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# Summary

With *direct reciprocity*, an agent responds in-kind to its direct experiences with another agent. The game theoretic framework of the prisoner’s dilemma is often used to investigate the evolution of cooperation through direct reciprocity. In the seminal work on the evolution of cooperation through direct reciprocity, the authors of [1] showed that, under certain conditions, cooperation based on direct reciprocity could become established in a population of unrelated individuals. This work prompted many follow on studies where the results have been debated and refined.

With *indirect reciprocity* an agent responds based on observations of interactions involving agents other than itself. The driving force behind indirect reciprocity is reputation [2]. An agent’s reputation contributes to its perception as trustworthy by other agents. Agents learn the reputations of other agents and thereby learn which agents can be trusted to cooperate and which are likely to defect.

In one of the seminal works on the evolution of cooperation through indirect reciprocity, the authors of [3] introduced a theoretical framework for analyzing the evolution of cooperation through indirect reciprocity. The framework is based on a simple game theoretic construct involving two player roles: a donor and a recipient. The donor is offered the opportunity to incur a cost *c* in order to provide a benefit *b* to the recipient. The game is repeated for several rounds with any two players interacting at most once. Since *b*>*c*, all agents stand to benefit if all agree to cooperate. However, the temptation to defect and exploit the largess of cooperators threatens the stability of community-wide cooperation.

Within this framework, the authors proposed two scales for tracking an agent’s reputation. The image *score* is a scale from -5 to +5 that is used to measure an agent’s reputation. An agent’s score is reduced by one when it takes an action that is deemed to be “bad” and increased by one when it takes an action that is deemed to be “good”. The agent’s score does not change if increasing or decreasing its score would cause it to be less than -5 or greater than +5. The *image* is a binary scale consisting of two states: good and bad. An agent’s image is set to bad if it takes an action that is deemed to be “bad” and set to good if it takes an action that is deemed to be “good”. When image is used, an agent’s reputation depends only on the last action it has taken.

To use the reputation tracking scales described above, a reputation *assessment rule* must be used to determine whether the action taken by an agent is deemed bad or good. The authors propose a simple assessment rule that is now referred to as *scoring*. The scoring assessment rule considers any defection to be bad and any cooperation to be good.

When an agent takes an action that is deemed to be “bad”, its image is set to bad.

When the agent takes an action that is deemed to be “bad”, its score is reduced by one unless the agent’s score is already equal to the minimum score. When the agent takes an action that is deemed to be “good”, its score is increased by one unless its score is already equal to the maximum score.

The authors introduce a simple strategy now referred to as *scoring* in the literature. The strategy consists of a simple assessment rule for tracking agent reputations and a simple action rule that an agent can use to decide whether to donate to the potential recipient.

The simple assessment rule takes two forms. The first form involves tracking agent reputations using an *image score* that ranges from -5 to +5. Each agent starts with an image score equal to zero. The agent’s image score is increased by one (up to +5) each time the agent cooperates and decreased by one (down to -5) each time the agent defects. The second form simplifies the image score down to two *images*: *bad* and *good*. Each agent starts with a good image and then its image is determined based on the last action it has taken. If the agent cooperates, its image becomes good. If the image defects, its image becomes bad.

The authors proposed a simple action rule that only depends on the reputation of the recipient. When using the image score form of reputation assessment, the rule specifies to cooperate when the recipient’s reputation is greater than a specified threshold *k*. When using the simplified good/bad image form of reputation assessment, the rule specifies to cooperate if the agent has a good reputation and defect otherwise.

(the authors do consider strategies that take into account the recipient’s reputation)

(briefly describe results)

Obviously, different assessment rules and action rules are possible and, since the publishing of this paper, much debate has ensued regarding which assessment rule and action rule combination is most likely to lead to a cooperative outcome[2][3][4].

The image scoring strategy only takes into account the reputation of the potential recipient: an agent should donate to a potential recipient if that recipient has a good reputation and refuse to donate otherwise. There are at least two criticisms that can be leveled at this strategy. First, the factor that determines whether the agent will receive donations in the future is its own reputation. However, an agent following the scoring strategy does not consider its own reputation when deciding whether to donate or not [3]. Second, the strategy dictates that an agent refuses to donate to a bad agent. However, following this strategy causes the agent itself to become bad and thus puts the agent in a situation where it will not receive donations in the future [5]. Third, the assessment rule gives agents a good score for cooperating regardless of the reputation of the recipient. (…) Because of these two issues, it is questionable whether a rational agent would actually follow the scoring strategy.

Much of that debate has focused on whether scoring or standing constitutes an evolutionarily stable strategy that promotes cooperation.

An alternative strategy, attributed to Sugden [2], is the *standing* strategy. The assessment rule used by the standing strategy discriminates between justified and unjustified defections. Defecting against a bad agent is labeled as justified while defecting against a good agent is labeled as unjustified. An agent is given a bad reputation if they engage in unjustified defection but otherwise labeled as good. An agent following the standing strategy focuses on maintaining its good standing. Therefore, the action rule used by agents following this strategy dictates that the agent should cooperate if they have a bad reputation or if the recipient has a good reputation.

This standing strategy seems to overcome the deficiencies of the scoring strategy and several authors have analyzed the relative performance of the two strategies using computer simulations.

Some authors have analytically evaluated the possible strategies… (MORE HERE…)

Analytic strategies make simplifying assumptions in order to make the problem tractable…

Here I am concerned about the approaches taken by the authors to evaluate the strategies and not about the results of the experiments.

In [3], the authors consider a model in which the population is divided among *g* groups each consisting of *n* members. During each generation, *m* rounds of donor-recipient interactions are played. For each round, two individuals are chosen randomly with one playing the role of the potential donor and the other playing the role of the potential recipient. The donor chooses to donate or not based on its action rule. Its decision may depend on its own reputation, the reputation of the potential recipient or both. The reputations of agents are public and determined based on an assessment rule that is shared by all agents. If the potential donor provides help to the potential recipient, then the usual pay-offs are provided to the players.

After the completion of *m* interactions, the local within-group and global cross-group reproductive probabilities for each action rule are determined as follows. For each group, the pay-offs earned by each action rule in the previous generation are summed and normalized to produce the local within-group reproductive probability for each action rule. To produce the global cross-group reproductive probabilities, the pay-offs earned by each action rule are summed and normalized across all groups.

The action rule followed by each individual in the next generation is determined as follows. With probability p, the individual’s action rule is derived from the local group using the within-group reproductive probability. With probability 1-*p*, the individual’s action rule is derived using the global cross-group reproductive probability. When determining the action rule for an individual in the next generation, a mutation occurs with probability *μ*. When a mutation occurs, the individual’s action rule is selected from among all available action rules with equal probability.

In order to improve the fidelity of the model as it relates to real world scenarios, the authors introduce a probability ε that an agent will take an action that is different from the action prescribed by its strategy. (Implementation error)

(perception error)

The authors conduct two different sets of experiments. In the first set of experiments, they take the scoring assessment rule as a given and evaluate the evolutionary stability of several different action rules.

The authors investigate two assessment rules: *scoring* and *standing*. For the scoring assessment rule, the form of the rule in which an agent’s reputation is an integer between -5 and +5 is used. For the standing assessment rule, the binary good/bad assessment is used.

In the context of the scoring assessment rule, the authors consider three different actions rules:

* The agent provides help if its own image score is less than a threshold *h*
* The agent provides help if the recipient’s image score is greater than or equal to a threshold *k*. This is the action rule proposed in [1].
* The agent provides help if its own image score is less than a threshold *h* and the recipient’s image score is greater than or equal to a threshold *k*
* (Other strategies not studied by [1])

The authors evaluate the success of these strategies using computer simulations.

In the context of the standing assessment

In [5], the authors use a variation of the approach used in [3]. The assessment rule is limited to the simplified binary version in which the agent’s reputation can be one of two values: good or bad. In addition, each agent tracks a private assessment of other agents’ reputations and this assessment is not necessarily based on observing all interactions.

The authors clearly define a strategy as consisting of two parts: assessment rule and action rule. The assessment rule determines how an agent assigns a new reputation to a donor based on the agent’s last action and the reputation of the two participants when the action was taken. Given two possible actions that a potential donor can take, two possible reputation scores for the potential donor, two possible reputation scores for the potential recipient and two possible reputation scores that can be assigned to the potential donor there are 256 possible assessment rules to consider. The authors consider three assessment rules: scoring, standing and judging. The composition of each of these rules is described in the following table.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Observed Situation** | | | **Assigned Reputation** | | |
| **Donor Reputation** | **Recipient Reputation** | **Donor Action** | **Scoring** | **Standing** | **Judging** |
| Good | Good | Donate | Good | Good | Good |
| Good | Bad | Donate | Good | Good | Bad |
| Bad | Good | Donate | Good | Good | Good |
| Bad | Bad | Donate | Good | Good | Bad |
| Good | Good | Refuse | Bad | Bad | Bad |
| Good | Bad | Refuse | Bad | Good | Good |
| Bad | Good | Refuse | Bad | Bad | Bad |
| Bad | Bad | Refuse | Bad | Bad | Bad |

The action rule determines the action that an agent should take based on the reputation of the two participants. Given two possible reputation scores for the potential donor, two possible reputation scores for the potential recipient and two possible actions that an agent can take there are 16 possible action rules to consider. The authors consider six of these assessment rules: CO, SELF, AND, OR, ALLD and ALLC. The composition of each of these rules is described in the following table.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Situation** | | **Action to Take** | | | | | |
| **Donor Reputation** | **Recipient Reputation** | **SELF** | **CO** | **AND** | **OR** | **ALLC** | **ALLD** |
| Good | Good | Refuse | Donate | Refuse | Donate | Donate | Refuse |
| Good | Bad | Refuse | Refuse | Refuse | Refuse | Donate | Refuse |
| Bad | Good | Good | Donate | Donate | Donate | Donate | Refuse |
| Bad | Bad | Good | Refuse | Refuse | Donate | Donate | Refuse |

Considering all possible combinations to the three 3 assessment rules and 6 actions rules listed above, 14 strategies can be constructed. The authors use computer simulations to evaluate the evolutionary stability of these 14 strategies in three different ways. First the authors conduct experiments in which all 14 strategies are present. In this case, they evaluate the performance of the strategies for different cost benefit ratios. In the second set of experiments, the authors keep the assessment rule fixed and evaluate the performance of the different actions rules in that environment. In the final set of experiments, the authors keep the action rule fixed and evaluate the performance of the different assessment rules in that environment.

Given this model, the assessment rules are fixed and not subject to evolutionary pressures.

In [6], the authors investigate the co-evolution of assessment rules and action rules in the context of the door-recipient game. The model employed by the authors considers evolution at two levels. At the base level, the authors consider the evolution of action strategies in the context of a fixed assessment rule. On top of this base level, the authors consider the evolution of social norms in the context of competition between groups of agents called tribes.

Let be a tribe of agents and be the *jth* member of that tribe. Let be the social norm used by tribe *Ti*, be the strategy followed by agent *aij* and be the reputation of agent *aij*. The reputation of each agent is considered public shared information.

The simulation proceeds in rounds and each round consists of two stages. During the first stage, each agent participates in one donor-recipient game with every other member of its tribe. The payouts received by each agent are tracked in order to calculate the fitness of each individual in the tribe.

Public goods games can also benefit from such a theoretical framework… ???

This framework has served as the basis for

The form of the basic donor-recipient game investigated in [1] is the following.

In order to avoid negative pay-offs, the amount c is added to the pay-offs for both the donor and recipient. At the beginning of each generation, the pay-offs of all group members have a pay-off *u0*, which can be zero or positive.

Since the experiments do not incorporate any strategies that use the round number as the basis for decisions, we will not be concerned with the “end effect” which removes the incentive to help in the last round and leads to cooperation unraveling in all previous rounds.

The donor-recipient game provides a framework for investigating indirect reciprocity.

## Critique, Observations, Improvements and Extensions

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