

INSTITUT FÜR INFORMATIK
der Ludwig-Maximilians-Universität München

ON THE ORIGIN OF ALTRUISM

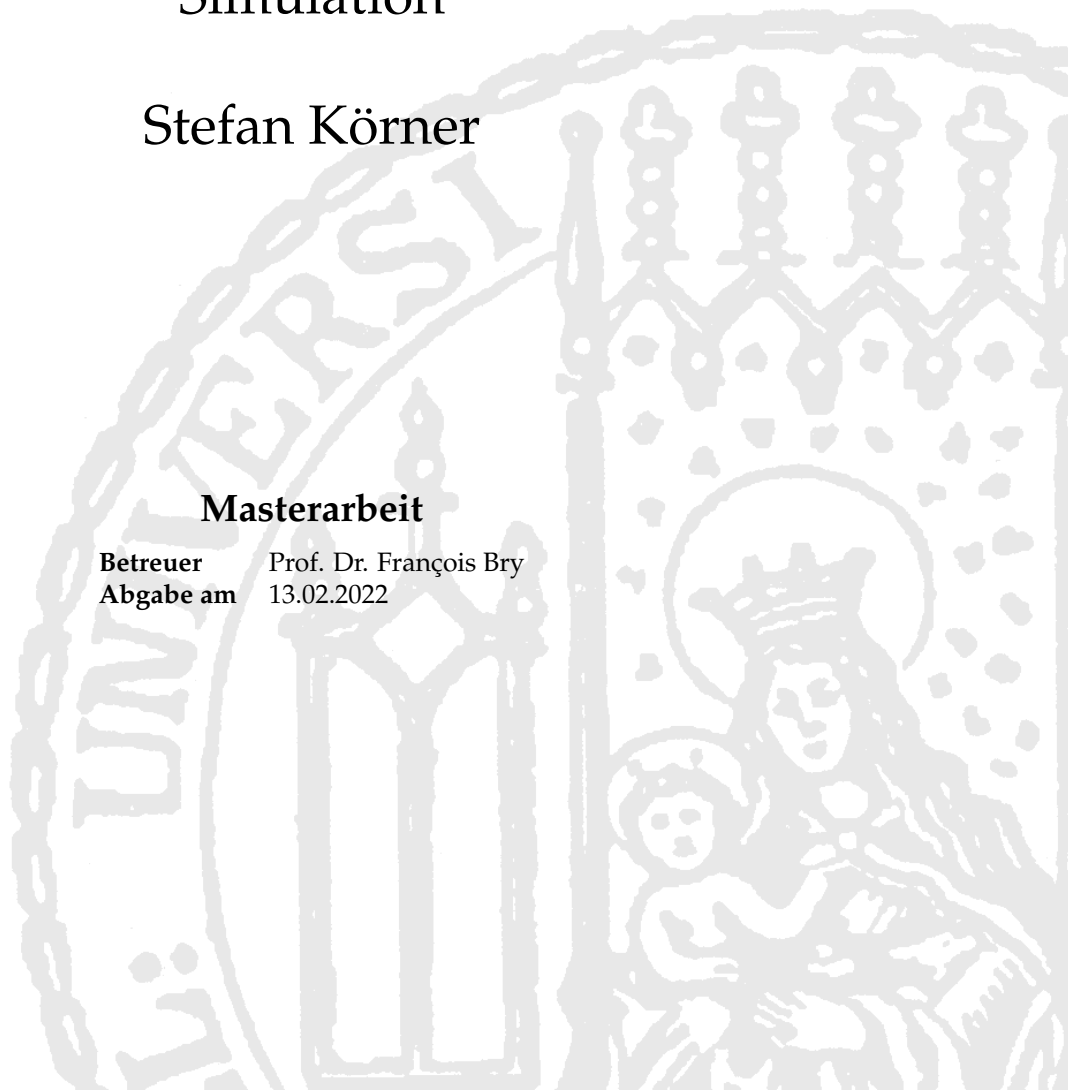
An Agent-Based Social Evolutionary Simulation

Stefan Körner

Masterarbeit

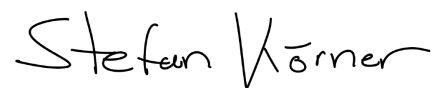
Betreuer
Abgabe am

Prof. Dr. François Bry
13.02.2022



Erklärung

Hiermit versichere ich, dass ich die vorliegende Arbeit selbstständig verfasst habe und keine anderen als die angegebenen Hilfsmittel verwendet habe.

A handwritten signature in black ink that reads "Stefan Körner". The script is cursive and fluid.

München, den 13.02.2022

Stefan Körner, Matr.: 11520129

Abstract

In this thesis, the most popular theories regarding the evolution of altruistic traits in humans are put to the test in a series of cross-generational agent-based simulations that mimic natural selection according to Darwin's three principles of inheritance, variation, and selection. The focus is put on the environmental circumstances that, according to each of these theories, may have led to the evolution of altruism. The results show that different conditions promote different types of altruism. Altruistic strategies based on group affiliation and cultural evolution have been the most successful across all environments, indicating that these strategies are likely to have played a key role in the evolutionary development of altruistic traits in humans. Other theories have shown great potential under more specific circumstances. Kin selection has not developed significantly in low- to mid-harsh conditions but has been effective under very harsh conditions while altruism based on the reputation of individual agents has proven to be an extremely effective strategy in the long run in low- to mid-harsh conditions but has completely fallen apart under very harsh conditions. It has also been found that the presence of altruism in a population has led to a considerably better survivability in harsh environments where no survival has been possible without cooperation. Higher individual altruistic sacrifices, however, have not improved survivability. Furthermore, it has been found that cheaters in altruistic systems might lead to the extinction of the whole population. Additionally, the social network topology developed has been analyzed with results indicating that altruists weaken their position within their closer social proximity while simultaneously gaining influence on a global scale.

Zusammenfassung

In dieser Arbeit werden die gängigsten Theorien bezüglich der Evolution altruistischer Verhaltensweisen beim Menschen in einer Reihe von generationenübergreifenden agentenbasierten Simulationen auf den Prüfstand gestellt, die die natürliche Selektion nach Darwins drei Prinzipien - Vererbung, Variation und Selektion - nachbilden. Der Schwerpunkt liegt dabei auf den Umweltbedingungen, die gemäß jeder dieser Theorien zur Evolution des Altruismus geführt haben könnten. Die Ergebnisse zeigen, dass unterschiedliche Umweltbedingungen verschiedene Arten von Altruismus begünstigen. Altruistische Strategien, die auf Gruppenzugehörigkeit und kultureller Evolution beruhen, waren unter allen Umweltbedingungen am erfolgreichsten, was darauf hindeutet, dass diese Strategien vermutlich eine Schlüsselrolle bei der Evolution der altruistischen Verhaltensweisen des Menschen gespielt haben. Andere Ansätze haben sich unter spezielleren Umweltbedingungen als sehr vielversprechend erwiesen. Die Kin-Selektion hat sich unter niedrigen bis mittleren Bedingungen nicht signifikant entwickelt, war aber unter sehr schwierigen Bedingungen effektiv, während sich Altruismus, der auf dem Ruf einzelner Akteure beruht, unter niedrigen bis mittleren Bedingungen langfristig als äußerst effektive Strategie erwiesen hat, aber unter sehr schwierigen Bedingungen völlig zusammengebrochen ist. Es wurde auch festgestellt, dass das Vorhandensein von Altruismus in einer Population zu einer erheblich besseren Überlebensfähigkeit in rauen Umgebungen geführt hat, in denen ohne Kooperation kein Überleben möglich gewesen wäre. Höhere individuelle Opferbereitschaft hat die Überlebensfähigkeit jedoch nicht verbessert. Außerdem hat sich gezeigt, dass Betrüger in altruistischen Systemen zum Aussterben der gesamten Population führen können. Darüber hinaus wurde die entstandene Topologie des sozialen Netzwerks analysiert. Die Ergebnisse zeigen, dass Altruisten ihre Position in ihrem engeren sozialen Umfeld schwächen, während sie gleichzeitig auf globaler Ebene an Einfluss gewinnen.

Acknowledgments

I would like to thank Professor Bry for introducing me to the truly fascinating topic of *computational ethics* and for enabling me to write this thesis while providing his continuous support and encouragement over the course of this project.

I would also like to thank the *Rechnerbetriebsgruppe Informatik* at LMU Munich for providing the considerable computational resources required to complete this project.

Contents

1	Introduction	1
2	Related Work	3
3	Theory and Terminology	5
3.1	Altruism	5
3.1.1	Characteristics of Altruism	5
3.1.2	Types of Altruism	6
3.1.2.1	Kin Altruism	6
3.1.2.2	Reciprocal Altruism	6
3.1.2.3	Group Selection	7
3.2	Evolution	8
3.2.1	Genetic Evolution	8
3.2.2	Cultural Evolution	9
3.2.3	Gene–Culture Coevolution	9
3.3	Agent-Based Social Simulation	11
4	Model	13
4.1	Purpose	13
4.2	Concepts	13
4.2.1	Minimal Interference	14
4.2.2	Law of Large Numbers	14
4.3	Structure	14
4.3.1	Population Model	14
4.3.2	Altruism Models	16
4.3.2.1	Greenbeard Model	17
4.3.2.2	Kin Selection Model	17
4.3.2.3	Reputation Model	17
4.3.2.4	Group Model	17
4.3.2.5	Culture Model	17
4.4	Inputs	17
4.5	Outputs	18
5	Implementation	21
5.1	Life Cycle	21
5.2	Altruistic Behavior	23
5.2.1	Unconditional	24

5.2.2	Greenbeard	24
5.2.3	Kin Selection	24
5.2.4	Reputation	25
5.2.5	Group	25
5.2.6	Culture	26
5.3	Verification	26
6	Exploratory Analysis	27
6.1	Methodology	27
6.2	Results	28
6.2.1	Benchmark	28
6.2.2	Greenbeard Model	29
6.2.3	Kin Selection Model	31
6.2.4	Reputation Model	32
6.2.5	Group Model	34
6.2.6	Culture Model	36
7	Network Analysis	39
7.1	Path Length, Clusters, and Hubs	39
7.2	Connectivity of Altruists	44
8	Discussion	47
8.1	Limitations	47
8.2	Findings	48
8.2.1	Different Conditions Promote Different Types of Altruism	48
8.2.2	Altruism Leads to a Considerably Better Survivability in Harsh Environments	48
8.2.3	Higher Individual Sacrifice Does Not Improve the Survivability	48
8.2.4	Cheaters Destabilize Altruistic Systems Significantly	49
8.2.5	Altruists Lose Local Influence While Gaining Global Influence	49
8.3	Future Work	49
9	Conclusion	51
A	Correlation Data	53
	Bibliography	57

List of Figures

3.1	Plotting the Trivers example.	8
3.2	Processes of gene–culture coevolution	10
3.3	How altruism could have evolved by means of gene–culture coevolution.	11
4.1	Model structure.	15
4.2	Life cycle of an adult agent.	16
6.1	Benchmark: Total number of agents over time, with different values for <i>child bearing cost</i>	29
6.2	Benchmark: Distribution of types of agents by <i>child bearing cost</i> during the first 500 steps.	29
6.3	Greenbeard: Distribution of types of agents with <i>child bearing cost</i> = 6 and fake greenbeards present and absent.	30
6.4	Greenbeard: Total number of agents, with different values for <i>child bearing cost</i> and no fake greenbeards present.	30
6.5	Greenbeard: Total number of agents, with different values for <i>child bearing cost</i> and fake greenbeards present.	31
6.6	Kin selection: Distribution of types of agents by <i>child bearing cost</i>	32
6.7	Kin selection: Distribution of types of agents by <i>min relationship</i>	32
6.8	Reputation: Distribution of types of agents by <i>child bearing cost</i> during the first 5,000 steps.	33
6.9	Reputation: Average reputation for the first 5,000 steps.	33
6.10	Reputation: Average food units per agent type by <i>life expectancy</i>	34
6.11	Reputation: Total number of agents in the reputation model over time, with different values for <i>child bearing cost</i>	34
6.12	Group: Distribution of types of agents by <i>child bearing cost</i> during the first 500 steps.	35
6.13	Group: Distribution of agent groups by <i>group number</i>	35
6.14	Group: Food distribution, by <i>child bearing cost</i>	36
6.15	Culture: Distribution of types of agents, by <i>child bearing cost</i> during the first 500 steps.	37
6.16	Culture: Group distribution.	37
6.17	Culture: Altruism culture per group, by <i>migration rate</i>	38
6.18	Culture: Average network connections per agent type.	38
7.1	Relationship between the number of agents on the network and the characteristic path length.	40

7.2	Network of the reputation model at step 100.	42
7.3	Network of the group model at step 100.	42
7.4	Network of the kin selection model at step 200.	43
7.5	Network of the greenbeard model with no fake greenbeards at step 500. . . .	43
7.6	The neighborhood connectivity of agents and their altruistic acts.	45
7.7	The betweenness centrality of agents and their altruistic acts.	46

List of Tables

4.1	Model input parameters.	18
4.2	Model output values.	19
5.1	Relatedness values of different relationships.	24
6.1	Used parameter values by submodel.	28
7.1	Network characteristics of all models	41
A.1	Correlations for the benchmark model.	54
A.2	Correlations for the greenbeard model.	54
A.3	Correlations for the kin selection model.	55
A.4	Correlations for the reputation model.	55
A.5	Correlations for the group model.	56
A.6	Correlations for the culture model.	56

List of Algorithms

1	The agent life cycle.	22
2	Determining the amount of food units agents acquire per step.	22
3	Reproducing agents.	23
4	Altruism mechanisms.	23
5	Determining the maximum amount of food an altruist is willing to give. . . .	24
6	Altruistic behavior of unconditional altruists.	24
7	Altruistic behavior of greenbeards.	24
8	Altruistic behavior of kin selection agents.	25
9	Altruistic behavior of reputation agents.	25
10	Altruistic behavior of group agents.	26
11	Altruistic behavior of culture agents.	26

CHAPTER 1

Introduction

“La joie que nous inspirons a cela de charmant que, loin de s’affaiblir comme tout reflet, elle nous revient plus rayonnante.” [The joy which we inspire has this delightful property, that, far from growing faint, like other reflections would, it returns to us more radiant than before.] [19]

When Jean Valjean, the protagonist of Victor Hugo’s 1862 novel *Les Misérables*, a convict on the run, is confronted with the choice whether to keep on walking or to risk his life and carefully crafted cover to help a stranger who had fallen beneath a wagon, he does not hesitate to choose the latter. And again, a little while later, he risks exposing himself to the policeman who is looking for him to save an innocent woman from prison. This disregard for himself and his freedom when others are in need continues from there on, and leads to exposing himself as the wanted man he actually is in order to save another man’s life. He is willing to help anyone with no regards whether they have met before or even wronged him in the past, and he does all this without expectations of receiving any benefits from it. Jean Valjean is what one would call an “altruist”.

While, of course, Valjean is the product of Hugo’s imagination, this type of selfless behavior is certainly not unheard of. It can be observed throughout the history of mankind and in the realms of animals. Until today, the origins of altruism as an evolutionary occurrence have not been fully discovered yet. This work contributes to the evolving area of *computational ethics* by using a cross-generational agent-based simulation to put the most popular theories regarding the evolution of altruistic traits in humans to the test. The focus is put on the environmental circumstances that may have led to the evolution of altruism according to each of these theories. The outcomes of this approach are promising. First, different environmental conditions promote different types of altruism. Second, altruism leads to a considerably better survivability of a population in high-cost environments. Third, higher individual sacrifice does not improve the survivability. Fourth, cheaters destabilize altruistic systems significantly. Finally, altruists lose local influence while gaining global influence.

The paper is structured as follows. Chapter 2 gives an overview of the related work in the area of evolution, with a focus on approaches that employ simulations. In chapter 3, some theoretical background that this paper builds upon is given, namely theories and research regarding altruism, evolution, and agent-based simulation. Chapter 4 presents the model that is the basis of this paper, namely its purpose, the concepts, its structure, the

different submodels, its inputs, and, finally, its outputs. In chapter 5, the implementation details are addressed, and some key algorithms are presented. Chapter 6 then presents the results of the exploratory analysis of the outcomes of the simulation for each model. In chapter 7, the social networks that the agents have formed during the simulations are analyzed regarding clustering, connectivity, and the position of altruists in the social network. Chapter 8 discusses the limitations of the used approach, the findings that are derived from the results, and some suggestions for future work on this topic are laid out. Finally, chapter 9 concludes this paper by summarizing its key points.

CHAPTER 2

Related Work

The emergence of altruism among humans and other species has puzzled researchers for centuries, from Charles Darwin himself, who sought to solve this evolutionary riddle in *The Descent of Man, and Selection in Relation to Sex* [6], all the way to contemporary evolutionary biologists like Richard Dawkins, who gave his own take on the evolution of altruism in *The Selfish Gene* [7]. With empirical studies on evolution being highly impractical, the field of the study of altruism was in need of new methods to help explore it further. Attempts were made to formalize cooperative evolution mathematically, as Robert Trivers did in *The Evolution of Reciprocal Altruism* [30], allowing for the study of altruism to continue outside the purely empirical context. One of the first researchers to utilize computers to explore cooperation strategies and let them compete with each other digitally was Robert Axelrod in *The Evolution of Cooperation* [4]. Since then, multiple others have followed his lead, with the increase in computing power and the availability of new tools allowing for more and more complex models. Most notably are some works of Herbert Gintis [14, 15] in which he used simulations to show the theoretical sustainability of some cooperative strategies. With his publication, *The Structural Evolution of Morality* [2], J. McKenzie Alexander was one of the first to utilize agent-based models to investigate the emergence of cooperation while also considering different social networks topologies; a similar approach to what will be used in this paper.

However, some have also voiced their concerns regarding the idea to even try to simulate the complexity the human decision-making process inherently has, among them Eckhart Arnold in his book *Explaining Altruism: A Simulation-Based Approach and its Limits* [3]. In it, he dismisses most simulations as trivial and even claims for them “not [to be] of great scientific relevance” [3, p.12]. Yet, he fails to recognize that in science most models rely on some type of simplification. Simulations should capture important mechanisms and illustrate how these mechanisms may have contributed to the occurrence of the phenomena under investigation by evaluating the efficacy of these mechanisms. [33] This holds true, especially when it comes to the simulation of evolution, where the possibility to test hypotheses rapidly and reliably helps generate an understanding that would otherwise be hard to attain. Nevertheless, Arnold makes a lot of good points in his book regarding the creation of a scientific simulation that have found application in the simulation used in this paper.

CHAPTER 3

Theory and Terminology

In the following chapter, the status quo regarding the research of the evolution of altruism among humans is laid out. First, in section 3.1.1 the term “altruism” is defined by its characteristics and the different types of altruism that are distinguished in scientific literature are laid out in section 3.1.2. Then the relevant evolutionary mechanism are covered in section 3.2. Finally, the method of agent-based simulation that is used in this paper to explore the evolution of altruism is addressed in section 3.3.

3.1 Altruism

While altruism in philosophic terms is only referred to as “altruism” if the altruistic action is done with the conscious intention of helping another, in a biological sense an altruistic action is evaluated by the consequences that an action has on the reproductive fitness of the individuals in question. By acting altruistically, an individual reduces its own expected number of offspring in favor of another individual’s expected number of offspring. Altruism is a commonly observed trait in animals and humans. Vervet monkeys, for example, give alarms to alert other monkeys to the presence of predators, thus increasing their peers’ chances of survival while drawing the predators’ attention to themselves. Ant workers are themselves sterile and have no chances of reproducing themselves, effectively having a reproductive fitness of zero. Yet, they protect and feed their queen at enormous costs to themselves. [23]

3.1.1 Characteristics of Altruism

For the purpose of this paper, altruism is characterized according to [3, p.21-22] by four key points according to that all have to be met in order for a behavior to be considered altruistic:

1. The individual’s behavior benefits another individual.
2. The behavior comes with an associated cost to the acting individual.
3. An equal return of the cost is not guaranteed for the acting individual.
4. The individual is acting of its own free will.

3.1.2 Types of Altruism

In scientific literature three main types of altruism are distinguished: kin altruism, reciprocal altruism and group selection.

3.1.2.1 Kin Altruism

Kin selection refers to the theory that individuals are more likely to act altruistically towards another individual the closer they genetically are to each other. In the face of genetic evolution, this makes sense since the closer the individuals genetically are, the more likely they are to share common genes. Helping a close relative to produce offspring is - in evolutionary terms - nearly as good as raising offspring oneself.

According to Hamilton's rule, this can be formalized as follows:

$$r \times B > C. \quad (3.1)$$

In this inequation, r is the genetic distance between the individuals, B is the benefit of acting altruistically in terms of the number of offspring gained by the recipient and C is the cost of acting altruistically in terms of the number of offspring lost by the donor. If the formula holds true, it would be advantageous to the individual to act altruistically. [10]

Example 1. A well-nourished monkey could benefit from feeding his brother's starving offspring. Given that the average genetic relatedness between siblings is 0.5, meaning that they share about 50% of genes, the benefit of feeding the offspring is 1 and the relative cost of feeding a tiny monkey is rather small, e.g., 0.25. [10]

$$\begin{aligned} r \times B &> C \\ \implies 0.5 \times 1 &> 0.25 \\ \implies 0.5 &> 0.25 \end{aligned}$$

Hamilton's rule holds true, and thus the monkey would gain from acting altruistically, since the genetic relatedness to its brother's child outweighs the benefits of keeping the food to itself.

3.1.2.2 Reciprocal Altruism

Reciprocal altruism refers to altruistic acts that are carried out with the expectation to get a similar or even better benefit in return. Unlike kin selection, which relies on common descent as a clue to whether acting altruistically towards an individual is sensible, reciprocal altruism relies on different criterions: past behavior and interaction. The past behavior of another individual provides a cue whether the individual is willing to "pay back" the altruistic favor at a later time. [28]

According to R. Trivers, founder of the concept of reciprocity, altruism can be formalized as follows:

The following formula and table are taken from [3, p.71].

$$\frac{1}{p^2} (\sum B_k - \sum C_j) > \frac{1}{q^2} \sum B_m, \quad (3.2)$$

where p is the portion of altruists,
 q is the portion of non-altruists,
 B_k is the altruistic benefit an altruist receives,
 B_m is the altruistic benefit a non altruist receives, and
 C_j represents the cost that an altruist takes upon itself for bestowing an altruistic act (on either an altruist or a non-altruist).

The idea of this inequation is that the average fitness of an altruist (the left-hand side of the inequation) must be higher than the average fitness of a non-altruist (the right-hand side of the inequation) for altruism in a population to prevail. This would occur if the benefits the non-altruists receive are kept small, which in turn reduces the costs of altruistic acts. [30] argues that altruists observing the behavior of their peers and only helping those who they consider to be altruistic themselves would lead to the inequation to hold. Apart from the past behavior and interactions, another indication to whether the individual is willing to act altruistically towards another individual could be certain genetic traits that correlate with the altruistic gene. An exemplification often used in evolutionary biology for this is the so-called “greenbeard altruism”. The greenbeard effect is a thought experiment developed by [17] and [7] that illustrates the idea of individuals having a greenbeard as a signal to others that they carry the altruistic gene. With altruists being able to reliably distinguish between those who carry the same trait as them and those who do not, the right-hand side of the inequation would always be zero; thus they should be able to sustain altruism indefinitely. [5]

However, [3] points out that the inequation does not necessarily only describe reciprocal altruism but can be seen as a more general inequation of altruism. [3, p.72]

Example 2. In a population of $n = 10$ individuals, 5 individuals are carrying the altruistic allele, which means $p = q = 0.5$. The cost of an altruistic act on the altruistic population is $\sum C_j = 1 - (0.5(1 - \sum B_m))$, while being equally beneficial to both the altruistic and non-altruistic population ($\sum B_k = \sum B_m = 1.5$).

The inequation is solved as follows:

$$\begin{aligned} \frac{1}{p^2}(\sum B_k - \sum C_j) &> \frac{1}{q^2} \sum B_m \\ \implies \frac{1}{0.25}(1.5 - 1.25) &> \frac{1}{0.25} \\ &\implies 1 \not> 4 \end{aligned}$$

Since the average fitness of an altruist is not actually higher than the average fitness of a non-altruist, the inequation does not hold. Thus, altruism does not prevail in this example. The consequence of this would be, that, in an environment where altruists act altruistically towards anyone without any consideration, they would ultimately die out. Plotting this example (fig. 3.1) shows that the altruistic population can survive as soon as $\sum B_m$ is smaller than 0.66. Hence, for altruism to be sustainable in this population, the altruists would have to find a way to deny non-altruists the benefit of altruistic acts at least one third of the time ($\frac{\text{Required } \sum B_m}{\text{Given } \sum B_m}$) by applying strategies like reciprocity.

3.1.2.3 Group Selection

Another highly discussed type of altruism is group selection. Darwin himself best explained the idea:

“A tribe including many members [...] ready to aid one another, and to sacrifice themselves for the common good, would be victorious over most other tribes, and this would be natural selection.” [6, p.166]

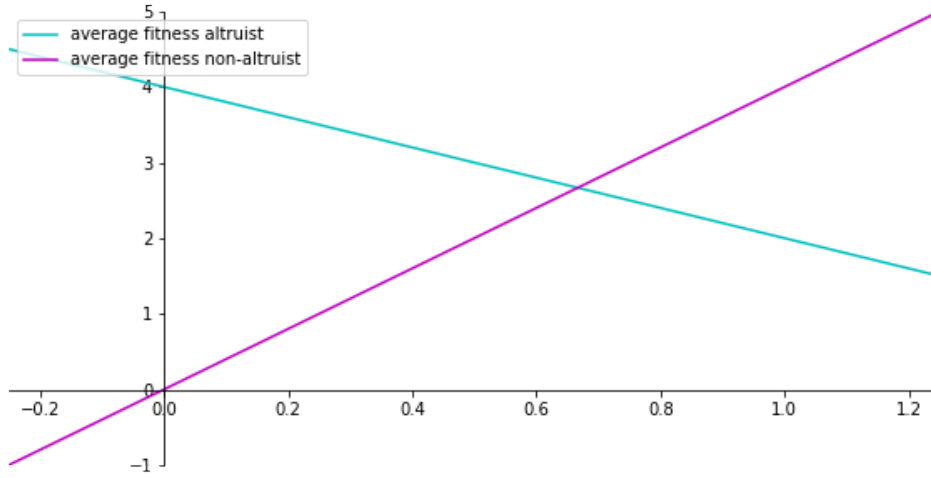


Figure 3.1: Plot for example 2 with the x-axis representing the value ΣB_m

Simply put, groups in which members help each other in times of need and are willing to sacrifice themselves for the common good are more likely to survive and thereby have greater reproductive success than groups in which the members are not willing to help each other. This theory is supported by the fact that, in evolutionary terms, relative fitness is more important than absolute fitness. Yet, the hypothesis of group selection is not unproblematic, as it requires some controversial assumptions to hold. For example, it requires substantial genetic differences between groups and a very limited migration rate between them, as otherwise the genetic differences between groups could be too insignificant to be relevant. [31, p.8]

3.2 Evolution

In this paper, the concept of evolution will be used to explain the emergence of altruism among humans. Three types of evolution are the subject of this paper: genetic evolution, cultural evolution and gene–culture coevolution.

3.2.1 Genetic Evolution

When referring to the term *genetic evolution* in the context of this paper, what is implied, is evolution in a biological, “Darwinian” sense. Biological evolution describes a change in genetic traits of a population over generations. These changes can occur through mutation or genetic recombination. Certain alterations in traits lead to a change in the individual’s fitness and through the process of natural selection such traits might become more or less predominant within the population. [9]

The fact that all human cultures show some kind of altruistic behavior indicates that the altruistic trait is at least partly genetically determined.

According to Darwin’s theory, evolution only requires three elements for the process to work: *inheritance, variations and selection*. Inheritance is necessary not to lose new, improved traits over generations, while variations make evolutionary improvements possible by mutating genes. Finally, selection implies that differences in traits matter, either by having a positive or a negative impact on the fitness of the individual carrying this trait compared to other individuals. [1]

3.2.2 Cultural Evolution

“For an understanding of the evolution of modern man we must begin by throwing out the gene as the sole basis of our ideas on evolution.” [7, p.191]

The theory of cultural evolution tries to quantify the social changes that occur when the behavior of individuals in a group changes through the influence of other members of the group. Culture in this instance refers to the behavior adopted by copying observed or taught behavior of others. It is assumed that the same core principles of Darwinianism can explain cultural evolutionary processes, since there are sufficient similarities between cultural development processes and evolution in nature to warrant such a transfer. The aforementioned elements *inheritance*, *variations*, and *selection* are still required. Yet, they take a different form than in the genetic biological sense. Inheritance can take place, e.g., through learning or imitation, while variations would, for example, occur when learnings are not understood correctly. The third component, selection, is harder to specify in cultural evolution than in its biological counterpart. However, it can be assumed that individuals want to adapt behaviors that they regard as successful and reject those that they do not. [3, p.40-44]

3.2.3 Gene–Culture Coevolution

Gene-culture coevolution is the process of genetic evolution and cultural evolution influencing each other in a continuous feedback loop. Genetic changes can lead to cultural changes that in turn influence genetic evolution via modifications of the population structure and an altered selection pressure and vice versa (see fig. 3.2).

An example for this kind of coevolution is the tolerance or intolerance of lactose in different cultures. While the majority of adult humans cannot digest milk, in certain cultures the opposite can be observed. A probable explanation for this phenomenon is that the lactose digestion gene has evolved in response to the history of domesticating cows in these civilizations. In northwest Europe, India and western Africa, there is a long-standing history of the domestication of cattle and consumption of milk. So, the majority of the population in these regions has the ability to digest lactose. In contrast, the far east regions of the world have barely any history of milk ingestion and the lactose gene is rarely found. Statistical work has shown, that the history of the domestication of cattle and consumption of milk is the best predictor for the presence of the lactose gene. [25, p.191-192] In retrospective, it is of course hard to tell which came first: the culture of regularly ingesting milk or the evolution of the lactose gene. However, it is clear that both have thrived side by side and given rise to each other, with effects lasting to this day.

Regarding the evolution of altruism, gene-culture coevolution is believed to be the most likely explanation of how the altruistic trait has been able to evolve in human society. [12, 31] It unifies the theories of kin altruism, reciprocal altruism and group selection while it mitigates its controversial issues (see section 3.1.2.3) by considering the possibility that altruism is not only genetically determined but also culturally. Cultural changes in behavior driven by intergroup conflicts that manifest more prosocial norms and punishment of individuals that do not follow these norms would lead to genetic evolution naturally selecting for cooperative and altruistic behavior. [31]

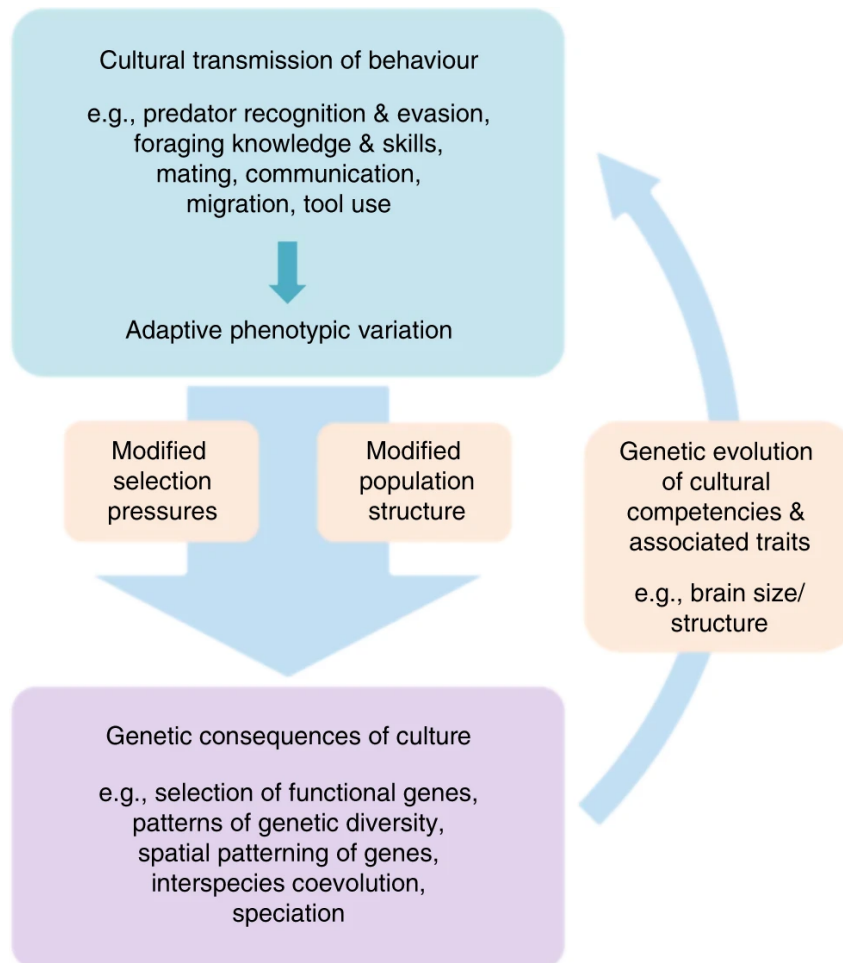


Figure 3.2: Processes of gene–culture coevolution. Source: [32]

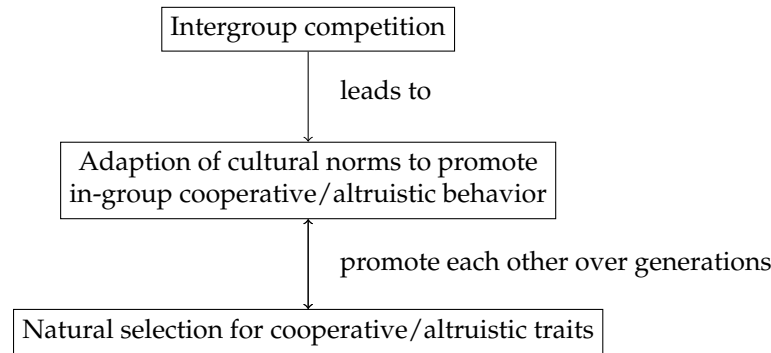


Figure 3.3: How altruism could have evolved by means of gene–culture coevolution.

3.3 Agent-Based Social Simulation

Agent-based social simulation unifies three scientific fields: the social sciences, computer science and statistics. It is a form of simulation based on agents interacting with their environment and with each other in a way that makes it possible to study their behavior. The agents are modeled as individuals, in the sense that they have unique identity and behavior that can be modeled using sets of rules. Crucially, the agents' behavior can be determined and altered by direct interactions between them. This modelling technique has been applied to successfully simulate traffic and evacuation flows, stock development, the spread of epidemics, and much more. [29]

For the purpose of this paper, two types of simulation will be used to study the emergence of altruism:¹

Proof-of-Possibility Simulations are used to prove or disprove the theoretical possibility of certain phenomena under very specific conditions. The goal is to find parameters under which a phenomenon can occur. Based on the parameters, certain conclusions can be drawn regarding whether the phenomenon could occur in the real world and under which preconditions.

Exploratory Simulations are meant to discover new phenomena that are not yet known to the conductor of the simulation. These simulations are run on a large scale with a variety of different parameters.

¹The terms “Proof-of-Possibility Simulations” and “Exploratory Simulations” were established in [3, p.194]

CHAPTER 4

Model

While most previous attempts at modeling the evolution of altruism have relied on running a series of game-theoretical sequences with static agents and static environments, the model developed for this paper is more focused on the dynamics of evolution. Thus, this model reflects the evolution of a population over thousands of years and hundreds of generations. Agents live their lives, find partners, reproduce and ultimately die, leaving their children to carry their genetic inheritance. This allows for a variety of phenomena to occur that would not be possible in models that omit the process of evolution. First, in section 4.1 the purpose of the model is described, and some design concepts are discussed in section 4.2. Then the different submodels and their respective purpose are listed in section 4.3. Finally, the different inputs and outputs of the model are described in section 4.4 and section 4.5.

4.1 Purpose

What this model aims at is to mimic the evolutionary processes that have led to altruism among humans as it occurs in today's day and age. A variety of inheritable traits relating to altruistic action are present in the initial model population. Since the evolutionary fitness of a genetic trait is measured in relation to other traits, the different altruistic traits are compared to a control group composed of non-altruists and unconditional altruists. Based on the changes in the distribution of the traits among the population over hundreds of generations, the sustainability of the different traits is benchmarked. The model also supports complex social networks, which allows for the development of relationships and group dynamics to be tracked and analyzed.

4.2 Concepts

When designing the model, some core design concepts have been decided on. Namely, the concept of minimal interference and the law of large numbers.

4.2.1 Minimal Interference

The model is built to minimize outside interference by the modeler. Only some environmental variables and behavioral rules are provided, everything else, including the development of the population and social network, develops organically.

4.2.2 Law of Large Numbers

A lot of the underlying processes and mechanisms in this model rely on randomness to circumvent some inherently hard-to-model real life processes, such as finding food. The law of large numbers, first proved by mathematician Jakob Bernoulli, states that “as the number of identically distributed, randomly generated variables increases, their sample mean (average) approaches their theoretical mean” [11]. Based on this theorem, the number of iterations the model is run is as high as economically feasible to extract results that are as meaningful as possible.

4.3 Structure

The model is separated into multiple submodels that model certain processes, as can be seen in fig. 4.1. Together, the `BaseModel`, `AgingModel`, `ReproductionModel` and `EatingModel` are the basis of the simulation by modelling the lifecycle of a population. The `AltruismModel` and its submodels allow for altruistic actions to take place under submodel-specific circumstances.

4.3.1 Population Model

The population model consists of the submodels `BaseModel`, `AgingModel`, `ReproductionModel` and `EatingModel`. It models all integral parts of an evolving population, like the lifecycle of agents and the social network that connects them. The initial population consists of agents of different ages and with no connection to each other. Every step in the model emulates one year in the life of an agent. In each step, the agent needs to consume food in order to survive. In the core population model, food must be found by the agent itself. The amount of food the environment supplies each step is finite, providing a natural limit to how many agents can live in a given environment. As soon as an agent comes of age, it searches for a partner. Once two partners have found each other, they have the possibility to produce offspring in each step. However, this comes at a cost to both their food supplies. Agents form relationships with their parents, partners, children, and siblings with varying strength, which allows for graph analysis regarding clustering, average path length, and hub tendencies.

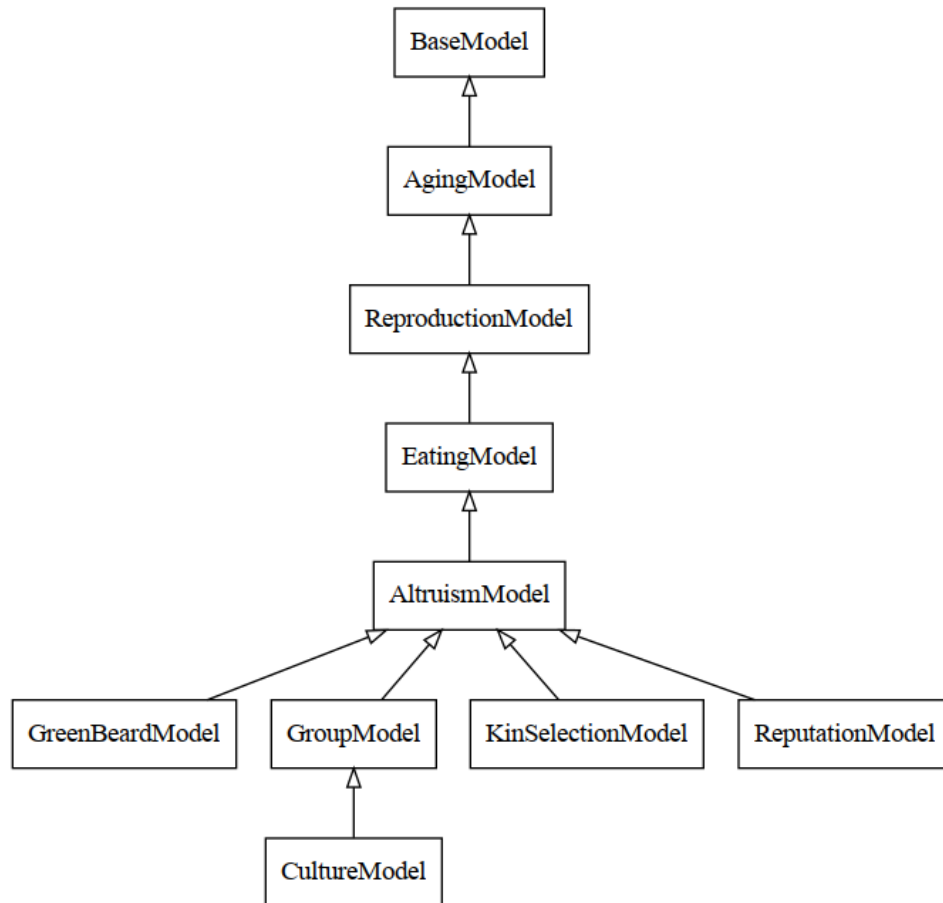


Figure 4.1: Model structure. Due to the object-oriented nature of the simulation, every model inherits from its parents models. `BaseModel`, `AgingModel`, `ReproductionModel` and `EatingModel` are responsible for modelling their respective functions in the population. The models that are children of the `AltruismModel` model the different types of altruism that are the subject of this paper.

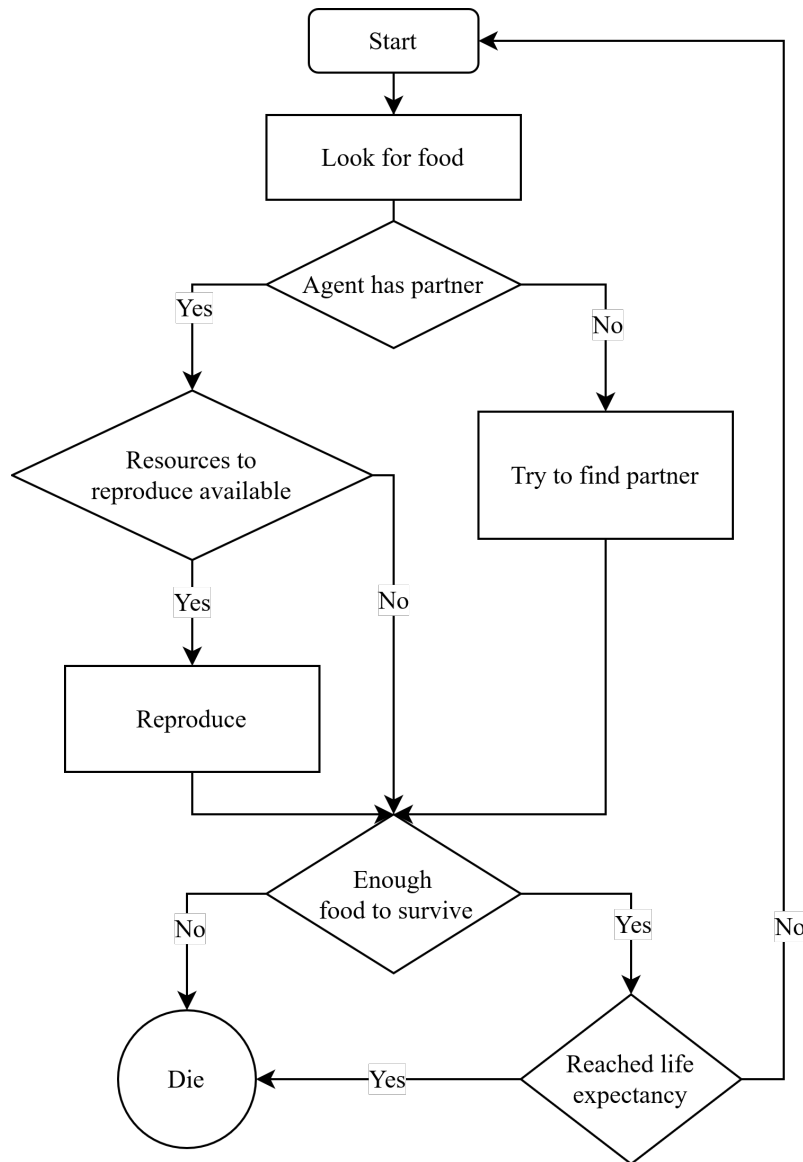


Figure 4.2: Life cycle of an adult agent.

4.3.2 Altruism Models

The altruism models extend the population model (section 4.3.1) by giving agents the opportunity to share some of their food supply with other agents that would otherwise starve. However, since food is also an important requirement for reproducing, this hurts the giving agent's evolutionary fitness significantly. Different types of altruistic agents use different strategies to determine whether they help another agent in need. The maximum percentage of its food an agent would be willing to give away each round is determined by a model-wide parameter. In their respective models, each type of altruism is evaluated regarding its evolutionary sustainability by pitching it against the control group that consists of agents that will always give away their food if they get the chance and agents that will never share their food with anyone.

4.3.2.1 Greenbeard Model

The greenbeard model is based on the concept of reciprocity (see section 3.1.2.2). Greenbeard altruists will act altruistic towards others they believe to be greenbeards as well (section 3.1.2.2) if given the chance. The literal "greenbeard" itself is of course purely theoretical, since no known correlation between the altruistic gene and any genetic characteristic that is easily distinguishable does exist. However, it is suggested that humans have the ability to resolve social dilemmas by being able to identify and interact selectively with trustworthy partners. [13, p.94] Critics of this theory often argue that even if such a trait existed, mutations could lead to the eventual evolution of "freeloaders" that, while carrying the distinguishable trait of an altruist, don't act like an altruist, which is, why the possibility of such mutants is also explored in this paper's model. [12, p.35]

4.3.2.2 Kin Selection Model

The kin selection model relies on the genetic relatedness between agents to determine whether they would be willing to help each other in times of need (see section 3.1.2.1). If more than one agent in the agent's genetic neighborhood requires help, the agent will always choose the closest relative to give food to. The minimum level of relatedness that is required between agents to act altruistically is determined by a model-wide parameter.

4.3.2.3 Reputation Model

In the reputation model, agents carrying the altruistic gene are willing to help those whose reputation is higher than the average reputation in the population. If an agent acts altruistically, its reputation increases. This model is based on the theory of reciprocity as well.

4.3.2.4 Group Model

At initialization, each agent is randomly assigned to a group. The agents only seek partners in their designated group and pass their group membership on to their children. The agents are only willing to help those who are part of their group. Based on a model-wide parameter, migration between groups can take place in each step. Only "bachelors", agents that are of age and have no partner, are allowed to migrate.

4.3.2.5 Culture Model

The culture model is based on the group model. Additionally, each group has a culture value that determines the overall willingness to help each other. This culture value changes over time depending on how the agents act. The decision whether the agent acts altruistically or not is heavily influenced by the culture value in their group.

4.4 Inputs

Different models require certain model-wide parameters to be set, which are described in table 4.1. Each parameter range serves the purpose of covering the various circumstances of the environment as comprehensively as possible, as well as the preconditions under which altruistic action may be possible. For example, the *child bearing cost* parameter determines how much food is needed to reproduce, thus regulating the harshness of the environment while *level of sacrifice* determines how generously food is given away by altruistic agents, thus determining the overall effect of altruism on donors and givers.

Parameter	Description	Model
<i>num agents</i>	The initial number of agents in the model.	Base
<i>life expectancy</i>	Tuple that determines the minimum and the maximum age an agent can reach.	Aging
<i>agent limit</i>	The maximum number of agents the simulation can have.	Reproducing
<i>child bearing cost</i>	Cost for reproducing in food units paid by both parents.	Reproducing
<i>mutation chance</i>	Probability of a child taking on a trait different from the traits of both parents.	Reproducing
<i>food multiplier</i>	Determines the amount of food available at every step in the environment ($num\ agents \times food\ multiplier$).	Eating
<i>finding max</i>	Determines how much food a single agent can possibly find at each step.	Eating
<i>level of sacrifice</i>	The percentage of the available amount of food an altruistic agent is willing to give away at each step.	Altruism
<i>fake greenbeards</i>	Determines if “fake” greenbeards are part of the simulation (see section 4.3.2.1).	Greenbeard
<i>min relationship</i>	The minimum relationship strength required for a kin selection agent to act altruistically.	Kin selection
<i>group number</i>	Initial number of groups in the simulation.	Group
<i>migration rate</i>	Chances of an agent migrating to a different group at each step.	Group

Table 4.1: Model input parameters.

4.5 Outputs

The model produces a variety of outputs, some at the end of the model execution and some at each step. A full list of output parameters can be found in table 4.2. These outputs are used in chapter 6 to analyze the sustainability of different altruistic strategies.

Parameter	Description	Model
<i>total agents</i>	Number of agents per step.	Base
<i>agent types</i>	Number of agents per step by agent type.	Base
<i>agent neighbors</i>	Average number of neighbors per agent type.	Base
<i>food distribution</i>	Distribution of agents above and below the median amount of food units.	Eating
<i>food distribution by type</i>	Average amount of food units per agent type.	Eating
<i>trivers values</i>	Calculated fitness values for altruists and non-altruists according to eq. (3.2).	Altruism
<i>average reputation</i>	Average agent reputation.	Reputation
<i>agent groups</i>	Number of agents per group.	Group
<i>agent neighbors by group</i>	Average number of graph neighbors per agent group.	Group
<i>groups culture</i>	Culture values per group.	Culture

Table 4.2: Model output values.

CHAPTER 5

Implementation

The source code for the simulation, including instructions on how to run the different models, can be found here: <https://github.com/koerners/thesis-simulation>.

For the implementation of the simulation Python 3.8.10 has been chosen. Some notable additional packages include `mesa` [20], which provides a framework for agent-based simulation, as well as `networkx` [16], which is used for the network components of the simulation. For analyzing the generated data the packages `pandas`¹, `scipy`² and `matplotlib`³ have been used. For a more in-depth analysis of the network graph, the software `Cytoscape`⁴ has also been of great use. The computational power required to run the simulation in multiple different configurations and iterations for hundreds of agent generations has made it impractical to use a single computer. Instead, Simple Linux Utility for Resource Management (`slurm`) has been used to distribute the computational workload onto clusters provided by the Institute of Informatics at LMU Munich.

In the following chapter, the implementations of some key components of the simulation are covered, and some key algorithms are presented. In section 5.1 the implementation of the core life cycle model is shown while section 5.2 presents the implementations for the various types of altruistic agents. Finally, section 5.3 gives an overview of the verification practices utilized to ensure that the simulation is working as intended.

5.1 Life Cycle

The life cycle of a single agent has been implemented according to section 4.3.1, as can be seen in algorithm 1. The life expectancy of an agent is determined by taking a random number between the minimum and maximum model-wide *life expectancy* parameter. While the life expectancy is not reached, the agent has to find food to survive. The logic of food finding can be seen in algorithm 2. It is mainly defined by a model wide parameter, *finding max*, which in conjunction with the parameter *child bearing cost* regulates the

¹<https://pandas.pydata.org/>

²<https://scipy.org/>

³<https://matplotlib.org/>

⁴<https://cytoscape.org/>

overall harshness of the environment. In each step, the agent must consume one unit of food to survive. The chances of finding $x \in \{0, 1, 2, \dots, \text{finding max}\}$ food units each round are $\frac{1}{\text{finding max}+1}$. Therefore, in an environment with $\text{finding max} = 3$ the chances of an agent getting no (0) food units, assuming that there is still some left, are $\frac{1}{4}$. Food is also the limiting factor when it comes to reproducing (algorithm 3) as agents not only have to find a suitable partner but also have to have a certain amount of food, determined by the model wide parameter *child bearing cost*, which is deducted from the agent's food resources when procreating. If the agent and its partner meet the requirements to reproduce, the resulting offspring randomly inherits the altruistic trait of one parent. If the model parameter *mutation chance* is set, the child can also mutate to a different type of agent that is present in the model. In this case, the mutant always becomes a different type than any of the parents, with the probability determined by the parameter.

At the end of each step, the agent has the option to act altruistically. At this point, the behavior diverges between agents according to their respective altruistic traits.

Algorithm 1 The agent life cycle.

Require: parameters marked by * are set by the model.

```

1: is alive  $\leftarrow$  true
2: age  $\leftarrow$  0
3: food  $\leftarrow$  0
4: partner  $\leftarrow$  None
5: life expectancy  $\leftarrow$  random(minAge*, maxAge*)
6: while is alive do
7:   food  $\leftarrow$  food + FINDFOOD() ▷ see algorithm 2
8:   if age  $\geq$  18 then
9:     if partner then
10:      REPRODUCE(partner) ▷ see algorithm 3
11:    else
12:      partner  $\leftarrow$  FINDPARTNER()
13:    end if
14:  end if
15:  age  $\leftarrow$  age + 1
16:  food  $\leftarrow$  food - 1
17:  ALTRUISTICACT(food) ▷ see algorithm 4
18:  if age > life expectancy or food < 0 then
19:    is alive  $\leftarrow$  false
20:  end if
21: end while

```

Algorithm 2 Determining the amount of food units agents acquire per step.

Require: parameters marked by * are set by the model.

```

1: function FINDFOOD
2:   return RANDOM(0, finding max*)
3: end function

```

Algorithm 3 Reproducing agents.

Require: parameters marked by * are set by the model.

```

1: function REPRODUCE(partner)
2:   if food > child bearing cost* then
3:     if partner food > child bearing cost* then
4:       if RANDOM(0,1) ≤ mutation chance* then
5:         child ← non parent type    ▷ The child mutates to a type different than the
        parents
6:       else
7:         child ← RANDOM(trait, partner trait)    ▷ The child inherits the altruistic
        trait of one of the parents
8:       end if
9:       food ← food − child bearing cost*
10:      partner food ← partner food − child bearing cost*
11:    end if
12:  end if
13: end function

```

5.2 Altruistic Behavior

The underlying calculation of altruistic behavior is implemented as shown in algorithm 4. In each step, the maximum sacrifice an agent would be willing to make is determined. This value is calculated as shown in algorithm 5 and depends on the model wide parameter *level of sacrifice* as well as the agent's own food supply. While the agent still has food to give to someone else, it looks for agents that have no food left and would otherwise starve at the end of the step. If the trait-specific conditions defined in the *IsWillingToHelp(peer)* functions (algorithms 6 to 11) hold true, the agent gives one food unit to its peer. The benefit of an altruistic action is defined as one (1). Thus, the cost of an altruistic action can be considered as

$$\frac{1}{\max(1, \text{child bearing cost})} \quad (5.1)$$

since the donor hurts its own reproductive fitness by giving away food.

Algorithm 4 Altruism mechanisms.

Require: parameters marked by * are set by the model.

```

1: function ALTRUISTICACT(food)
2:   max sacrifice ← DETERMINEMAXSACRIFICE()    ▷ see algorithm 5
3:   for max sacrifice do
4:     for peer in agents do
5:       if peer food < 1 then
6:         if ISWILLINGTOHELP(peer) then    ▷ see algorithms 6 to 11
7:           peer food ← peer food + 1
8:           food ← food − 1
9:         end if
10:      end if
11:    end for
12:  end for
13: end function

```

Algorithm 5 Determining the maximum amount of food an altruist is willing to give.

Require: parameters marked by * are set by the model.

```

1: function DETERMINEMAXSACRIFICE
2:    $max\ sacrifice \leftarrow 0$ 
3:   if  $level\ of\ sacrifice^* = 1$  then
4:      $max\ sacrifice \leftarrow food$ 
5:   else
6:      $max\ sacrifice \leftarrow level\ of\ sacrifice^* \times food$ 
7:   end if
8:   return  $MAX(1, max\ sacrifice)$ 
9: end function

```

5.2.1 Unconditional

The unconditional altruist does not differentiate between agents when it comes to helping them. Accordingly, its *IsWillingToHelp* function (algorithm 6) will always return *true*.

Algorithm 6 Altruistic behavior of unconditional altruists.

```

1: function ISWILLINGTOHELP(peer)
2:   return true
3: end function

```

5.2.2 Greenbeard

Greenbeard altruists check whether their peers are greenbeard altruists as well, and only help them if they are.

Algorithm 7 Altruistic behavior of greenbeards.

```

1: function ISWILLINGTOHELP(peer)
2:   return peer is greenbeard
3: end function

```

5.2.3 Kin Selection

The logic of decision (algorithm 8) for the kin selection model is slightly more complicated, as it also considers Hamilton's Rule (see section 3.1.2.1). Kin altruists only iterate through a list of their relatives when looking for agents they want to help. The relatedness parameter r for different kinds of relationships is set as shown in table 5.1.

Relationship	r
Partner	1
Sibling	2
Child \leftrightarrow Parent	3

Table 5.1: Relatedness values of different relationships.

When using the benefit and cost values defined in section 5.2 Hamilton's rule solves as

follows:

$$\begin{aligned}
 & r \times B > C \\
 \implies r \times 1 & > \frac{1}{\max(1, \text{child bearing cost})} \\
 \implies r & > \frac{1}{\max(1, \text{child bearing cost})}
 \end{aligned}$$

Thus, limiting the parameters in the simulation to $r \in \{1, 2, 3\}$ and *child bearing cost* $\in \{2, 3, 4, \dots\}$ ensures that Hamilton's rule holds true for any interaction between relatives. For the purpose of the simulation, a model wide parameter *min relationship* can be set to determine the minimum relatedness an agent has to have with another one to help it. In any case, the agent will always help the agent in need with the highest relatedness parameter r first.

Algorithm 8 Altruistic behavior of kin selection agents.

Require: parameters marked by * are set by the model.

```

1: function ISWILLINGTOHELP(peer)
2:   if relationship  $\geq$  min relationship* then
3:     if peer is closest relative in need then
4:       return true
5:     end if
6:   end if
7:   return false
8: end function

```

5.2.4 Reputation

The implementation of the reputation model is comparatively straightforward. Each agent starts with a reputation of zero, which is increased with each altruistic act. For each interaction, the average population reputation is calculated and compared to the reputation of the agent that requires help. Constraining the reputation to positive integers leads to a stepwise increase in average reputation, giving plenty of chance for other agents to also increase their reputation before being affected by a change in the average reputation.

Algorithm 9 Altruistic behavior of reputation agents.

Require: parameters marked by * are set by the model.

```

1: function ISWILLINGTOHELP(peer)
2:   return peer reputation  $\geq$  average reputation*
3: end function

```

5.2.5 Group

Group altruists determine whether to help another agent based on group affiliation. For the implementation, this only requires a simple equality check. Agents are randomly distributed into different groups at the model initialization and inherit their group to their children. Based on the *migration rate* parameter, agents can also migrate between groups under certain circumstances (section 4.3.2.4).

Algorithm 10 Altruistic behavior of group agents.

```

1: function ISWILLINGTOHELP(peer)
2:   return peer.group = group
3: end function

```

5.2.6 Culture

The determining factor for the culture agent's altruistic decision is its groups' culture of cooperation, which is a value between zero and one that represents the likelihood of an agent helping another one in the same group. The different groups start out with different initial culture values, which then change based on the agents' actions. Acting altruistically slightly increases the culture value and vice versa.

Algorithm 11 Altruistic behavior of culture agents.

Require: parameters marked by * are set by the model.

```

1: function ISWILLINGTOHELP(peer)
2:   if peer.group = group then
3:     if  $\text{RANDOM}(0, 1) \leq \text{group culture}^*$  then
4:       return true
5:     end if
6:   end if
7:   return false
8: end function

```

5.3 Verification

To ensure the correctness of the implementation, standard software verification practices have been used. This includes unit tests with at least 95% coverage as well as the use of a linter to catch subtle bugs early on, which is especially important since `Python` is dynamically typed. All used packages are well established and tested. Furthermore, each implemented model has been manually verified to ensure it produces plausible data.

CHAPTER 6

Exploratory Analysis

In this chapter, the results that the different simulations produce with different parameters are analyzed. First, in section 6.1, the applied methodology for running and analyzing the simulations is described. Then, in section 6.2.1 the results of the benchmark model with only unconditional altruists and non-altruists are assessed. The results of the other models with the varying altruistic strategies are evaluated in sections 6.2.2 to 6.2.6.

6.1 Methodology

Each model has been run with every possible set of combinations of the parameters listed in table 6.1. The explicit parameter values used have been chosen to represent environments of varying harshness, while also altering the disposition of the altruists to act altruistically. To satisfy the requirements of the law of large numbers (see section 4.2), every simulation has been run for up to twenty times with different seeds for each set of parameters. For the analysis, the runs with the same parameters but with different seeds have been averaged. The number of steps, or “years” in the context of the model, has been set to 5,000. Depending on the *life expectancy* parameter, this results in a total of 90 to 180 generations, which has proven sufficient for the purpose of this simulation.

Parameter	Values	Model
<i>num agents</i>	{100}	Base
<i>life expectancy</i>	{(25, 35), (60, 70)}	Aging
<i>agent limit</i>	{5,000}	Reproducing
<i>child bearing cost</i>	{0, 2, 4, 6}	Reproducing
<i>mutation chance</i>	{0, 0.05}	Reproducing
<i>food multiplier</i>	{5}	Eating
<i>finding max</i>	{2, 3}	Eating
<i>level of sacrifice</i>	{0.2, 0.5, 0.8, 1.0}	Altruism
<i>fake greenbeards</i>	{True, False}	Greenbeard
<i>min relationship</i>	{1, 2, 3}	Kin selection
<i>group number</i>	{2, 4, 6}	Group
<i>migration rate</i>	{0.0, 0.05, 0.15}	Group

Table 6.1: Used parameter values by submodel. A range of values is assigned to each parameter that are then used for the simulations. It was found that the parameters *num agents* and *food multiplier* do not influence the results of the models in any relevant way; thus only one value has been assigned to each one.

6.2 Results

To isolate the relevant factors and parameters of each of the models, the correlations of all inputs and outputs have been calculated for each one. Based on these correlations, plots have been created to investigate the influence of especially significant parameters. The following section summarizes the most relevant results. The full set of generated plots can be accessed here: <https://github.com/koerners/masterthesis-data/tree/master/results/simulation>.

6.2.1 Benchmark

The benchmark model is used to set a baseline for the results of the other models. It only contains the control group consisting of unconditional altruists and non-altruists. The resulting correlation matrix (table A.1) shows significant correlations as to the parameter *child bearing cost*. Plotting the total number of agents in the simulation for each possible *child bearing cost* value from table 6.1 results in fig. 6.1. It clearly shows that, while the population thrives with a low *child bearing cost*, it struggles with higher ones, ultimately leading to extinction.

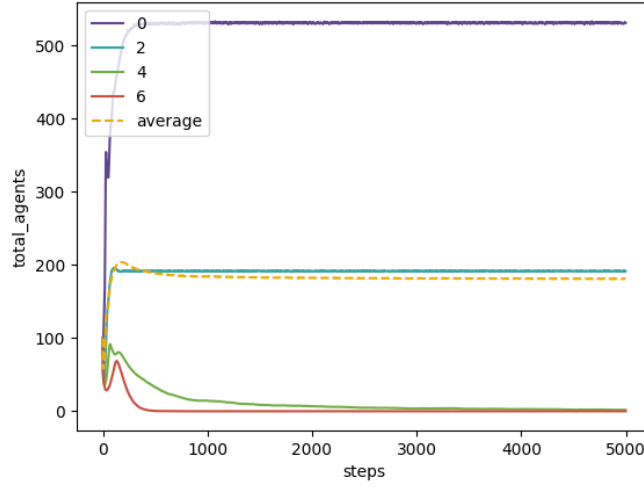


Figure 6.1: Total number of agents over time, with different values for *child bearing cost*. The population does not manage to survive in the two harshest environments.

An interesting observation can be made regarding the parameter *child bearing cost* when looking at the distribution of the different types of agents (fig. 6.2). At a low cost, the unconditional altruists go extinct in less than 75 steps, while they are able to survive considerably longer in the high-cost environment. However, the unconditional altruists were unable to prevail in the long run with any of the tested configurations. The implications of this will be discussed in section 8.2.

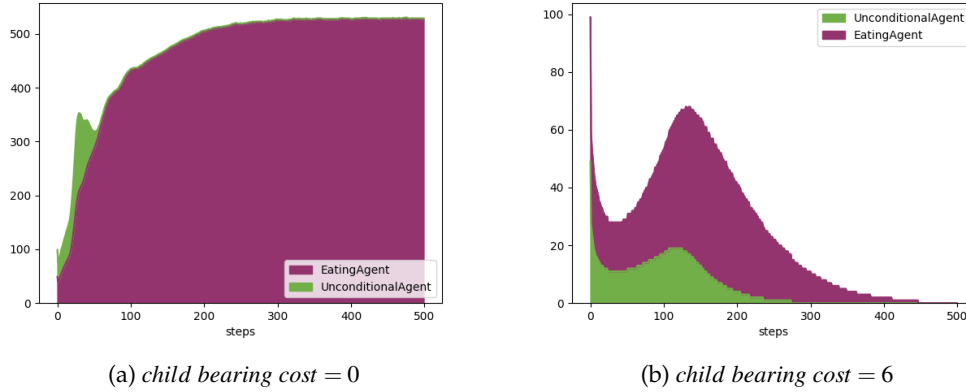


Figure 6.2: Distribution of types of agents by *child bearing cost* for the first 500 steps. Purple: non-altruists; green: unconditional altruists. Unconditional altruists survive considerably longer under harsher conditions (b).

6.2.2 Greenbeard Model

The results of the greenbeard model show how powerful altruism can be if no one is able to take advantage of altruists. Vice versa, it shows how easily the presence of cheaters can lead to the extinction of whole populations, as shown by the negative correlations (table A.2)

between the *allow fake greenbeards* parameter and the *final agents*, *average fitness altruists* and *average fitness non altruists* values. In fig. 6.3 this difference between cheaters (fake greenbeards) being present and being absent is especially obvious. The presence of fake greenbeards in harsher environments leads to the swift extinction of the population as a whole, while their absence leads to the real greenbeards taking over the population and establishing a stable population that even survives the harshest of environments.

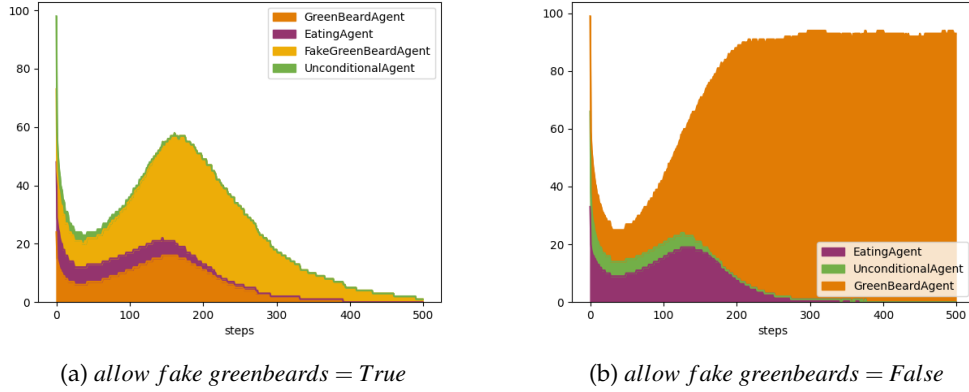


Figure 6.3: Distribution of types of agents with *child bearing cost* = 6 and fake greenbeards present (a) and absent (b) during the first 500 steps. *Purple*: non-altruists; *green*: unconditional altruists; *orange*: real greenbeards; *yellow*: fake greenbeards. If fake greenbeards are present in the simulation, the population will go extinct in less than 500 steps. If fake greenbeards are absent, the population and especially the real greenbeards will prosper.

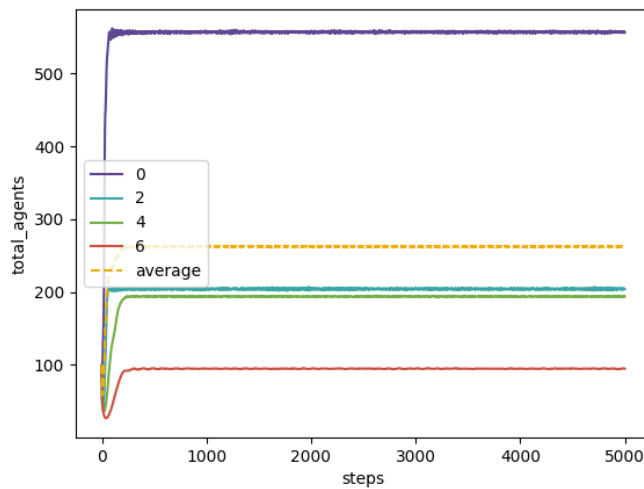


Figure 6.4: Total number of agents, with different values for *child bearing cost* and no fake greenbeards present. The population is thriving in all environments.

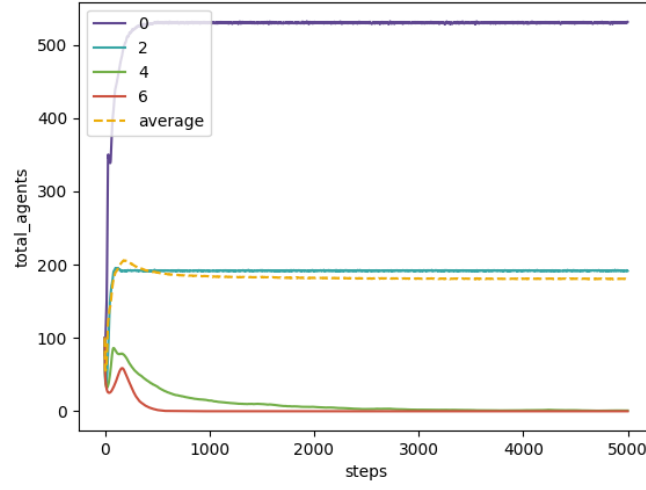


Figure 6.5: Total number of agents, with different values for *child bearing cost* and fake greenbeards present. The population cannot survive in the two harshest environments.

6.2.3 Kin Selection Model

The kin selection model shows how altruism directed towards genetic relatives can lead to the sustainability of populations even in the harshest environments. As can be seen in fig. 6.6 the kin selection agents only provide a small but stable part of the overall population in low-cost environments. This is to be expected especially for *child bearing cost* = 0 since the constraints of Hamilton's rule as defined in section 5.2.3 don't hold true. In harsher environments, however, the kin selection agents prevail and oust the other types of agents. An interesting observation regarding the *min relationship* parameter can be observed in fig. 6.7. The higher the relationship threshold before an agent is willing to help the other, the better the sustainability of kin selection altruists. This is also indicated by the positive correlation of *min relationship* and the *average fitness altruists* (table A.3).

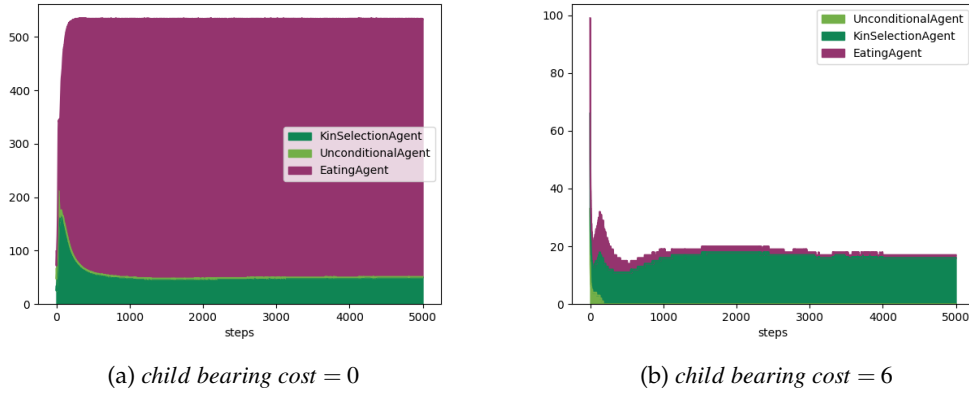


Figure 6.6: Distribution of types of agents by *child bearing cost* for the first 5,000 steps. *Purple*: non-altruists; *green*: unconditional altruists; *dark green*: kin selection altruists. Only being a minority of the population in the low-cost environment, the kin selection altruists are the only agent type to prevail in the high-cost environment.

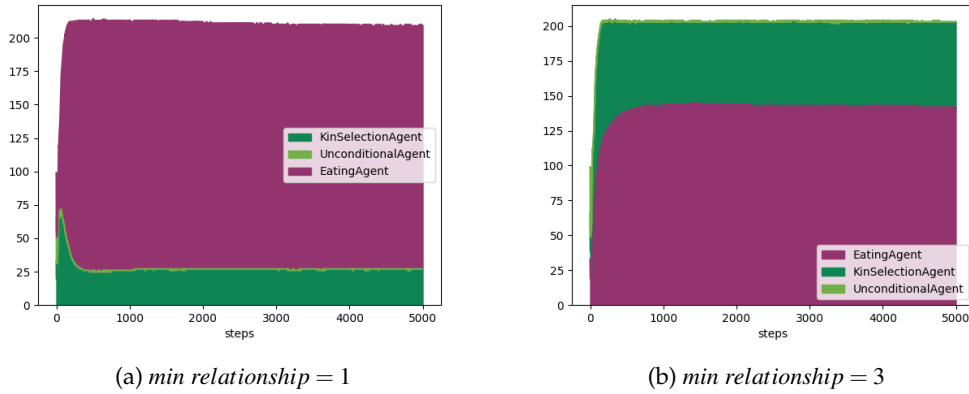


Figure 6.7: Distribution of types of agents by *min relationship*. *Purple*: non-altruists; *green*: unconditional altruists; *dark green*: kin selection altruists. A higher value leads to a larger number of kin altruists.

6.2.4 Reputation Model

The results of the reputation model indicate that informed altruism has a considerable impact on the sustainability of altruistic traits. The data demonstrates that altruism based on reputation not only makes altruism sustainable but makes it thrive in low to medium-cost environments (fig. 6.11). However, in the environment associated with the highest cost for reproducing (fig. 6.8 b), the population will die out after only a few generations. An interesting observation regarding the average reputation of the agents is that a higher life expectancy not only increases the average reputation of the agents (fig. 6.9), but also that if the overall population has a higher life expectancy, reputation-based altruists are more likely to possess more food compared to their non-altruistic counterparts (fig. 6.10). Counterintuitively, the *level of sacrifice* parameter does not seem to have any effect on the average reputation of the agents (fig. 6.9). Furthermore, the *level of sacrifice* does not seem

to correlate with any other parameters (table A.4). Another key finding of the model is the positive effect of the presence of the reputation altruists on the overall development of the population. Compared to the benchmark model where the population does not manage to survive in the two second-harshes environments (fig. 6.1), the population of this model manages to survive in all but the harshest environment through the presence of the reputation agents. (fig. 6.11).

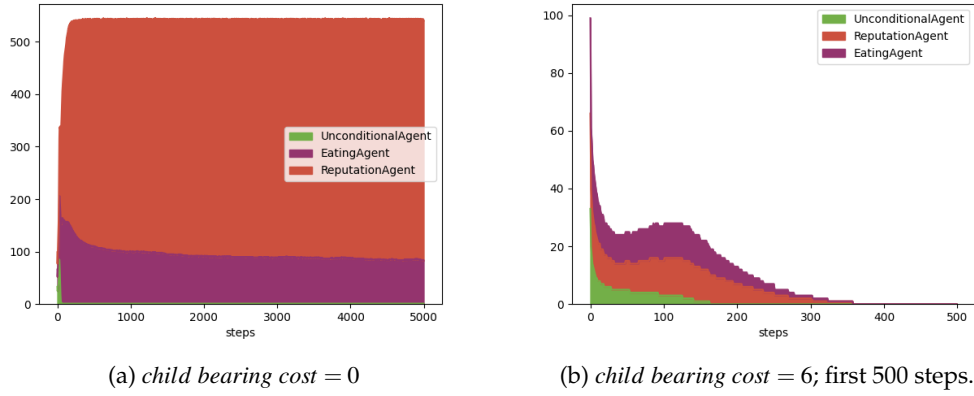


Figure 6.8: Distribution of types of agents by *child bearing cost*. *Purple*: non-altruists; *green*: unconditional altruists; *red*: reputation altruists. The reputation-based altruists take over the majority in the low-cost environment but don't prevail in the highest cost one.

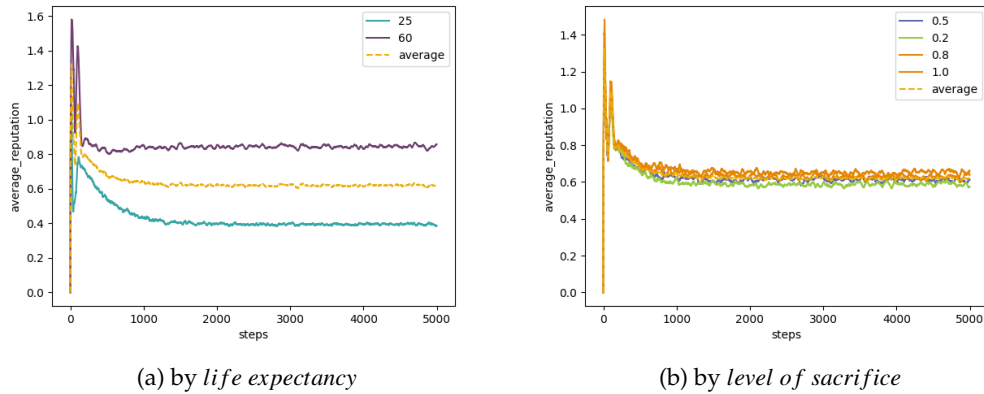


Figure 6.9: Average reputation for the first 5,000 steps. While a higher *life expectancy* leads to an overall higher reputation, the *level of sacrifice* does not seem to affect it.

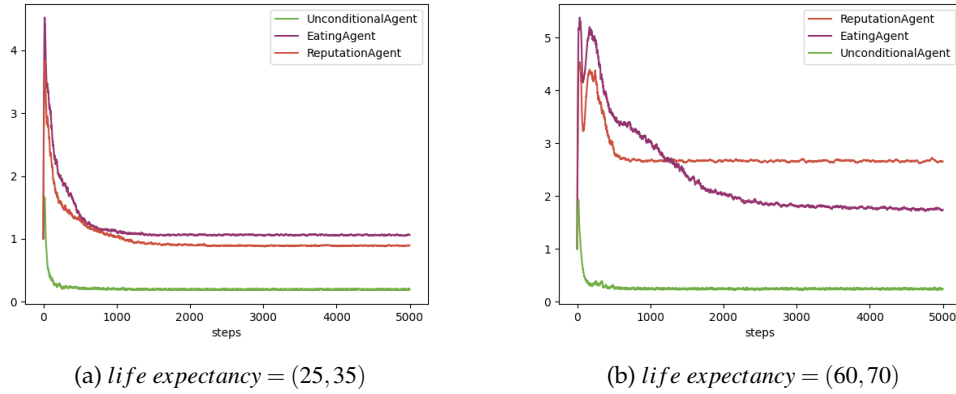


Figure 6.10: Average food units per agent type by *life expectancy*. Purple: non-altruists; green: unconditional altruists; red: reputation altruists. With a higher *life expectancy* reputation altruists surpass non-altruists regarding the amount of food units they possess on average.

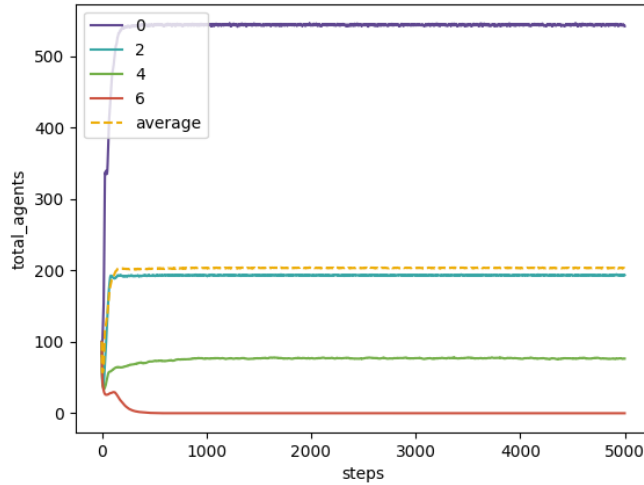


Figure 6.11: Total number of agents in the reputation model over time, with different values for *child bearing cost*. The population manages to survive under all but the harshest conditions.

6.2.5 Group Model

Altruism based on group affiliation turns out to be a highly effective strategy. The results show the group altruists reliably taking over the majority of the population in environments of all harshness (fig. 6.12). An interesting observation is that there always tends to be one group that takes over the majority after only a few generations (fig. 6.13). A finding regarding the inequality among agents is that the distribution of food among agents in low-cost environments is considerably more uneven than in high-cost environments (fig. 6.14). This could be explained by the fact that the group altruists are more likely to take over

the absolute majority of the population in high-cost environments; thus the food units are more evenly distributed since they are willing to share among each other.

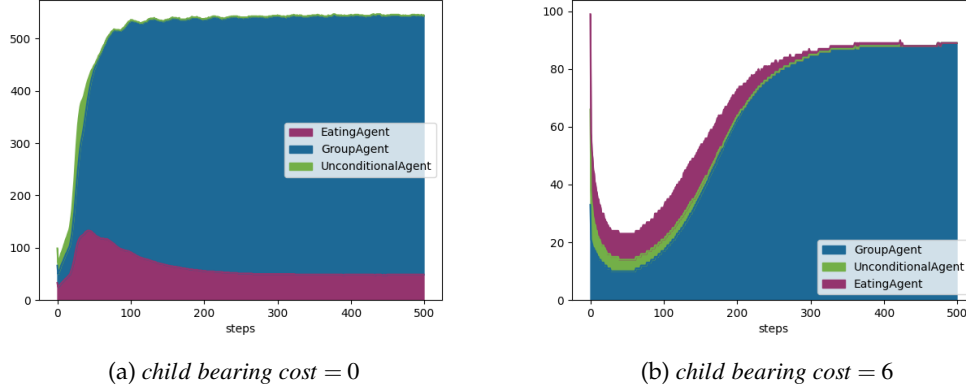


Figure 6.12: Distribution of types of agents by *child bearing cost* for the first 500 steps. *Purple*: non-altruists; *green*: unconditional altruists; *blue*: group altruists. Group altruists thrive in all environments and are the only type to survive in high-cost environments.

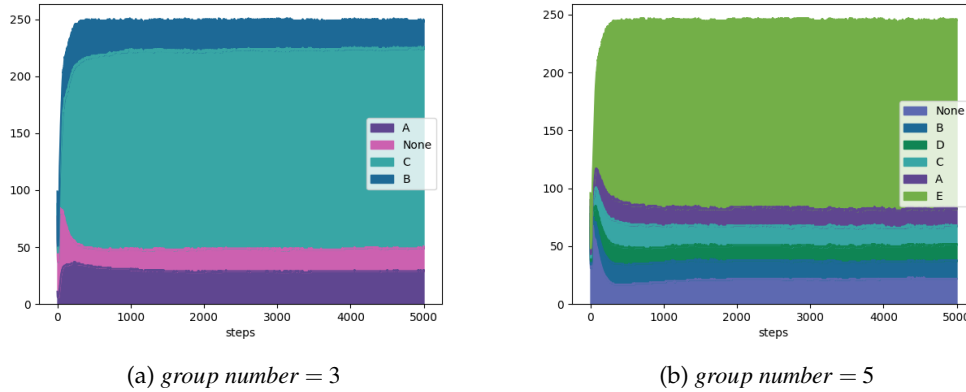


Figure 6.13: Distribution of agent groups by *group number*. In every configuration one group takes over the majority of population in a short time.

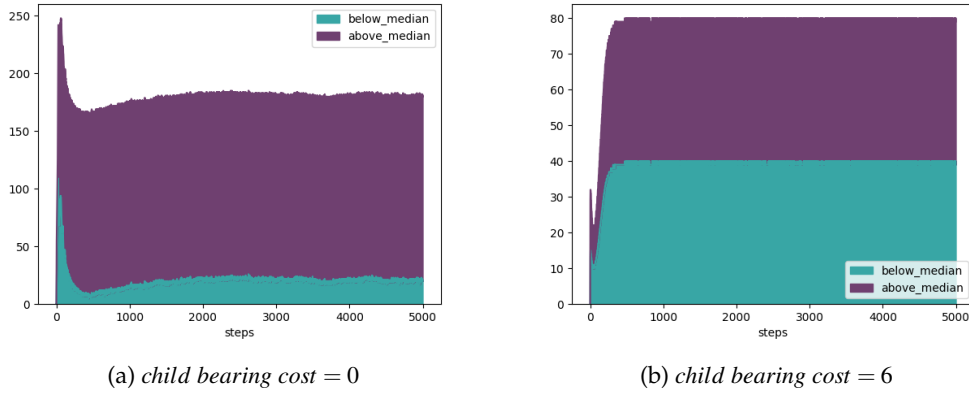


Figure 6.14: Food distribution based on the median, by *child bearing cost*. *Purple*: agents who have more food than the median; *turquoise*: agents who have a below-median amount of food. In low-cost environments, the amount of food is unevenly distributed among agents. In high-cost environments, the amount of food is distributed evenly.

6.2.6 Culture Model

The results of the culture model show that altruism influenced by culture is one of the most effective strategies discussed in this paper. Culture agents not only take over the majority of the population in the low-cost environments but also thrive in the high-cost ones (fig. 6.15). The initial helping culture of the groups highly influences their development. The group with the highest initial helping culture takes over the majority in only a short time (fig. 6.16). This in turn improves the chances of survival for every group member in the high-cost environments. The helping culture values of groups with a low initial helping culture value tend to gradually decline, while a higher initial value tends to stay stable over generations (fig. 6.17). A stabilizing factor to the helping culture value seems to be the migration rate. If migration between groups is encouraged, the initial fluctuation as well as the decline of culture values tend to be reduced. Culture agents also tend to have a significantly better developed social network compared to their peers (fig. 6.18).

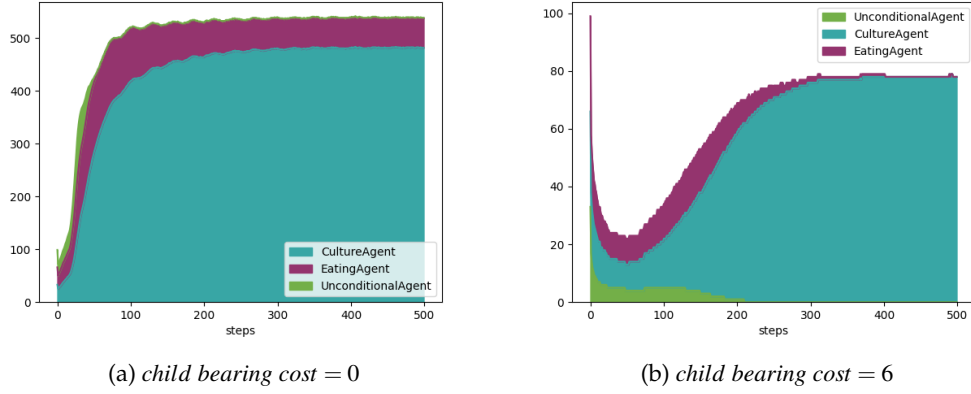


Figure 6.15: Distribution of types of agents, by *child bearing cost* for the first 500 steps. *Purple*: non-altruists; *green*: unconditional altruists; *turquoise*: culture altruists. The culture agents constitute the majority in any configuration. In the harshest environment, the culture agents are the only type to survive.

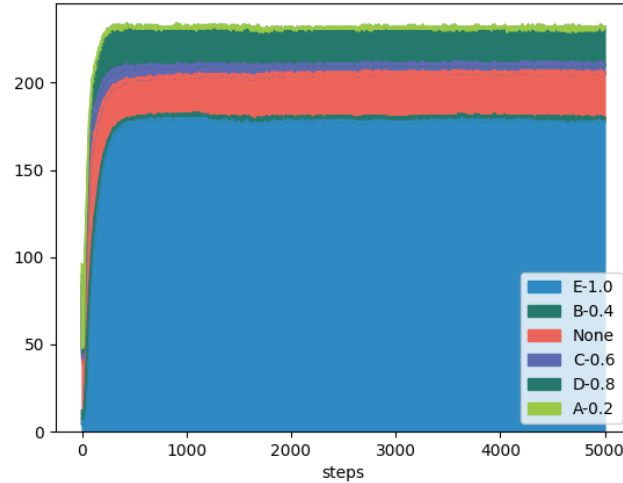


Figure 6.16: Group distribution with *group number = 5*. The group with the highest initial helping culture (indicated by the digits behind the group initials) comprises the majority of the population after only a few generations.

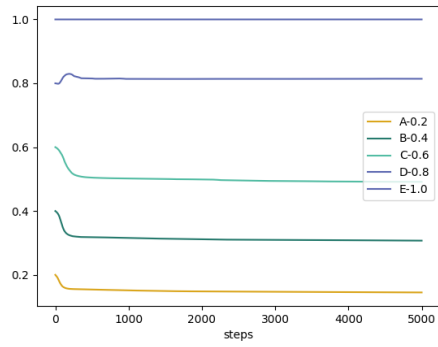
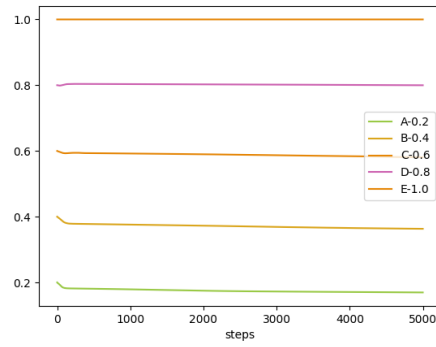
(a) *migration rate* = 0.0(b) *migration rate* = 0.15

Figure 6.17: Altruism culture per group, by *migration rate*. Migration stabilizes the culture within the groups.

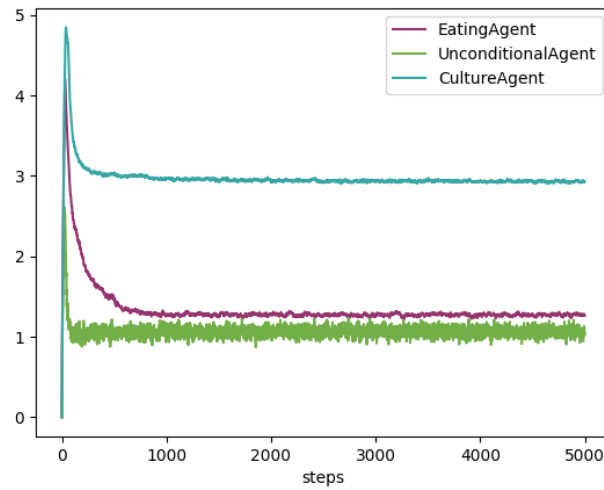


Figure 6.18: Average network connections per agent type with *group number* = 5. The culture agents have a significantly more developed social network compared to their peers.

In addition to the analysis of the exploratory results, the social networks that the agents have formed during the simulations are analyzed. Parameter values that yielded promising results in section 6.2 have been isolated, and the models were run with them for 500 steps. The results of this analysis regarding clustering and connectivity are summarized in section 7.1. Furthermore, the relationship between the number of altruistic acts an agent has committed and its position in the social network has been analyzed. The complete series of generated networks can be explored interactively here: <https://koerners.github.io/masterthesis-data/>.

7.1 Path Length, Clusters, and Hubs

For the analysis of the network, the metrics of characteristic path length, network clustering coefficient and network heterogeneity are integral. The characteristic path length is defined as the expected distance between two connected agents in a network. It is calculated for the graph $G = (V, E)$ as follows:

$$l(G) = \frac{1}{|V| * (|V| - 1)} \sum_{s \in V} \sum_{t \in V \setminus \{s\}} \sigma_{st}, \quad (7.1)$$

where σ_{st} is the number of edges in a shortest path between nodes s and t . In the case of an unconnected graph, the equation is modified to sum over all connected node pairs. [27]

The network clustering coefficient of an undirected network gives an overall indication of the clustering in a network. It is defined as the average of the clustering coefficient of all nodes in the network, where the clustering coefficient of a node n is the number of edges between the neighbors of n relative to the maximum number of edges that could exist between the neighbors of n . This can be formalized for the graph $G = (V, E)$ as follows:

$$cc(G) = \frac{1}{V} \sum_{n \in V} \frac{2e_n}{N_n - 1}, \quad (7.2)$$

where N_n is the number of neighbors of n , and e_n is the maximum number of edges that could exist between the neighbors of n . [21]

The final figure, the network heterogeneity, is an indication as to the tendency of the network to contain hubs. According to [8] the network heterogeneity for a graph G can be formalized as:

$$h(G) = \frac{\sqrt{\text{variance}(c)}}{\text{mean}(c)}, \quad (7.3)$$

where c is the connectivity distribution, where the connectivity of an agent n is equal to the number of directly connected agents.

The results of the network analysis are summarized in table 7.1. One interesting observation has been made regarding the relationship between the number of agents in a network and the expected distance between two connected agents. As can be seen in fig. 7.1, the path length increases at a rate of 1.05 with every added 100 agents until it reaches approximately 6.5 where it converges. Interestingly, this is in line with the small-world phenomenon, which states that any two people in the world are connected through a maximum of about six other people. [2, p. 45-46] The fact that this phenomenon occurs by itself indicates that the model might be a good approximation for real social networks. The outliers in the data visualized in fig. 7.1 tend to be populations that are about to go extinct, which suggests that the growth rate stated beforehand is a good indicator for a healthy social network.

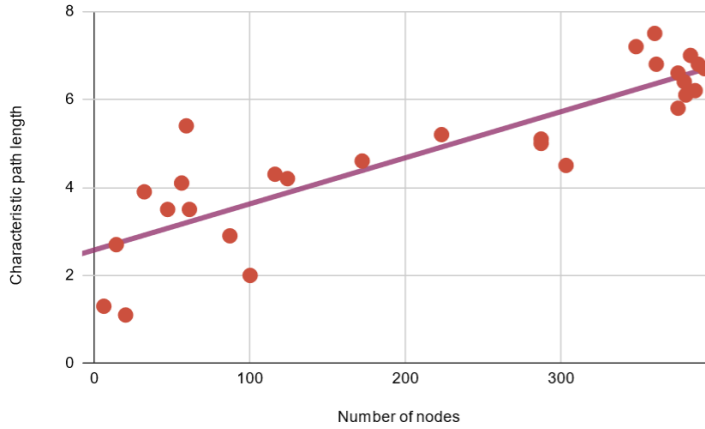


Figure 7.1: Relationship between the number of agents on the network and the characteristic path length. With every increase of 100 agents, the path length increases at a rate of about 1.05 until it converges at approximately 6.5.

The visual inspection of networks with distinct values for the clustering coefficient and heterogeneity reveals interesting details. The reputation model at step 100 has a relatively low clustering coefficient while having a rather high heterogeneity. Looking at the corresponding graph (fig. 7.2) reveals a network of agents that is far spread, but the subnetworks are well-connected through hubs. The opposite value combination with a high clustering coefficient and low heterogeneity can be observed at step 100 of the group model (fig. 7.3). The cluster of group agents in the upper left is highly interconnected with little tendency to hubs, which is a result of its interconnectivity. High clustering is also given at step 200 of the kin selection model. The visualization (fig. 7.4) reveals one fully connected network of

	Step	Nodes	Avg. neighbors	Characteristic path length	Clustering coefficient	Heterogeneity
Benchmark	100	303	6.9	4.5	0.62	0.39
	200	375	5.7	5.8	0.62	0.42
	300	100	2.3	2	0.26	0.5
	400	20	3.6	1.1	0.9	0.14
	500	1	-	-	-	-
Greenbeard (with fake)	100	59	3.5	5.4	0.5	0.44
	200	2	-	-	-	-
	300	0	-	-	-	-
Greenbeard (without fake)	100	287	6.2	5.1	0.65	0.41
	200	388	4.9	6.8	0.55	0.42
	300	380	5.42	6.1	0.57	0.39
	400	379	5.1	6.4	0.58	0.41
	500	383	5	7	0.6	0.39
Kin selection	100	32	2.7	3.9	0.49	0.53
	200	47	5.3	3.5	0.78	0.4
	300	61	5.78	3.5	0.65	0.45
	400	116	5.5	4.3	0.63	0.43
	500	223	5.3	5.2	0.63	0.43
Reputation	100	56	3.1	4.1	0.3	0.64
	200	14	2.7	2.7	0.6	0.32
	300	6	2	1.3	0.58	0.35
	400	0	-	-	-	-
Group	100	124	6.2	4.2	0.75	0.35
	200	287	6.4	5	0.65	0.39
	300	348	5.1	7.2	0.64	0.42
	400	360	5	7.5	0.62	0.38
	500	361	5.4	6.8	0.61	0.38
Culture	100	87	5.6	2.9	0.72	0.4
	200	172	5.9	4.6	0.66	0.4
	300	386	4.9	6.2	0.52	0.37
	400	375	4.8	6.6	0.56	0.37
	500	392	5.2	6.7	0.59	0.4

Table 7.1: Network characteristics of all models for the first 500 steps with *child bearing cost* = 6, *life expectancy* = (60,70), *mutation chance* = 0.05, *finding max* = 3, *level of sacrifice* = 0.5, *min relationship* = 1, *group number* = 5, and *migration rate* = 0.05. The term *average neighbors* indicates the average connectivity of a node in the network. *Characteristic path length* gives the expected distance between two connected nodes. The *clustering coefficient* is the average of the clustering coefficients for all nodes in the network. The *heterogeneity* reflects the tendency of a network to contain hub nodes. [21]

agents, with smaller clusters spread throughout it. An example of average values for clustering and heterogeneity is the greenbeard model without fake greenbeards at step 500. Visually (fig. 7.5), the network resembles a well-developed network with few but strong hubs with smaller branches reaching out.

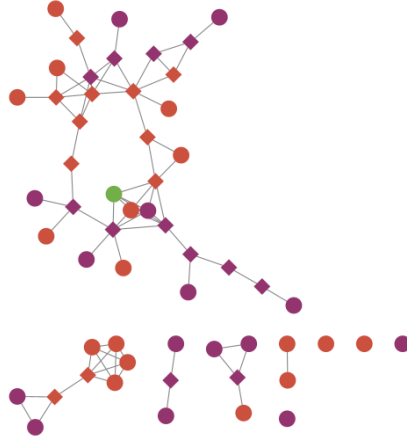


Figure 7.2: Network of the reputation model at step 100 with *child bearing cost* = 6, *life expectancy* = (60, 70), *mutation chance* = 0.05, *finding max* = 3, and *level of sacrifice* = 0.5. Purple: non-altruists; green: unconditional altruists; orange: reputation agents. Diamond-shaped nodes exhibit hub-tendencies.

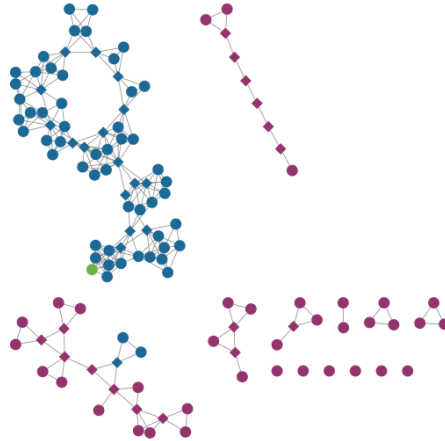


Figure 7.3: Network of the group model at step 100 with *child bearing cost* = 6, *life expectancy* = (60, 70), *mutation chance* = 0.05, *finding max* = 3, *level of sacrifice* = 0.5, *group number* = 5, and *migration rate* = 0.05. Purple: non-altruists; green: unconditional altruists; blue: group altruists. Diamond-shaped nodes exhibit hub-tendencies.

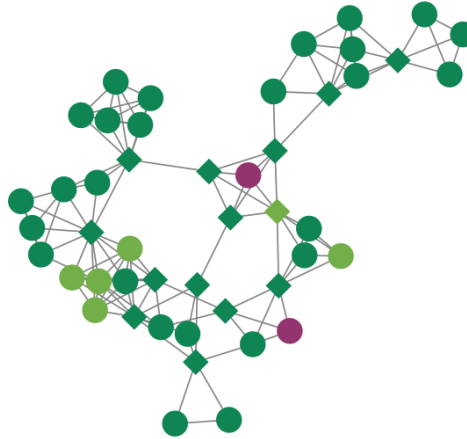


Figure 7.4: Network of the kin selection model at step 200 with *child bearing cost* = 6, *life expectancy* = (60,70), *mutation chance* = 0.05, *finding max* = 3, *level of sacrifice* = 0.5, and *min relationship* = 1. Purple: non-altruists; green: unconditional altruists; dark green: kin selection altruists. Diamond-shaped nodes exhibit hub-tendencies.

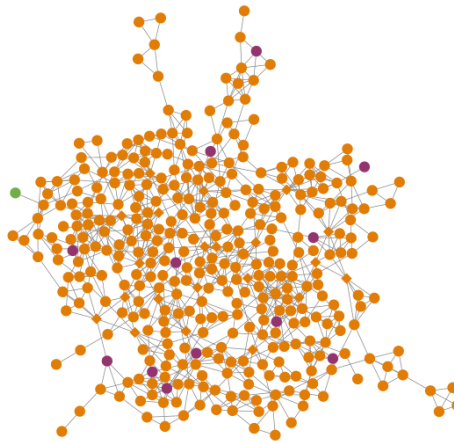


Figure 7.5: Network of the greenbeard model with no fake greenbeards at step 500 with *child bearing cost* = 6, *life expectancy* = (60,70), *mutation chance* = 0.05, *finding max* = 3, and *level of sacrifice* = 0.5. Purple: non-altruists; green: unconditional altruists; orange: real greenbeards. Diamond-shaped nodes exhibit hub-tendencies.

7.2 Connectivity of Altruists

To analyze the position that altruists have in a social network regarding their connectedness, the number of altruistic acts of the agents has been put in relation to their neighborhood connectivity (fig. 7.6) and betweenness centrality (fig. 7.7). The neighborhood connectivity is used as a metric for the semi-local connectedness of the agents. It is defined as the average connectivity of all the neighbors of agent n and can be formalized as:

$$NC_n = \sum_{k \in N(n)} \frac{N(k)}{N(n)}, \quad (7.4)$$

where $N(n)$ is the set of neighbors of agent n . [26]

The betweenness centrality is used to measure the global connectedness of agents. The betweenness centrality of agent n can be defined as:

$$C_b(n) = \sum_{s \neq n \neq t} \frac{\sigma_{st}(n)}{\sigma_{st}}, \quad (7.5)$$

where s and t are agents different from n ,
 σ_{st} denotes the number of shortest paths from s to t , and
 $\sigma_{st}(n)$ is the number of σ_{st} that n is a part of. [21]

The analysis of the semi-local connectedness of altruists, as shown in fig. 7.6, indicates that the more often an agent has acted altruistically, the less likely it is to inhabit a key position within its closer environment. In all examined networks, the correlation between the number of committed altruist acts and the neighborhood connectivity is negative. However, when examining the global position of altruistic agents, the opposite can be observed (fig. 7.7). The more altruistic actions an agent has committed, the more likely it is to have an influential position within the global network. This effect is especially noticeable in the greenbeard (fig. 7.7 a) and culture models (fig. 7.7 c), but also to a lesser degree in the kin selection model (fig. 7.7 b) and group model (fig. 7.7 d).

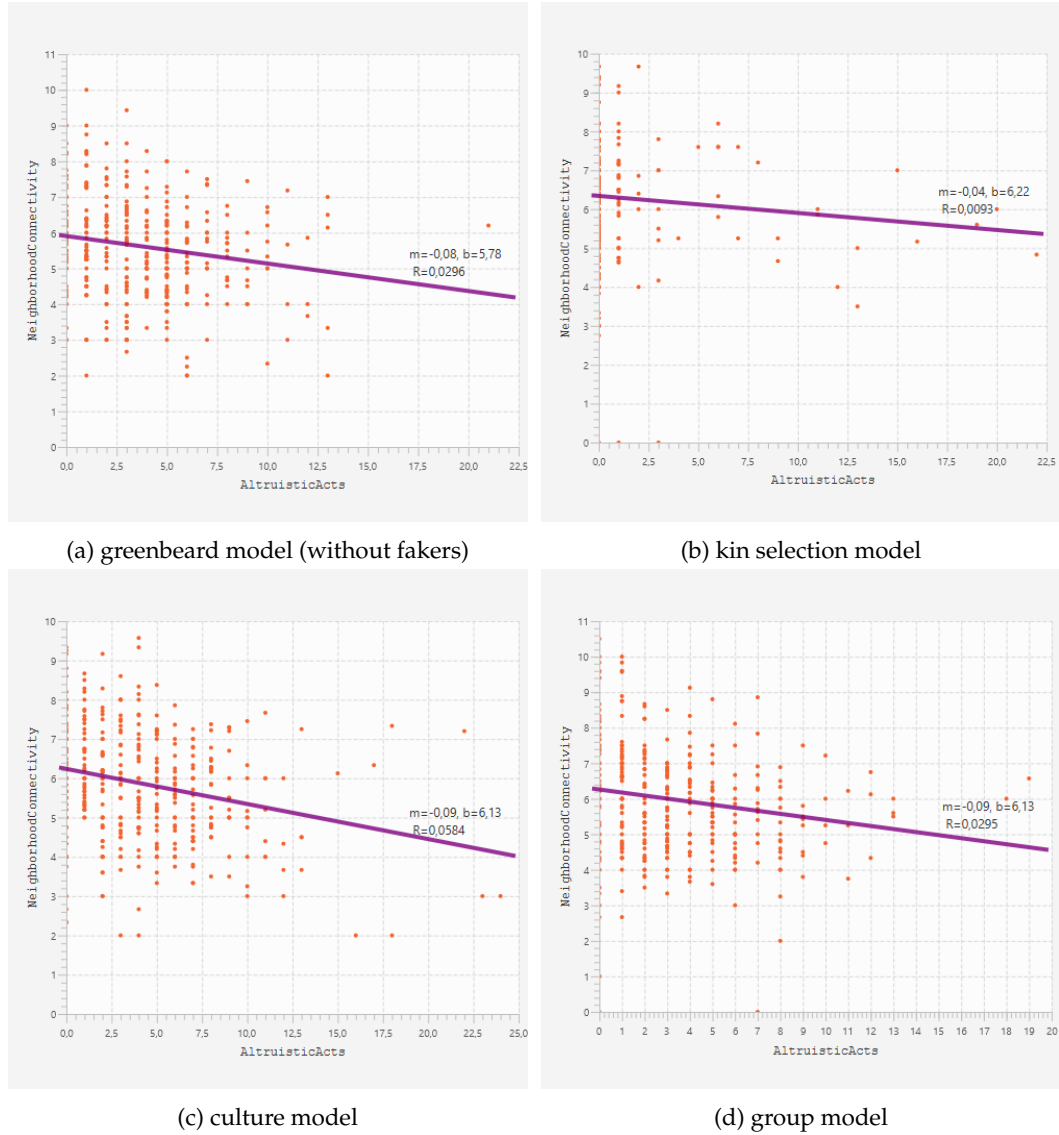
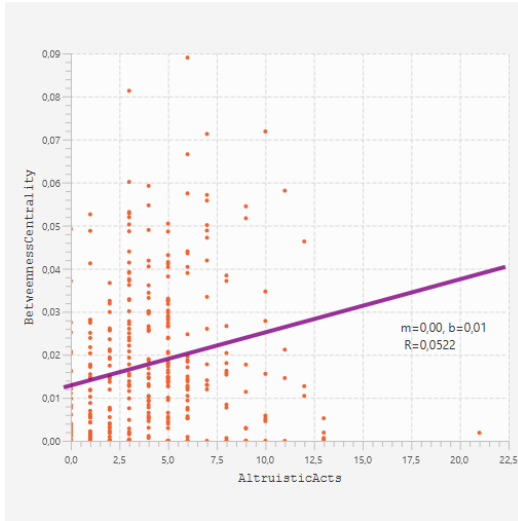
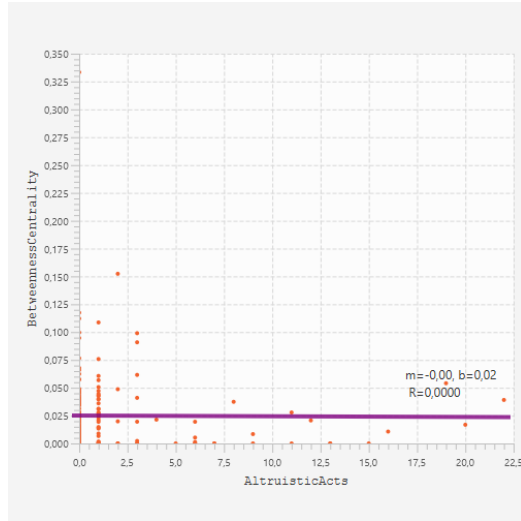


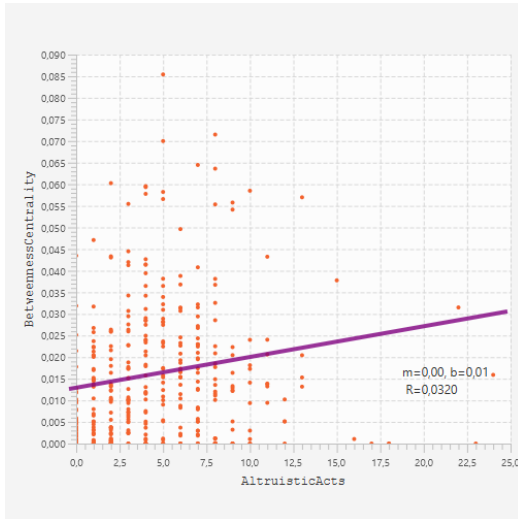
Figure 7.6: The neighborhood connectivity of agents and their altruistic acts for the first 500 steps with *child bearing cost* = 6, *life expectancy* = (60,70), *mutation chance* = 0.05, *finding max* = 3, *level of sacrifice* = 0.5, *min relationship* = 1, *group number* = 5, and *migration rate* = 0.05. The neighborhood connectivity of an agent n is defined as the average connectivity among all neighbors of the agent n . [21] The number of altruistic acts correlates negatively with the neighborhood connectivity across all models.



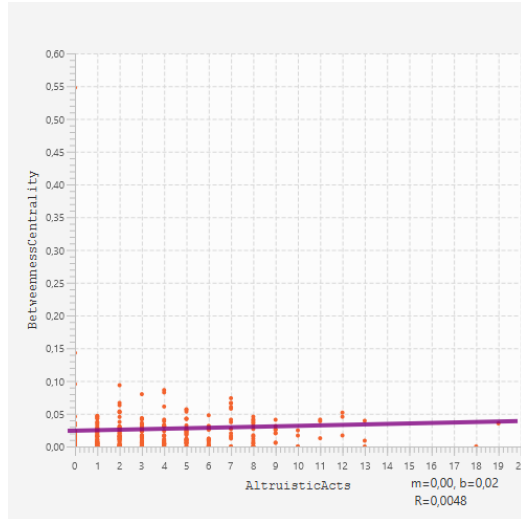
(a) greenbeard model (without fakers)



(b) kin selection model



(c) culture model



(d) group model

Figure 7.7: The betweenness centrality of agents and their altruistic acts at step 500 with *child bearing cost* = 6, *life expectancy* = (60,70), *mutation chance* = 0.05, *finding max* = 3, *level of sacrifice* = 0.5, *min relationship* = 1, *group number* = 5, and *migration rate* = 0.05. In all but the kin selection model the correlation is positive.

In this chapter, the findings of this paper's work are presented in section 8.2 and suggestions for further research into this topic are provided in section 8.3. But before that, the limitations of the used approach are discussed in section 8.1.

8.1 Limitations

Using simulations as a scientific method has its own considerable drawbacks. The nature of simulations dictates that the modeler has to make assumptions regarding the modelled system and omit parts of the systems that are not deemed relevant. Some notable limitations are the following:

1. Randomness is a significant factor for almost all integral parts of the simulation. This is to circumvent the underlying complexity of real life processes that are not considered essential to this model. To mitigate this partially, the simulation has been run many times with different seeds.
2. In some places, the simulation leaves the possibilities for agents wide open, e.g., when it comes to the age of the partners they can choose. In other places, the agents are restricted quite heavily. This degree of restriction has been influenced by the modeler's opinion regarding what processes might be important for the system in question and which are negligible. This kind of opinionated development is unavoidable to some degree. It should, however, be taken into account when reviewing the findings.
3. The available computing power has somewhat limited the number of possible parameters testable in the available amount of time. On a four-core processor, some models have taken up to a week of continuous calculation to complete, even with heavy optimizations regarding their performance. Thus, not all parameters have been tested for their full range.
4. Especially in the social sciences, models are evaluated regarding their reproducibility in the real world. The model in its current form can most likely never be evaluated in this way. Evolution has been happening over the course of thousands of years, and it's impossible to go back to the beginning of society when altruism has most likely

evolved and have people fill out questionnaires about whom they would save from starvation and whom they would let die. However, it is the point of simulations and scientific models in general to open up possibilities where other scientific methods cannot be applied. In physics, systems under investigation are regularly stripped down to their most fundamental parts and assumptions have to be made in order to formalize real-world phenomena into models.

I most certainly do not claim having done justice to the complexity of human evolution and decision-making in the roughly 2,500 lines of code that this simulation consists of. Nevertheless, I hope to have captured its most essential mechanisms and dynamics. It is still important to stress that any findings and conclusions drawn from the results of the model are not necessarily transferable to the real world and always have to be considered in the context of this specific model.

8.2 Findings

All the presented findings have to be considered under the pretense of the model used in this paper with all its limitations and assumptions, especially but not limited to those listed in section 8.1.

8.2.1 Different Conditions Promote Different Types of Altruism

The results show that theories of altruism based on group affiliation and cultural evolution have been the most successful across the different conditions they have been tested under. Other types of altruism have shown great potential under more specific circumstances: Kin selection does not develop significantly in low- to mid-harsh conditions but is rather effective under very harsh conditions. While the reputation strategy has performed brilliantly under nearly all circumstances it's been presented with, it has completely failed to do so in the harshest environment. A likely explanation for this is that there simply hasn't been enough time for the reputation mechanisms to develop due to the harshness of the environment. This indicates that strategies that work "out of the box" like kin selection where the relationship between agents has been clear from the beginning and therefore help has been distributed without delay, are in the short term more powerful when it comes to the survival in harsh environments.

8.2.2 Altruism Leads to a Considerably Better Survivability in Harsh Environments

In very harsh conditions, it is not possible for a population to survive if there are no altruists present at all. This leads to the conclusion that the evolution of altruism has most likely been a product of harsh environments where populations could not have survived without helping one another.

8.2.3 Higher Individual Sacrifice Does Not Improve the Survivability

While the results show that altruism can be a highly effective strategy, it does not seem to matter too much whether altruists are willing to sacrifice only a little of what they have, or, if they are willing to sacrifice all that they have. On the contrary, if altruists are willing to sacrifice everything they have, they are not able to contribute to the gene pool, which leads to altruists dying out. Thus, the population is unable to sustain itself in harsher environments. A lower level of individual sacrifice with a high portion of altruists proves to be the most effective combination for long-term success in harsh environments.

8.2.4 Cheaters Destabilize Altruistic Systems Significantly

The results of the greenbeard model (section 6.2.2) demonstrate how easy it is for freeloaders or cheaters to destabilize an otherwise well-functioning system if the system itself cannot adapt to these cheaters. Very stable systems might tolerate a certain number of cheaters, but if their number rises to a critical level, the system collapses. This effect is similar to the herd-immunity effect in the case of diseases, where a small percentage of the population without immunity can take down the whole system by providing hosts for mutations and blocking health care resources. Research regarding how the issue of cheaters could have been resolved through the evolution of altruistic punishment has been conducted, e.g., in [24].

8.2.5 Altruists Lose Local Influence While Gaining Global Influence

The network analysis indicates that altruists weaken their semi-local influence while gaining it on a global scale. This could be due to altruists strengthening the global network through their sacrifices, while weakening their semi-local connectedness. This leads to them having a weak semi-local position while on a global scale, they are highly influential.

8.3 Future Work

For an even better understanding of the presented model, the possibility of an “exhaustive” simulation could be considered. [22] An exhaustive simulation could include a much wider parameter value range, which the scope of this project, its time constraints and limited available computing power have made impractical to run the simulation with. Without the constraints of time and computing power, the network analysis could also be extended to cover a much wider parameter range than in this paper. Furthermore, the network could be made to react dynamically to altruistic actions, e.g., by creating and modifying links between the donor and receiver. Unfortunately, this idea had to be abandoned in this project due to the limited computing power. Also, some further modifications to the model itself could be made incrementally, e.g., to make certain processes like the finding of a partner more realistic. However, an endeavor like this could lead down a path of trying to simulate processes that lack the empirical research that is required to abstract them to a reasonable degree. Furthermore, the presented findings could be compared comprehensively to real-life data gathered by evolutionary biologists.

CHAPTER 9

Conclusion

This thesis reports on using a cross-generational agent-based simulation to put the most popular theories regarding the evolution of altruistic traits in humans to the test and contributes to the evolving area of *computational ethics*. Chapter 2 presented the literature regarding the evolution of altruistic traits and the existing simulation-based approaches to this topic. It also discussed the objections of those who do not agree with this approach. Accordingly, the presented model was developed to complement existing models while incorporating the criticism of others. After introducing the theoretical background for this paper in chapter 3, the newly developed model and its submodels were described in chapter 4. The presented model consisted of a population model that mimics a population of up to 5,000 agents that live, eat, reproduce, and die in environments of varying harshness over the course of hundreds of generations. This population model then was extended by different submodels that incorporate different altruistic strategies according to the theories that were discussed in chapter 3. In chapter 5, the implementation of the model and the most relevant algorithms were presented. The results that this model has produced were then analyzed in chapter 6 focusing on comparing the relative evolutionary development of benchmark genes and a gene that employs the submodel specific altruistic strategy. In chapter 7, the social networks the agents have formed during the simulations were analyzed regarding their small-world-properties, clustering, hub tendencies and the influence altruists have over the network. In chapter 8, the limitations of the approach that was used, which were mostly those one would expect from a simulation-based approach to such a complex topic, were discussed.

The findings of this thesis, described in section 8.2, can be summarized as follows. First, different environmental conditions promote different types of altruism. Group- and culture-based approaches have been the most successful across environments of varying harshness while kin selection and reputation-based altruism have shown high potential, but only under more specific environmental circumstances. Second, altruism leads to a considerably better survivability in high-cost environments. With effective altruistic strategies, populations have been able to survive and even thrive under conditions, where populations without sophisticated strategies have not been able to. Even individuals without altruistic strategies have been able to survive in high-cost environments if altruists with effective strategies were present in the population. Third, higher individual sacrifice does not improve survivability. In none of the experiments any improvement regarding the development of the population or traits has been noticeable when comparing different individual

levels of sacrifice as long as everyone has been willing to contribute at least a minimum. Fourth, cheaters destabilize altruistic systems significantly. The fake greenbeards have reliably contributed to the extinction of populations by pretending to be altruistic and thereby “cheating” the system. Finally, altruists lose local influence while gaining global influence. A significant loss of local influence has been noticeable with the increase of altruistic acts an agent has committed, while simultaneously a rise in its global influence has been observed. The model, as well as the analysis, can be extended in multiple ways in the future, some of which are discussed in chapter 8.

Had Jean Valjean, Victor Hugo’s figure cited in the introduction of this thesis, kept walking past the man under the wagon, had he decided to stay silent when he saw the injustice done to others, his life could have played out very differently. Maybe he could have gotten married and would have had children of his own. But instead, he shared the fate of the unconditional altruists this thesis considers, with his self-compassion subordinate to his altruism ultimately leading to his demise without having passed down his genetic inheritance. However, his actions have led to numerous lives being spared; thus he has in fact, like the altruists in this model, improved the overall survivability of his kind in the harsh and miserable environment that Hugo has painted around him. In the end Valjean’s greatest foe describes him as “a benevolent malefactor, merciful, gentle, helpful, [...] preferring to ruin himself rather than to ruin his enemy, saving him who had smitten him, kneeling on the heights of virtue, more nearly akin to an angel than to a man” [18]. He and his altruism probably inspired others, giving him a cultural, if not genetic, inheritance.

APPENDIX **A**

Correlation Data

	cbc	fa	fm	los	l	mc	afdf	afa	afna
child_bearing_cost (cbc)	1.0***	-0.84***	0.0	0.0	0.0	0.0	0.55***	0.45***	-0.5***
final_agents (fa)	-0.84***	1.0***	0.2***	0.0	0.02	0.0	-0.61***	-0.52***	0.62***
finding_max (fm)	0.0	0.2***	1.0***	0.0	-0.0	0.0	0.31***	-0.02	0.29***
level_of_sacrifice (los)	0.0	0.0	0.0	1.0***	-0.0	0.0	-0.0	-0.15***	-0.01
lifeexpectancy (l)	0.0	0.02	-0.0	-0.0	1.0***	-0.0	0.14***	-0.02	0.03
mutation_chance (mc)	0.0	0.0	0.0	0.0	-0.0	1.0***	-0.0	-0.38***	0.45***
avg_food_distribution_factor (afdf)	0.55***	-0.61***	0.31***	-0.0	0.14***	-0.0	1.0***	0.41***	-0.32***
avg_fitness_alt (afa)	0.45***	-0.52***	-0.02	-0.15***	-0.02	-0.38***	0.41***	1.0***	-0.77***
avg_fitness_non_alt (afna)	-0.5***	0.62***	0.29***	-0.01	0.03	0.45***	-0.32***	-0.77***	1.0***

Table A.1: Correlations for the benchmark model.

	afg	cbc	fa	fm	los	l	mc	afdf	afa	afna
allow_fake_greenbeards (afg)	1.0***	-0.0	-0.17***	-0.0	0.0	-0.0	0.0	0.41***	-0.26***	-0.26***
child_bearing_cost (cbc)	-0.0	1.0***	-0.73***	-0.0	0.0	0.0	0.0	0.53***	0.32***	0.1***
final_agents (fa)	-0.17***	-0.73***	1.0***	0.35***	0.0	0.07***	-0.0	-0.6***	-0.32***	0.22***
finding_max (fm)	-0.0	-0.0	0.35***	1.0***	0.0	0.0	0.0	-0.18***	-0.01	0.25***
level_of_sacrifice (los)	0.0	0.0	0.0	0.0	1.0***	0.0	-0.0	-0.03**	-0.09***	0.01
lifeexpectancy (l)	-0.0	0.0	0.07***	0.0	0.0	1.0***	0.0	0.08***	-0.01	0.1***
mutation_chance (mc)	0.0	0.0	-0.0	0.0	-0.0	0.0	1.0***	0.02*	-0.26***	0.27***
avg_food_distribution_factor (afdf)	0.41***	0.53***	-0.6***	-0.18***	-0.03**	0.08***	0.02*	1.0***	-0.04**	-0.05***
avg_fitness_alt (afa)	-0.26***	0.32***	-0.32***	-0.01	-0.09***	-0.01	-0.26***	-0.04**	1.0***	0.07***
avg_fitness_non_alt (afna)	-0.26***	0.1***	0.22***	0.25***	0.01	0.1***	0.27***	-0.05***	0.07***	1.0***

Table A.2: Correlations for the greenbeard model.

	cbc	fa	fm	los	l	mr	mc	afdf	afa	afna
child_bearing_cost (cbc)	1.0***	-0.78***	-0.0	0.0	-0.0	-0.0	0.0	0.5***	0.33***	-0.03***
final_agents (fa)	-0.78***	1.0***	0.32***	-0.01	0.12***	-0.01	-0.0	-0.52***	-0.35***	0.25***
finding_max (fm)	-0.0	0.32***	1.0***	0.0	-0.0	0.0	-0.0	0.34***	0.14***	0.27***
level_of_sacrifice (los)	0.0	-0.01	0.0	1.0***	-0.0	0.0	0.0	-0.0	-0.04***	-0.02*
lifeexpectancy (l)	-0.0	0.12***	-0.0	-0.0	1.0***	-0.0	0.0	0.06***	-0.1***	0.1***
min_relationship (mr)	-0.0	-0.01	0.0	0.0	-0.0	1.0***	0.0	0.06***	0.14***	0.04***
mutation_chance (mc)	0.0	-0.0	-0.0	0.0	0.0	0.0	1.0***	-0.01	-0.23***	-0.08***
avg_food_distribution_factor (afdf)	0.5***	-0.52***	0.34***	-0.0	0.06***	0.06***	-0.01	1.0***	0.47***	0.15***
avg_fitness_alt (afa)	0.33***	-0.35***	0.14***	-0.04***	-0.1***	0.14***	-0.23***	0.47***	1.0***	0.04***
avg_fitness_non_alt (afna)	-0.03***	0.25***	0.27***	-0.02*	0.1***	0.04***	-0.08***	0.15***	0.04***	1.0***

Table A.3: Correlations for the kin selection model.

	cbc	fa	fm	los	l	mc	afdf	afa	afna	ar
child_bearing_cost (cbc)	1.0***	-0.81***	-0.0	0.0	0.0	0.0	-0.15***	-0.07***	-0.42***	-0.59***
final_agents (fa)	-0.81***	1.0***	0.28***	-0.0	0.08***	0.0	0.17***	0.16***	0.48***	0.79***
finding_max (fm)	-0.0	0.28***	1.0***	-0.0	0.0	0.0	-0.2***	0.26***	0.08***	0.4***
level_of_sacrifice (los)	0.0	-0.0	-0.0	1.0***	0.0	-0.0	0.02	0.01	-0.02	0.03
lifeexpectancy (l)	0.0	0.08***	0.0	0.0	1.0***	0.0	-0.26***	-0.13***	-0.15***	0.26***
mutation_chance (mc)	0.0	0.0	0.0	-0.0	0.0	1.0***	-0.04*	0.13***	0.36***	0.07***
avg_food_distribution_factor (afdf)	-0.15***	0.17***	-0.2***	0.02	-0.26***	-0.04*	1.0***	-0.01	0.31***	0.02
avg_fitness_alt (afa)	-0.07***	0.16***	0.26***	0.01	-0.13***	0.13***	-0.01	1.0***	-0.03	0.44***
avg_fitness_non_alt (afna)	-0.42***	0.48***	0.08***	-0.02	-0.15***	0.36***	0.31***	-0.03	1.0***	0.26***
avg_reputation (ar)	-0.59***	0.79***	0.4***	0.03	0.26***	0.07***	0.02	0.44***	0.26***	1.0***

Table A.4: Correlations for the reputation model.

	cbc	fa	fm	gn	los	l	mr	mc	afdf	afa	afna
child_bearing_cost (cbc)	1.0***	-0.65***	-0.0	-0.0	0.0	-0.0	0.0	-0.0	0.79***	0.1***	0.04***
final_agents (fa)	-0.65***	1.0***	0.5***	-0.02	0.01	0.14***	0.02	-0.0	-0.81***	0.32***	0.34***
finding_max (fm)	-0.0	0.5***	1.0***	-0.0	-0.0	-0.0	0.0	0.0	-0.26***	0.6***	0.37***
group_number (gn)	-0.0	-0.02	-0.0	1.0***	0.0	0.0	0.0	-0.0	0.02	-0.04**	-0.02
level_of_sacrifice (los)	0.0	0.01	-0.0	0.0	1.0***	0.0	-0.0	-0.0	-0.05***	0.07***	0.02
lifeexpectancy (l)	-0.0	0.14***	-0.0	0.0	0.0	1.0***	0.0	-0.0	0.01	0.09***	0.08***
migration_rate (mr)	0.0	0.02	0.0	0.0	-0.0	0.0	1.0***	-0.0	-0.01	0.03*	0.02
mutation_chance (mc)	-0.0	-0.0	0.0	-0.0	-0.0	-0.0	-0.0	1.0***	0.06***	-0.02	0.43***
avg_food_distribution_factor (afdf)	0.79***	-0.81***	-0.26***	0.02	-0.05***	0.01	-0.01	0.06***	1.0***	-0.07***	-0.04***
avg_fitness_alt (afa)	0.1***	0.32***	0.6***	-0.04**	0.07***	0.09***	0.03*	-0.02	-0.07***	1.0***	0.3***
avg_fitness_non_alt (afna)	0.04***	0.34***	0.37***	-0.02	0.02	0.08***	0.02	0.43***	-0.04**	0.3***	1.0***

Table A.5: Correlations for the group model.

	cbc	fa	fm	gn	los	l	mr	mc	afdf	afa	afna
child_bearing_cost (cbc)	1.0***	-0.66***	0.0	0.0	-0.0	-0.0	0.0	-0.0	0.78***	0.1***	0.02
final_agents (fa)	-0.66***	1.0***	0.47***	-0.04***	0.01	0.14***	0.04***	0.0	-0.81***	0.29***	0.34***
finding_max (fm)	0.0	0.47***	1.0***	0.0	0.0	0.0	-0.0	0.0	-0.27***	0.56***	0.36***
group_number (gn)	0.0	-0.04***	0.0	1.0***	0.0	0.0	0.0	0.0	0.04***	-0.06***	-0.04***
level_of_sacrifice (los)	-0.0	0.01	0.0	0.0	1.0***	0.0	0.0	0.0	-0.05***	0.05***	0.02
lifeexpectancy (l)	-0.0	0.14***	0.0	0.0	0.0	1.0***	-0.0	0.0	0.0	0.07***	0.08***
migration_rate (mr)	0.0	0.04***	-0.0	0.0	0.0	-0.0	1.0***	0.0	-0.03**	0.07***	0.04**
mutation_chance (mc)	-0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0***	0.05***	-0.02	0.42***
avg_food_distribution_factor (afdf)	0.78***	-0.81***	-0.27***	0.04***	-0.05***	0.0	-0.03**	0.05***	1.0***	-0.1***	-0.06***
avg_fitness_alt (afa)	0.1***	0.29***	0.56***	-0.06***	0.05***	0.07***	0.07***	-0.02	-0.1***	1.0***	0.29***
avg_fitness_non_alt (afna)	0.02	0.34***	0.36***	-0.04**	0.02	0.08***	0.04**	0.42***	-0.06**	0.29***	1.0***

Table A.6: Correlations for the culture model.

Bibliography

- [1] Christoph Adami. *Simulating evolution: how close do computer models come to reality?* 6.10.2019. URL: <https://theconversation.com/simulating-evolution-how-close-do-computer-models%5C-come-to-reality-57538> (visited on 10/08/2021).
- [2] J. McKenzie Alexander. *The structural evolution of morality*. 1. publ., transferred to digital printing. Cambridge [u.a.]: Cambridge Univ. Press, 2009. ISBN: 978-0-521-87032-0.
- [3] Eckhart Arnold. *Explaining altruism. A simulation-based approach and its limits*. eng. Vol. Bd. 11. Practical philosophy. Heusenstamm: Ontos-Verl., 2008. 310 pp. ISBN: 9783868380071.
- [4] Robert M. Axelrod. *The evolution of cooperation*. eng. rev. ed. New York, NY: Basic Books, 2006. 241 pp. ISBN: 0-465-00564-0. URL: <http://www.loc.gov/catdir/enhancements/fy0834/2008297795-b.html>.
- [5] Laurence Belcher and Philip Madgwick. *Where does altruism come from? Discovery of 'greenbeard' genes could hold the answer*. 14.11.2020. URL: <https://theconversation.com/where-does-altruism-come-from-discovery-of-greenbeard-%5C%20genes-could-hold-the-answer-123208> (visited on 11/30/2021).
- [6] Charles Darwin. *The descent of man and selection in relation to sex*. eng. Digitally print. vers.; [Nachdr. der Ausg.] London 1871. Vol. 1. Cambridge library collection. Cambridge: Cambridge Univ. Press, 2009. 423 pp. ISBN: 9781108005098.
- [7] Richard Dawkins. *The selfish gene*. eng. 2. ed., 30th anniversary ed. Oxford: Oxford Univ. Press, 2009. 360 pp. ISBN: 0199291144.
- [8] Jun Dong and Steve Horvath. "Understanding network concepts in modules". eng. In: *BMC Systems Biology* 1.1 (2007). Journal Article Research Support, N.I.H., Extramural Research Support, Non-U.S. Gov't, p. 24. ISSN: 1752-0509. DOI: 10.1186/1752-0509-1-24. eprint: 17547772. URL: <https://bmcsystbiol.biomedcentral.com/articles/10.1186/1752-0509-1-24>.
- [9] Encyclopedia Britannica. *Evolution*. URL: <https://www.britannica.com/science/biology/Evolution> (visited on 01/27/2022).
- [10] Encyclopedia Britannica. *Hamilton's rule*. URL: <https://www.britannica.com/science/Hamiltons-rule> (visited on 11/05/2021).
- [11] Encyclopedia Britannica. *Law of large numbers*. URL: <https://www.britannica.com/science/law-of-large-numbers> (visited on 01/04/2022).

- [12] Ernst Fehr and Urs Fischbacher. "Human Altruism – Proximate Patterns and Evolutionary Origins". In: *Analyse & Kritik* 27 (2005). URL: <https://www.semanticscholar.org/paper/Human-Altruism-%E2%80%93-Proximate-Patterns-and-Origins-Fehr-Fischbacher/907b7f8ec5f385e9a07081f79100ccdd22d8904>.
- [13] Robert H. Frank. "Altruists with Green Beards: Still Kicking?" In: *Analyse & Kritik* 27.1 (2005), pp. 85–96. DOI: 10.1515/auk-2005-0104.
- [14] Herbert Gintis. "Strong reciprocity and human sociality". eng. In: *Journal of theoretical biology* 206.2 (2000). Journal Article Research Support, Non-U.S. Gov't, pp. 169–179. ISSN: 0022-5193. DOI: 10.1006/jtbi.2000.2111. eprint: 10966755.
- [15] Herbert Gintis et al. "Explaining altruistic behavior in humans". In: *Evolution and Human Behavior* (2003). URL: <https://www.semanticscholar.org/paper/Explaining-altruistic-behavior-in-humans-Gintis-Bowles/8ba6b4fa72b4809732cf61265088ba9d2e1a9b31>.
- [16] Aric A. Hagberg, Daniel A. Schult, and Pieter J. Swart. "Exploring Network Structure, Dynamics, and Function using NetworkX". In: *Proceedings of the 7th Python in Science Conference*. Ed. by Gaël Varoquaux, Travis Vaught, and Jarrod Millman. Pasadena, CA USA, 2008, pp. 11–15.
- [17] W. D. Hamilton. "The genetical evolution of social behaviour. I". In: *Journal of theoretical biology* 7.1 (1964). PII: 0022519364900384, pp. 1–16. ISSN: 0022-5193. DOI: 10.1016/0022-5193(64)90038-4.
- [18] Victor Hugo. *Les Misérables Complete in Five Volumes*. Trans. Isabel F. Hapgood. Judith Boss and David Widger. 2008. URL: <https://www.gutenberg.org/files/135/old/135-h.htm>. 2019-05-19.
- [19] Victor Hugo. *Les misérables Tome II*. 2006. URL: <https://www.gutenberg.org/files/17493/17493-h/17493-h.htm>.
- [20] Jackie Kazil, David Masad, and Andrew Crooks. "Utilizing Python for Agent-Based Modeling: The Mesa Framework". In: *Social, Cultural, and Behavioral Modeling*. Ed. by Robert Thomson et al. Cham: Springer International Publishing, 2020, pp. 308–317. ISBN: 978-3-030-61255-9.
- [21] Max Planck Institute for Informatics. *NetworkAnalyzer Help*. 18.05.2018. URL: <https://med.bioinf.mpi-inf.mpg.de/netanalyzer/help/2.7/index.html#settings> (visited on 01/23/2022).
- [22] Itsuki Noda et al. "Roadmap and research issues of multiagent social simulation using high-performance computing". en. In: *Journal of Computational Social Science* 1.1 (2018). jan, pp. 155–166. ISSN: 2432-2725. DOI: 10.1007/s42001-017-0011-8. (Visited on 03/06/2021).
- [23] Samir Okasha. *Biological Altruism*. 2003. URL: <https://plato.stanford.edu/entries/altruism-biological/> (visited on 01/11/2021).
- [24] R. Boyd et al. "The evolution of altruistic punishment". In: *Proceedings of the National Academy of Sciences of the United States of America* (2003). URL: <https://www.semanticscholar.org/paper/The-evolution-of-altruistic-punishment-Boyd-Gintis/elcb5b49698f6bc5b74baef9bed662db0f42b864>.
- [25] Peter J. Richerson. *Not By Genes Alone. How Culture Transformed Human Evolution*. eng. Chicago, IL: University of Chicago Press, 2008. 343 pp. ISBN: 9780226712840. URL: <http://gbv.eblib.com/patron/FullRecord.aspx?p=481218>.

- [26] Abbas Salavaty, Mirana Ramialison, and Peter D. Currie. "Integrated Value of Influence: An Integrative Method for the Identification of the Most Influential Nodes within Networks". eng. In: *Patterns* 1.5 (2020). Journal Article The authors declare no competing interests., p. 100052. ISSN: 2666-3899. DOI: 10.1016/j.patter.2020.100052. eprint: 33205118. URL: <https://www.sciencedirect.com/science/article/pii/S2666389920300635>.
- [27] Falk Schreiber. "Characteristic Path Length". en. In: *Encyclopedia of Systems Biology*. Springer, New York, NY, 2013, p. 395. DOI: 10.1007/978-1-4419-9863-7_1460. URL: https://link.springer.com/referenceworkentry/10.1007%2F978-1-4419-9863-7_1460.
- [28] Joan B. Silk. "Reciprocal altruism". eng. In: *Current biology : CB* 23.18 (2013). Journal Article, R827-8. DOI: 10.1016/j.cub.2013.03.052. eprint: 24070439. URL: [https://www.cell.com/current-biology/pdf/S0960-9822\(13\)00354-0.pdf](https://www.cell.com/current-biology/pdf/S0960-9822(13)00354-0.pdf) (visited on 08/11/2021).
- [29] The Economist. *Agents of change*. 2010. URL: <https://www.economist.com/finance-and-economics/2010/07/22/agents-of-change> (visited on 11/09/2021).
- [30] Robert L. Trivers. "The Evolution of Reciprocal Altruism". In: *The Quarterly Review of Biology* 46.1 (1971), pp. 35-57. ISSN: 0033-5770. DOI: 10.1086/406755.
- [31] Michael Vlerick. "Explaining human altruism". En;en. In: *Synthese* (2020). PII: 2890, pp. 1-19. ISSN: 1573-0964. DOI: 10.1007/s11229-020-02890-y. URL: <https://link.springer.com/article/10.1007/s11229-020-02890-y>.
- [32] Hal Whitehead et al. "The reach of gene-culture coevolution in animals". eng. In: *Nature Communications* 10.1 (2019). Journal Article Review, p. 2405. ISSN: 2041-1723. DOI: 10.1038/s41467-019-10293-y. eprint: 31160560. URL: <https://www.nature.com/articles/s41467-019-10293-y>.
- [33] Kevin J.S. Zollman. *Review: Explaining Altruism: A Simulation-Based Approach and its Limits*. 21.09.2021. URL: <https://ndpr.nd.edu/reviews/explaining-altruism-a-simulation-based-approach-and-its%5C-limits/> (visited on 09/22/2021).