Evolution of Cooperation in Agent-based Models

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1 Introduction

Language provides us with the means for sophisticated communication and is arguably a key difference that sets us apart from non-human animals. Communication plays an important role in cooperation, for example, communication has been found to foster cooperation (Crawford, 2019). What are the necessary conditions for a species to evolve the capability to communicate and subsequently cooperate? This question is still left unanswered, although Számadó et al. (2021) suggests that reputation plays a key role in cooperation.

Generally, reputation provides information about the likely behaviour of another individual (Tennie et al., 2010). As such, an individual's reputation guides the behaviour of others toward that individual. Applied to cooperation, prior research has investigated two distinct reputation-based systems: indirect reciprocity (IR) systems and reputation-based partner choice (RBPC) systems. In IR systems, if an agent helps another agent, they are more likely to receive help by a third agent in the future. Thus, agents build a reputation that has an influence on their future chances of receiving help. Similarly in RBPC systems, agents also build up a reputation based on their helping behaviour toward others. Unlike in IR systems, agents' reputations have an influence on their reproductive chances rather than receiving help. Roberts et al. (2021) compared these two systems and argued that the latter scenario is more relevant in interactions amongst humans, thus RBPC systems deserve more attention.

Another construct related to cooperation is gossip. Gossip occurs when a sender communicates information about a target to a receiver. In natural settings for example, gossip was often found to contain information about another person's cooperativeness and serves as a way to update that person's reputation (Dores Cruz et al., 2021). In addition, Dunbar (2004) argue that a key function of gossip is to limit exploitation of cooperative agents by free riders. In this context, a free rider is an agent, who reaps the benefits of cooperating while not paying the costs of cooperating. In simulations of the prisoner's dilemma, for example, Enquist and Leimar (1993) showed that cooperative communities can be driven to extinction by repeatedly being exploited by free riders. The authors cite gossip as one of the potential mechanisms that can limit the success of free riders.

This study investigates current theories of cooperation presented in Számadó et al. (2021) from an evolutionary perspective. Indirect reciprocity (IR) and reputation-based partner choice (RBPC) can both explain human cooperative behaviour, however, one question that arises from the literature is whether cooperation can evolve under the assumptions of both theories.

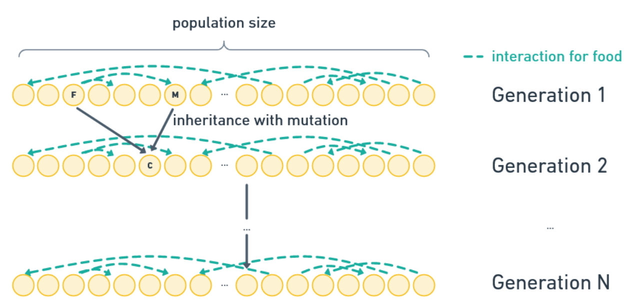
Agent-based simulations are a good tool for answering this question as they allow us to directly compare how different assumptions and pressures play out in complex circumstances. Concretely, these simulations will be used to formalize theories of RBPC and IR as biological mechanisms with the goal of investigating their evolutionary plausibility. Since free riders have been identified to be problematic for the evolution of cooperation (Enquist & Leimar, 1993), the biological models were tested how free riders affect cooperation. In addition, the models are extended to enable agents to adapt their behaviour based on prior experiences. Finally, we explore the effect of gossip on the stability of cooperation against free riders.

2 Biological Models of Cooperation

All models in this paper follow the general structure presented in Figure 1. For details regarding all hyperparameters and pseudo code of the simulations, see Appendix A (for the entire code, see the corresponding GitHub repository [1].

Figure 1

Simulation Setup



Note. Reproduction with inheritance occurs after all interactions of a generation have taken place.

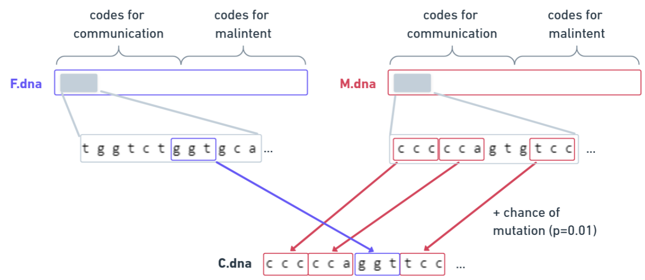
At a bare minimum, a biological model of evolution needs to implement the three main principles of evolution outlined

[1] https://github.com/philipp-hellwig/evolution-cooperation

by Darwin: variation, inheritance, and differential survival (Fitch, 2010). Variation and inheritance are loosely based on the biological process as seen in Figure 2. Differential survival is implemented by the fact that if agents do not acquire enough food they die and thus cannot reproduce.

Figure 2

Variation and Inheritance of Traits



Note. The DNA sequence is inherited in triplets. The probabilities of child C inheriting a triplet from mother M or father F are $p = 0.5$.

Since we are interested in cooperation, agents have two continuous traits: communication and malintent. In total, there are 15 triplets that code for each trait. Each time a triplet matches the arbitrary sequence defined for the given trait (e.g., the triplet "cat"), it increases the probability of communicating or showing malintent by $\frac{1}{15}$. During each generation, agents are repeatedly presented with food opportunities, in which they have the following three options:

1. Do not communicate and acquire food by themselves (hermit strategy).

2. Communicate with intentions of sharing food (cooperation strategy).

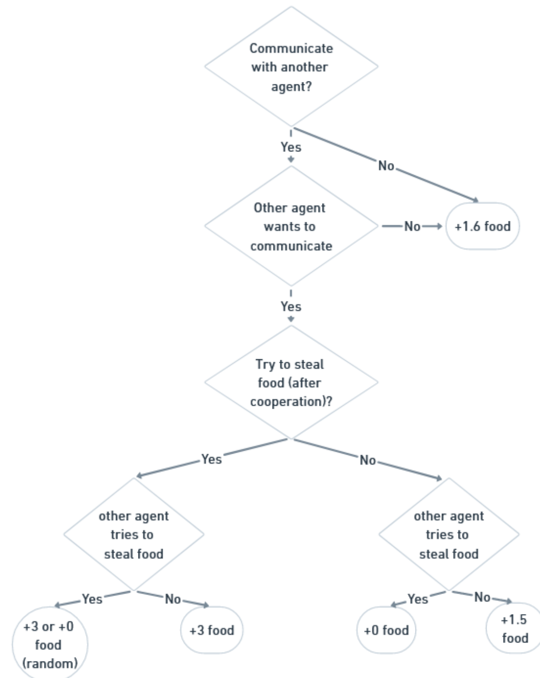
3. Communicate with intentions of taking all food for themselves (free rider strategy).

An interaction always involves two agents, all possible outcomes of an interaction are presented in Figure3.

Cooperation occurs when both agents communicate with good intentions. I adopt the definition of cooperation by Számadó et al. (2021): "The production of mutual benefits at a cost to the individual". Following this definition, the cost for the individual for following the cooperation strategy is that they receive slightly less food or none at all if the other agent steals the food than if they had simply not communicated. The mutual benefit of cooperating is that both individuals gain reputation. While it is possible for agents to survive by only following the hermit strategy, they miss out on gaining reputation. Finally, agents can maximize their food by following the free rider strategy. Another potential upside of

Figure 3

Decision Flowchart for Food Opportunities



this is that they can effectively starve other agents, increasing their own reproductive chances indirectly.

The long-term outcomes of following one of the three strategies consistently are shown in Figure 4. Following the hermit strategy guarantees survival while following the cooperation strategy can very easily end in starvation if free riders are present (i.e., the probability of others' malintent > 0). Finally, the free rider strategy is also viable for survival unless almost all other agents also deploy the free rider strategy.

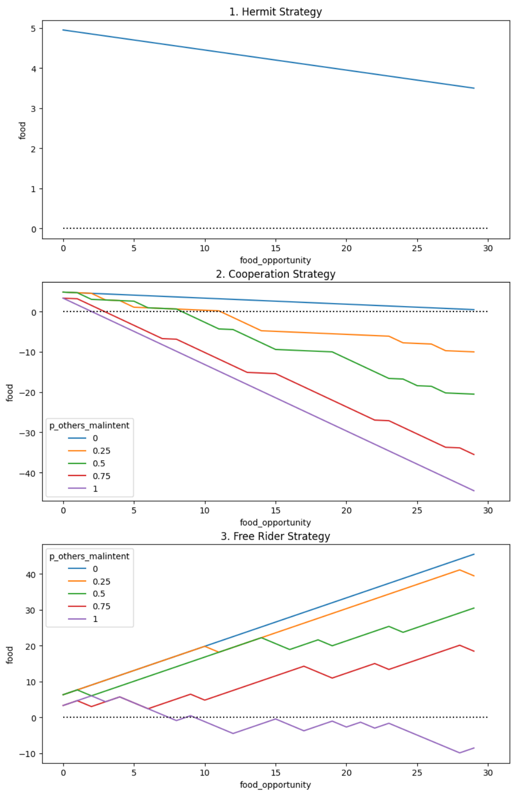
Agents' DNA sequences are initialized randomly and it is very unlikely for a random triplet to match the triple that codes for the trait. Therefore, most agents start out following the hermit strategy ($p(communicate) = p(malintent) = 0$). Agents follow the cooperation strategy if they have probabilities $p(communicate) = 1$ and $p(malintent) = 0$, agents follow the free rider strategy if they have the probabilities $p(communicate) = p(malintent) = 1$.

2.1 Reputation-based Partner Choice (RBPC)

This model assumes that reputations have an influence on sexual partner choice. Agents can gain reputation by cooperating with other agents. The reputation is used to calculate the reproductive chances for each individual using a categorical distribution.

Figure 4

Effects of Strategies on Long-term Food Reserves



Note. The dotted line denotes the threshold at which agents starve.

The simulations that were performed suggest that in RBPC systems communication emerges over time while malintent does not (Figure 5). Varying hyperparameters such as simulation length, population size, number of interactions, and food decay gave similar results.

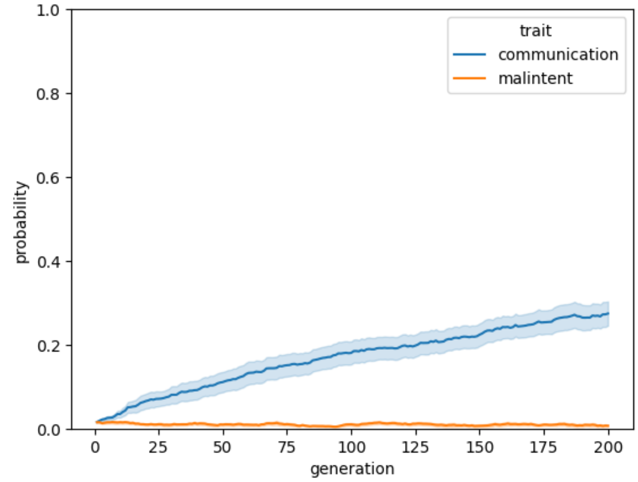
2.2 Indirect Reciprocity (IR)

In the IR model, agents also gain reputation which improves their chances to communicate instead of their chances to reproduce. In the simulations that were performed, neither communication nor malintent emerged over time (Figure 6). Similar to the RBPC model, running the IR model with different hyperparameters yielded similar results where neither of the traits emerged.

These results show that in RBPC models, sexual selective pressure leads to a hybrid between the hermit- and the cooperation strategy. In IR models, the prospect of being chosen more frequently as a cooperation partner does not exert enough pressure for agents to switch from a hermit strategy to a cooperative one.

Figure 5

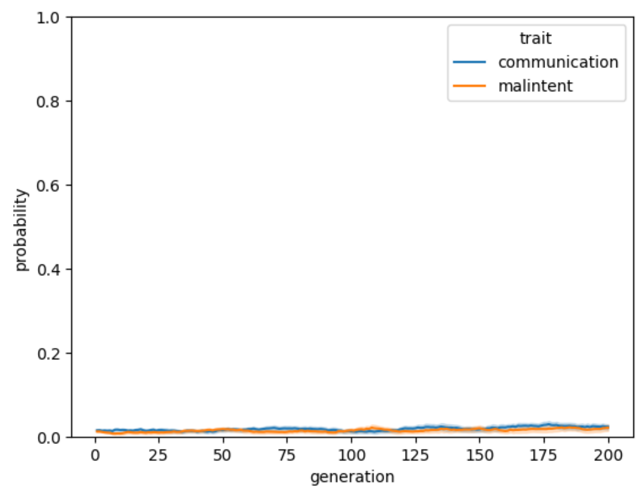
Cooperation emerges in the RBPC model



Note. Based on 20 replications of the RBPC model. The probability on the y-axis refers to the mean of the current generation's probabilities to communicate or steal food (i.e., malintent). The error bands represent 1 standard error from the mean.

Figure 6

Cooperation does not emerge in the IR model



Note. Based on 20 replications of the IR model. The probability on the y-axis refers to the mean of the current generation's probabilities to communicate or steal food (i.e., malintent). The error bands represent 1 standard error from the mean.

2.3 Limitations of Biological Models

The two previous models have two important downsides. First, the models treat reputation as a white box: every agent knows the reputation of another precisely, even when reputation resulted from interactions that the agent did not participate in. This is unrealistic because animals in the real world have incomplete information about the behaviour of others.

Second, agents have fixed probabilities throughout their interactions irrespective of the communication partner. This is unrealistic because most animals can distinguish between individuals and adapt their behaviour towards others based on their prior interactions. Both of these shortcomings will be addressed by taking a bayesian approach to adjusting these probabilities based on the communication partner and past interactions of the agents.

3 Bayesian RBPC Models

In this model, agents can update their probability to communicate with other agents based on the outcome of communication. Their prior is still informed by their DNA, however, they can learn to treat another agent differently based on the outcomes of their interactions. For example, agent 1 communicates with agent 2 $c(a_1, a_2)$ based on their prior:

$$P(c(a_1, a_2)) = Beta(\alpha, \beta)$$

This prior is determined by their inherited DNA sequence. Based on the outcome of their interaction, agent 1 can update their probability to communicate with agent 2 (since the Beta distribution is a conjugate prior, the posterior becomes $Beta(\alpha + 1, \beta)$ for a positive outcome, $Beta(\alpha, \beta + 1)$ for a negative one) [2].

Reproduction also works differently now to address the unrealistic assumption that agents have perfect knowledge of other agents' reputations. Instead, pairs of agents are sampled. The more positive previous interactions between the two agents were, the larger the probability of the pair reproducing. Then their probabilities to communicate with each other are used to reflect partner choice.

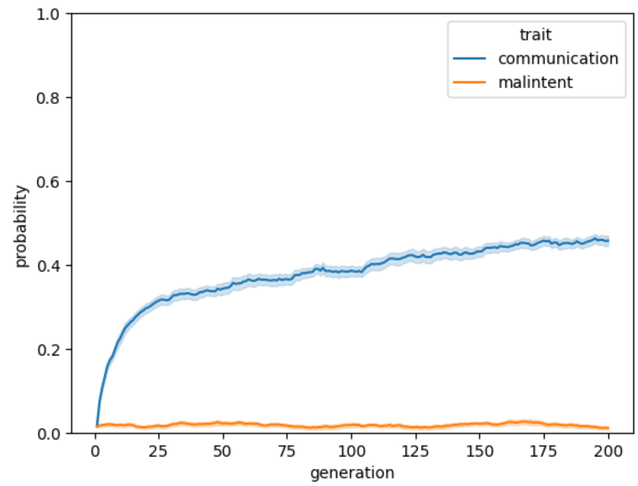
3.1 Free Riders and Gossip

Both RBPC models lead to competitive altruism where agents compete to be the most cooperative in order to maximize reproductive chances. A population that is too cooperative, however, is vulnerable to be taken advantage of. As Dunbar (2004) argues, free riders can be problematic for highly cooperative populations. He suggests that gossip can be an effective strategy for mitigating the impact of said free riders. Gossip can be simulated by enabling agents to share information about their last encounter with other agents.

Since adapting to free riders is essential for survival of highly cooperative agents, agents who do not learn from interactions (i.e., the biological RBPC model) should be least capable to adapt to free riders. Agents with the capability to learn from their experience (i.e., the bayesian RBPC model) should be more capable to adapt to free riders and agents that can learn from their experience and gossip about their past interactions should be most adept.

Figure 7

Cooperation emerges in the Bayesian RBPC model as well



Note. Based on 20 replications of the Bayesian RBPC model. The probability on the y-axis refers to the mean of the current generation's probabilities to communicate or steal food (i.e., malintent). The error bands represent 1 standard error from the mean.

To test these hypotheses, simulations were run on all three models where in two generations, a third of all agents' probabilities to steal food (malintent) were set to 1. Since getting your food stolen results in a higher chance of dying, how adept a generation was to intruders can be inferred by how many agents of that generation starved.

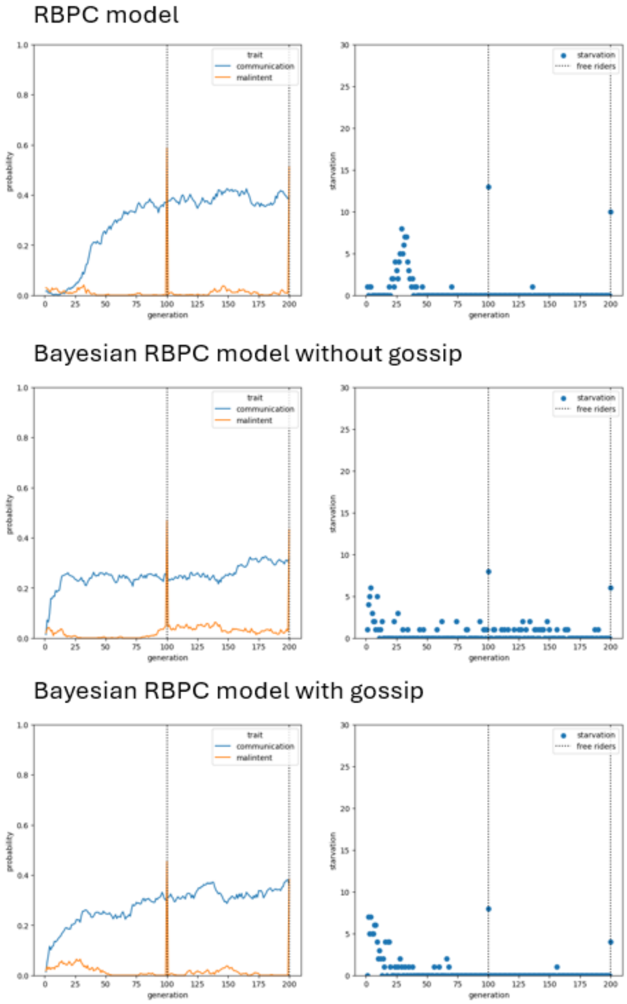
The simulations indicate that gossip helps agents that are very cooperative to protect themselves from agents with malintent as they show higher survival rates compared to the agents in the bayesian RBPC model without gossip. Surprisingly, survival rates in the biological RBPC model are not affected by the intruders. This might be due to a generally lower probability to communicate which leads to fewer opportunities for the intruders to steal food.

The communication matrices in Figure 9 indicate that agents in the simulation with gossip learned more easily to avoid communication.

[2] For a detailed explanation, see https://www.youtube.com/watch?v=hKYvZF9wXkk

Figure 8

Intruder simulations



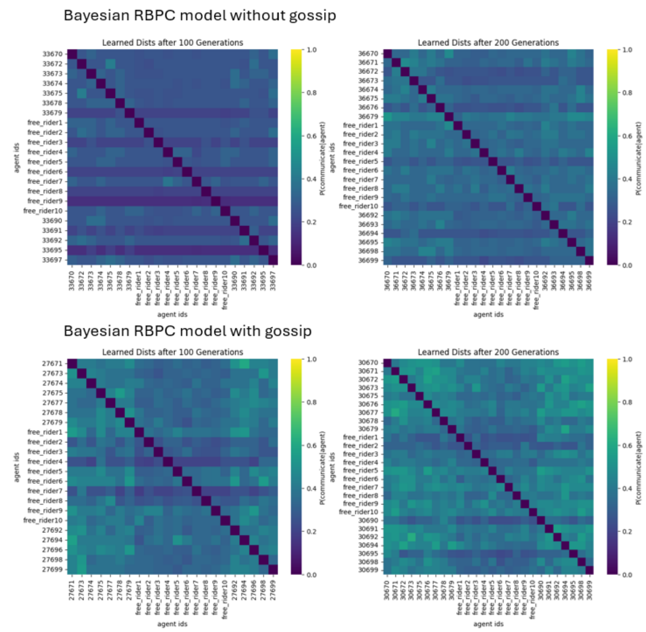
4 Conclusions and Discussion

The results indicate that the evolution of cooperation is evolutionarily more plausible due to reputation-based partner choice (RBPC) rather than indirect reciprocity (IR). Given the assumptions for all models, RBPC models consistently showed an emergence of cooperation while IR models did not. Consequently, these results also illustrate that cooperation is much easier to evolve from sexual selection rather than natural selection. This is because indirect reciprocity provides an agent with more food opportunities, however, these are only advantageous if they prevent the agent from starving.

However, this could also be a potential shortcoming of the presented models since differential survival does not exert much selective pressure. For example, there are cases in nature where hoarding food can be advantageous for survival, such as long droughts where food opportunities are sparse and in which natural selection is a stronger evolutionary pressure. Simulations that address these types of scenarios could be explored by future research.

Figure 9

Gossip helps reduce the probability to communicate with intruders.



Note. Each cell refers to the probability of $agent_{col}$ communicating with $agent_{row}$ at the end of this generation; yellow represents a probability of 1, blue represents a probability of 0.

Secondly, we see that bayesian RBPC simulations also consistently lead to an emergence of cooperation. Cooperation emerges even faster and generally reaches higher levels than in the biological RBPC models. One caveat to this finding is that reproductive chances are very closely tied to the probability to communicate in the bayesian RBPC models. Since this is the only factor that determines reproductive success but in reality it is only one of many factors, these models likely overestimate how quickly cooperation can evolve.

Finally, the results suggest that when cooperation is prominent in a population gossip can be an effective tool to protect cooperative agents from agents that try to take advantage of them. The simulations assumed that gossip is honest, however, this is not necessarily the case in real life. As Giardini et al. (2022) point out, agents have an incentive to use dishonest gossip to worsen the reputation of others and thereby improve their chances of reproductive success indirectly. Therefore, future research could explore what happens when gossip can be dishonest as well.

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Appendix
Hyperparameters and Simulation Pseudo Code

Hyperparameters

This is a list of all hyperparameters that can be changed in the simulation code. The numbers are the default settings for all simulations unless specified otherwise.

- **num_generations**=200: number of generations before simulation concludes
- **population_size**=30: number of agents in each generation
- **num_food_opportunities**=30: how many times each agent of a generation interacts for food
- **mu**=0.01: mutation rate per nucleotide when agents reproduce
- **class_variables:
  - **food_decay** = 1.65: how much food gets subtracted from the food counter each generation
  - **food_individual_consumption** = 1.6: how much food is rewarded when agent does not interact
  - **food_sharing** = 1.5: how much food is rewarded when agents share food
  - **food_stealing** = 3: how much food is rewarded when agent steals food after communication

Pseudo-Code

```python
def simulate_evolution(
    num_food_opportunities: int,
    num_generations:int,
    population_size:int,
    mu=0.01,
    **class_variables
    ):

    # adjust class variables if given:
    Agent.set_class_variables(**class_variables)

    # initialize first generation
    current_gen = [Agent(mu) for _ in range(population_size)]

    for gen in num_generations:
        for food_opportunity in num_food_opportunities:
            # apply food decay and food interactions:
            for agent in current_gen:
                agent.apply_food_decay()
                agent.found_food(other=np.random.choice(agent.cohort))
            # starve agents every 5 generations if their food_counter drops too low:
            if food_opportunity % 5 == 0:
                current_gen = [agent for agent in current_gen if not agent.starve()]

        # save data (mean probabilities of commmunication and malintent of current_gen)

        # simulate reproduction with reputation:
        if gen < num_generations:
            current_gen = reproduce(current_gen, mu, size=population_size)


    return data
```