 *2.4. Generations*

185 In one generation a certain number (g) of games are played. For each of these, two agents are
 186 chosen at random. These agents then decide if they trust each other by the process described in
 187 Section 2.2. If they do trust each other, they play the Prisoner’s Dilemma once (see Section 2.3)
 188 and the resulting payoffs are added to their respective total scores.

189 The average material payoff an agent has received from all its interactions (games played or
 190 games exited) with other agents is used to determine the offspring in the next generation. Each
 191 generation 10% of the population is replaced by new agents who are selected from the population
 192 (including those who previously left the system) using a tournament selection algorithm. Two
 193 contestants are picked at random from the population, and their average payoffs are compared.
 194 The one with the higher average payoff becomes a new agent. If both contestants have identical
 195 scores, the winner is picked at random.

196 The genotype of the new agent (α, β, x_i, w_i) is copied from the parent and then may experience
 197 mutation. The mutation rates for strategies, symbols, and weights determine the probability or
 198 degree that each individual component will be mutated. In the case of the symbol, a mutation
 199 consists of flipping the component to the opposite state (0 (off) to 1 (on) or vice versa). In the case
 200 of the motivations and weights, there is always a mutation draw from a Gaussian distribution with
 201 means equal to the parameter values after crossover. The level of mutation is set by the standard
 202 deviations of the Gaussian distributions (Table 3).

203 Note that the model includes two types of adaptation of the weights. Within a generation agents
 204 are able to update the weights in order to learn to recognize the agent types. Between generations
 205 agents derive weights from the previous generation, although those weights are somewhat altered
 206 by mutations.

Table 3
 List of parameters and their default values

Parameter	Value
Number of agents (n)	100
Number of symbols (s)	20
Learning rate (λ)	1.0
Steepness (γ)	2
Number of games per generation (g)	500
Mutation rate symbols	0.05
Standard deviation mutation w, α, β	0.1

207 3. Experimental design

208 Conventional rational choice theory predicts that selfish players will evolve toward avoiding
209 the game. I will show that the inclusion of recognition leads to a population of agents that are not
210 selfish and reach high levels of cooperation.

211 Parameter values for the default case are presented in Table 3. I will use this default case as a
212 reference for testing the sensitivity for a number of assumptions.

213 Each set of parameter values is used to simulate 50 runs, where each run consists of 1500
214 generations. Taking into account an initialization period, I report statistics for the last 1000 gen-
215 erations. I report the average and standard deviation of withdraw, cooperation, defection, payoffs,
216 the combinations of mutual cooperation, mutual defection, and cooperation/defection. I will ana-
217 lyze the influence of the number of symbols, the number of players, the learning rate, the mutation
218 rates, and the error probabilities.

219 4. Basic results

220 A typical experiment of the default case is depicted in Fig. 1. Initially, agents usually withdraw
221 from playing a game, but they learn quickly who to trust in playing a game and how to play it.
222 Fig. 1 shows that after about 200 generations cooperation reaches a high level, although periodic
223 collapses of cooperation can occur. These periodic collapses are caused by invasions of defectors
224 who express symbols that are recognized by others as symbols of trustworthiness. Such defectors
225 can emerge due to mutations and spread rapidly in a population of agents who recognize them
226 as being trustworthy. After a number of generations, the exploitive behavior of the defectors is
227 noticed, and cooperative agents have learned to recognize them, leading to an increase in the level
228 of cooperation within the total population.

229 Table 4 shows the basic statistics of the default case of 50 runs under the same conditions.
230 The results show that a level of cooperation is established (around 80%), which is significantly
231 different from the conventional prediction that all players will withdraw from playing the games.
232 The average value of parameter α is 0.75, and there is an intention to be altruistic, with β around
233 0.4. The standard deviation of β is relatively large, 0.16. The reason for this is that $\alpha \geq \beta$, and that

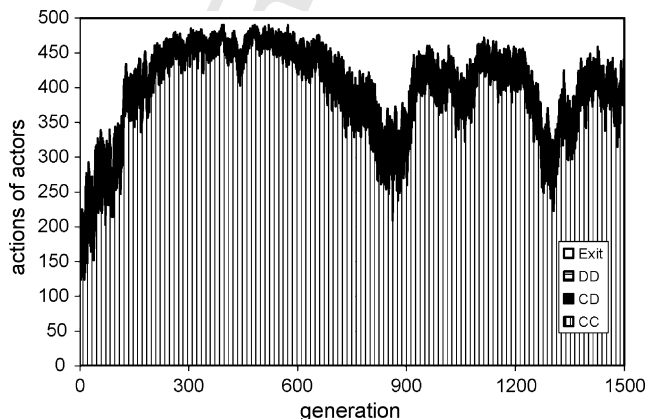


Fig. 1. Number of agents engaged in mutual cooperation (CC), mutual defection (DD), cooperation/defection (CD) or withdrawal from playing the game (Exit) for each generation.

Table 4

Basic statistics of the default case with the mean and standard deviation (parentheses) for 50 runs

Indicator	Value
Payoff	0.81 (0.15)
# CC games	405.7 (74.9)
# CD games	25.0 (9.4)
# DD games	0.7 (0.6)
# Withdrawn	68.6 (72.5)
Parameter α	0.76 (0.10)
Parameter β	0.41 (0.18)

234 when $\alpha > 0.25$ the agent will value cooperation over defection. Therefore, the value of β is less
235 influential than α and might therefore fluctuate more due to lower selection pressure.

236 The average values of α is higher than the empirical estimates in [Charness and Rabin \(2002\)](#),
237 but in empirical studies the level of cooperation in one-shot experiments is 50% instead of our
238 80%. We will explore in the following section how relaxing assumptions lowers the cooperation
239 levels, which are more in line with empirical observations.

240 In contrast to [Frank \(1987\)](#), my agents do not pay a price to get correct information on what
241 type of player the opponent is. The model of Frank predicts a 100% level of cooperation in such
242 a case, where 80% is reached in my simulations. The explanation is that a price is paid indirectly
243 for knowing the information of the opponent. Namely, they have to learn by trial and error, which
244 symbols are good predictors of trustworthiness. Since symbols related to the types of agents slowly
245 evolve over time, agents need to remain exposed to defectors in order to update their weightings
246 of the symbols. Furthermore, there is a cost of exploration since mutations have the probability
247 of changing cooperators into defectors.

248 Recently, [Skyrms \(2002\)](#) and [Miller et al. \(2002\)](#) explored the consequences of “cheap talk”,
249 costless signaling, on cooperation in Dilemma situations. Skyrms looks at stag hunt games and
250 bargaining games, while [Miller et al. \(2002\)](#) look at one-shot Prisoner Dilemma games. In both
251 studies cooperation can evolve, but this situation is unstable and rapidly disappears again. [Skyrms](#)
252 [\(2002\)](#) and [Miller et al. \(2002\)](#) assume that agents are selfish rational agents. I assume agents are
253 also rational, but due to evolutionary pressures, the average social-welfare preferences increase.
254 The fact that agents can decide not to play a game when they do not trust their opponent is
255 instrumental in the evolution of other social-welfare preferences. When the exit option is not
256 possible, no cooperation can evolve. This can be understood by the following reasoning. Suppose
257 you are a trustworthy agent who has to make a decision of cooperation or defection in a game
258 with a stranger. Suppose you do not trust your opponent; what do you do? If you cooperate, since
259 you are trustworthy, you can expect the sucker payoff, but if you defect, the opponent will view
260 you as non-trustworthy and adjust its weights for estimating trustworthiness of strangers. As a
261 consequence, agents evolve to defect frequently, and there is not a strong selection pressure to
262 weed out non-trustworthy agents. Hence the inclusion of the exit option and the evolution of
263 social-welfare preferences are crucial assumptions leading to my results.

264 5. Sensitivity analysis

265 The number of symbols can affect the level of cooperation. [Fig. 2](#) shows that a reduction
266 of the number of symbols to below 15 significantly reduces the average payoff. The average

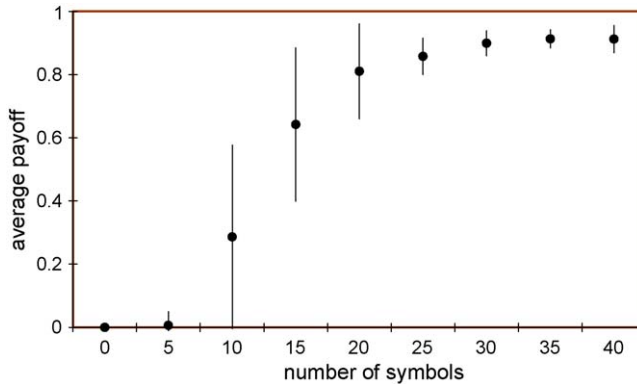


Fig. 2. The effect of the number of symbols on the average payoff. The dots refer to the average value of 50 runs; the lines represent the standard deviation of these 50 observations.

267 payoff reaches zero around five symbols, which can be interpreted to mean that there is not
268 enough diversity in symbols to distinguish trustworthy and non-trustworthy agents. Increasing
269 the number of symbols beyond 20, as in the default case, only slightly increases the average payoff.
270 There is a decreasing marginal return to the number of symbols. Note that for seven symbols all
271 agents can have a unique representation. In the simulation the agents are descendants affected by
272 mutations. This requires more symbols to derive enough diversity in the simulated population.

273 The next question is whether or not the results are the consequence of agents learning to
274 recognize trustworthiness in others. To test this, I varied the learning rate λ between 0 and 1. The
275 resulting statistics, depicted in Fig. 3, show that when the learning rate is below 0.3 the average
276 payoff drops significantly. When the learning rate is zero, the average payoff is zero, where
277 almost no agents play the game. These results show that cooperation in my model is sensitive to
278 the ability to learn to recognize whom to trust. Note that a high learning rate does not led to 100%
279 cooperation. The reason is that agents need to be confronted with defectors in order to update the
280 recognition ability of recognizing agent types with changed symbolic expressions.

281 In the previous experiments I draw the initial distribution of α and β between 0 and 1. We
282 investigated the effect of starting with different groups of players by sampling a narrower margin
283 of the parameter α . Fig. 4 shows that starting with agents biased toward selfish behavior results

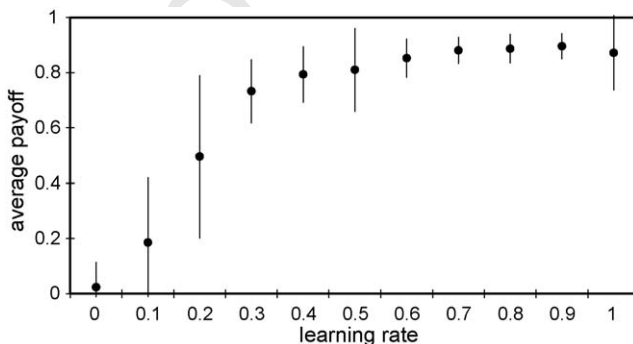


Fig. 3. The effect of the learning rate on the average payoff. The dot represents the average of 50 simulations; the lines represent the standard deviation.

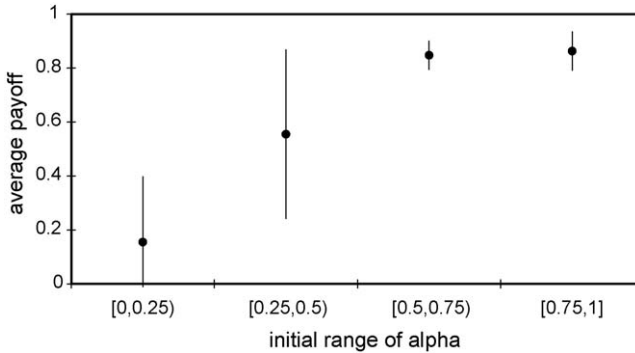


Fig. 4. The effect of the initial distribution of α on the average payoff after 1500 generations. The dot represents the average of 50 simulations; the lines represent the standard deviation.

284 in a modest average payoff level of 10%. Given the high variance of the outcomes, it shows
285 that groups can evolve into more cooperative agents. If we let the model run 10,500 generations
286 instead of 1500 generations, the average payoff eventually reaches 80% when the initial range of
287 α is between 0 and 0.25. Only when α is sampled from values between 0.5 and 1 does a stable
288 level of cooperation evolve within 1500 generations. I found that different initial samplings for β
289 did not affect the results. As explained before, the value of α is dominant whether the agent has
290 motivation to defect or not. In that result, the effect of α is dominant, at least in the short run, since
291 simulations (not shown) illustrate that after many generations the cooperation levels converge to
292 80% independent of the starting values.

293 Thus far, I have assumed that agents make their decisions probabilistically but do not make
294 mistakes. Suppose, for example, the agent tosses a biased coin to decide whether or not to trust
295 the agent and makes a mistake in reading the coin. How sensitive is the level of cooperation to
296 mistakes? In Fig. 5 an increase is observed in probability p_T , the mistake of trusting an untrust-
297 worthy opponent or the mistake of distrusting a trustworthy opponent, leading to a lower level of
298 payoff; this decrease is almost linear with the increase in the value of p_T .

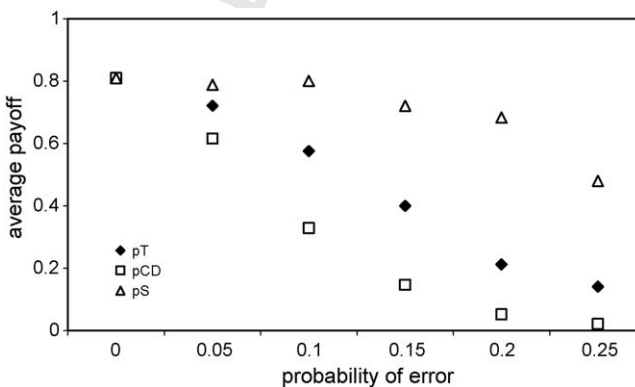


Fig. 5. The effect of the probabilities p_T , p_{CD} and p_S of making mistakes in trusting the opponent, deciding to cooperate or defect, and reading a symbol on the average payoff.

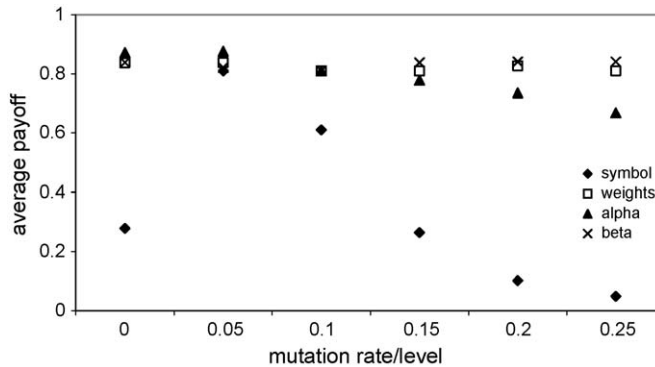


Fig. 6. The relationship between mutation rates for the symbols, the weights, and the social welfare preferences parameters, and the average payoff.

299 In a similar way the impact is assessed of making a mistake in deciding to cooperate. If an
 300 agent would normally cooperate, based on tossing the coin with probability as defined in Eq. (7),
 301 then the agent may make a mistake with probability p_{CD} . The results are relatively sensitive to
 302 these types of mistakes: a value of p_{CD} above 0.1 will reduce the average payoff to nearly zero.
 303 Making such mistakes is costly. Since most of the players are eager to cooperate, such mistakes are
 304 unintended defections, and this will affect the expected trust of opponents in an agent's symbols.
 305 This reduces the opportunities for the agent and its offspring to play games.

306 The third type of mistake is to misread the symbol, for example by overlooking a symbol of the
 307 opponent, which affects the estimated trustworthiness. The results shown in Fig. 5 illustrate the
 308 minor impact of this type of error. An explanation is that there is redundancy in the list of symbols
 309 that makes the estimation of trustworthiness robust for a certain degree of mistakes, but this does
 310 not hold for making errors in trusting other agents (p_T and p_{CD}) since such errors directly affect
 311 the level of cooperation.

312 The characteristics of the agents change over time due to mutations. This can be interpreted in
 313 two different ways. First, as a learning process, where agents copy the characteristics of successful
 314 other agents. Mutation rates for symbols and mutation levels for weights and social welfare
 315 preferences are in this case the degree of error made in imitation of other's behaviors. The second
 316 interpretation is that of parents and their offspring, where the offspring is taught certain norms
 317 of behavior, but not perfectly. In line with Tooby and Cosmides (1990), I assume that natural
 318 selection shapes decision rules and the cues they monitor. The degree of mutation can have an
 319 effect on the degree of cooperation as shown in Fig. 6. The most sensitive mutation rate is that
 320 of symbols. When agents perfectly copy the symbols, this will lead to a reduction in the variety
 321 of symbols. As was shown in Fig. 2, a reduction of symbolic diversity makes it more difficult
 322 to distinguish trustworthy and non-trustworthy agents. Perfect copies of symbols but not perfect
 323 copies of α and β lead to less information available to recognize agent types. On the other hand,
 324 when the mutation rate is high, agents are unable to learn which symbols relate to which types of
 325 players since they try to learn a secret code that is continuously changing.

326 The relatively low sensitivity of the not directly observable characteristics of the players is
 327 interesting since the results seem to be robust regarding the way agent characteristics are passed
 328 through generations. As long as the agents have similar, but not the same, symbols as their parents
 329 and have the ability to learn, imperfect transmissions of knowledge (weights) and norms (α and β)
 330 between "parent" and "offspring" do not affect long-term cooperation. The result for the weights

is not surprising since the agents update their weights due to learning within a generation. The relative insensitivity for α and β can be explained by the fact that once α is larger than 0.25, the temptation to defect is not valued with the highest utility, and a small mutation of α will not have a significant effect as long as the mutation does not cause α to be lower than 0.25.

6. Conclusions

A model was presented of agents playing one-shot Prisoner's Dilemma games with the option of withdrawal from playing the game when they expect that the opponent is not trustworthy. Over generations, agents evolve to those with social-welfare preferences roughly in line with experimental evidence. The inclusion of the ability to learn to recognize trustworthiness of others leads to levels of cooperation that are significantly higher than would be expected for one-shot Prisoner Dilemma games but are more in line with observations in laboratory experiments with communication.

Based on visual characteristics, agents seem to be able to estimate the trustworthiness of others to such a degree that a high level of cooperation can be maintained, and this result is robust for modest degrees of making errors. In most of my simulations I use a population of 100 agents, and experiments with 1000 agents showed that only a lower level of cooperation can be derived and that more symbols are needed to reach these levels of cooperation. Even when the initial population is dominated by selfish individuals, the evolution drives the model towards agents with a level of other regarding preferences that enables a high level of cooperation.

Although symbols can help to foster cooperation, I expect that specific types of symbols such as reputation symbols, and other forms of information transmission such as gossip, seem to be necessary to derive high levels of cooperation in larger groups. Nevertheless, the use of only visual symbols can explain a possible origin in using symbols as a way to detect cheaters. In this respect, this article contributes to the question why and when humans cooperate in non-repeated social Dilemmas and how this may affect the evolution of symbolic systems that foster cooperation in human societies.

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