Multi-Agent Simulation of Altruistic Behaviour in Predator-Prey Populations

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April 29, 2020

Personal Statement

This was a new project that I decided to undertake due to my own interest in the subject. I was inspired by an educational video series I had seen online entitled ‘Primer’ [Helps. J., 2018]. The series uses a simple simulation to depict the process of natural selection as well as discussing the concept of altruistic behaviour as a genetic strategy. I also had an interest in evolutionary computing and hoped to use this project to improve my programming skills, so I brought the idea to my supervisor. He suggested that I try and find some scientific papers on the subject and this led me to find several studies on predator-prey simulations as well as stochastic studies on altruism. I used a selection of these studies as the basis for much of my work. My supervisor helped me to find a direction to take the project and made sure that I focused on the aspects that were important for a scientific simulation. I constructed all of the simulations used in this project myself using a programme called ‘Processing’. Processing is an open-source graphical library with an integrated development environment based on the Java programming language. The simulations were based on the models used in the previous studies with the aim of adapting them to conduct my own studies on altruistic behaviour. As stated on my declaration of Covid-19 impact, I was unable to conduct any studies on altruism. I did manage to construct three simulations and I have discussed the different methodologies and possible altruistic variants in this report. I found that, when modelling a predator-prey population, the behaviour of the system is sensitive to small changes and it can be difficult to create a stable environment. However, I’m confident that with more time, I would have been able to produce a suitable model to begin introducing altruistic behaviour.

27/04/2020

Summary

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Ollie Dickson
29/04/2020

There is much debate in the scientific community as to the cause of altruistic behaviour observed in nature. Over the years, there have been many studies using different methodologies to try and give quantifiable explanations, some of which are discussed in the literature review of this report. Several of the papers on this subject use predator-prey populations as their test case, creating simulations to test their theories and often using the predators as potential altruists. The aim of this report was to build simulations based on these previous works and adapt them to experiment with altruistic behaviour in the prey population.

Three different simulations were created, two of which would be suitable to take forward for altruistic research. However, due to unforeseen conditions forcing the university to cease all project work, the simulations could not be adapted to introduce altruistic behaviour. Instead, the different methodologies behind each simulation are discussed in detail, as well as the behavioural tendencies of each system and possible variants that could be used to experiment with altruistic behaviour in the prey population. The two possible altruist models used different methods to simulate predator-prey populations. One used a cellular automaton structure, which consists of a lattice of cells that can change state. The different states determine whether a cell is predator, prey or empty. This model was able to support large populations and the interactions were determined by a few probability variables making it fairly simple to control the system behaviour. The other simulation consisted of a 2-dimensional mesh environment, in which, predators and prey would move around as individual objects. This simulation was more adaptable, and the predator and prey objects had localised variables representing real-life factors such as age and hunger to determine their behaviour. However, the complex logic structure and the functions required to control interactions between objects make this method more computationally demanding. This meant that there was a tighter limit on population size when compared to the cellular model. Complexity also makes it more difficult to control the system behaviour as there are many factors that can influence the result.

The cellular model would have been the most appropriate simulation to take forward and conduct altruistic studies, because it runs smoothly and would likely produce reliable results. Although, the spatial model has several advantages, producing a stable model may have been difficult in the given project time frame.

Declaration of Covid-19 Impact

Due to the Covid-19 situation, the university was forced to cease all ongoing project work, meaning that I was unable to continue working on my simulations. At this point, I was in the process of adjusting the simulation parameters to try and produce a stable model that could be adapted for altruistic conditions. This was extremely disappointing as I had put a lot of time into designing each model and I would now be unable to achieve the main aims of the project. As I had not managed to conduct any experimentation on altruistic behaviour, I adapted the focus of the project to discuss the existing simulations and the limited data that I had managed to collect.

School of Engineering – Incident Management

Project Status Declaration

This form is to be used in unforeseen circumstances necessitating the immediate cessation of practical project work during semester. It acts as a record of the current status of practical work (whether it be laboratory based, computational, or fieldwork). Due to circumstances, ***no further practical work is to be continued, regardless of the type of work or current status***. This ensures equality of opportunity for all students, regardless of the type of work being undertaken.

The form must be completed during a meeting with the student, and verified by the student, supervisor, and either the thesis examiner, or a second supervisor. **Any practical work beyond that stated in this form will not be considered in the final project assessment.**

A copy of the signed form must be included in the final project submission.

Name: Ollie Dickson ____________________________ Student number: s1530699 _____________

Work completed

All items of wholly, or partially completed work must be listed, indicating the percentage completion for each task. Reference can be made to an attached project plan if appropriate. **Please take care to provide a full detailed list of all work done.**

Three distinct simulations built with accompanying population data.

1. Spatial model with vectoral movement of single population with variable traits
   - Conducted a series of experiments and collected data on population size as well as the evolving traits of the individuals

2. Cellular automaton model with three-state cells depicting a predator prey population
   - Conducted a series of experiments collecting population data under varying conditions

3. Simplified spatial model of predator prey population
   - Conducted a series of experiments collecting population data under varying conditions

The simulations were completed and functioning, but the variables needed to be adjusted so the populations were more stable. In this sense the 1st simulation could be considered to be 100% complete, the 2nd 90% complete and the 3rd 80% complete.

Work not commenced

Any items of outstanding work that have not been started should be listed here.

I was in the process of adapting the third simulation to make the population boom bust cycles more stable so that I could begin designing altruism studies. Once stable conditions of the second and/or third simulations had been finalised, I would have proceeded to design variants of the simulation that incorporated altruistic behaviour. As I did not reach this stage, none of the altruistic studies intended for the project have been conducted.

Plans for completing project submission

State revised plans for producing the final project submission in the absence of any additional practical work beyond that already listed. For example, this may include literature based research, or more in-depth analysis of results already obtained. Dates for completion of each element should be given.

In the absence of any additional practical work, I will change the focus of my final report to discuss in detail the different simulation techniques I have experimented with so far and their respective merits. I will also discuss the possible strategies for investigating altruistic behaviour I would have implemented in each simulation. I will support these sections with some additional research.

Declaration

To the best of our knowledge, this form is an accurate record of the project status and revised

completion plans on 20/03/2020 (date)

Student: ____________ (Signature)

Supervisor: Livio Gibelli

Second sup./Thesis examiner: ____________

Acknowledgements

I would like to pay my special regards to my project supervisor, Livio Gibelli, who has helped guide my research and decision making and has also shown great interest and support for the project.

I would also like to show my gratitude to Daniel Shiffman, a professor at New York University Tisch School of the Arts, who has provided free books and tutorials online to teach programming. Most of the programming techniques used to build these simulations, I learned from his book, 'The Nature of Code'.

Contents

1 Notation

Animat – A general term to describe an individual in a predator-prey simulation

Fitness – a term used in evolutionary algorithms to describe the quality of an individual

Mutation – a random change applied to a specific individual's characteristics as part of an evolutionary programme

Cellular Automata – a discrete grid of cells, each cell having a finite number of states that can be used to produce patterns or for mathematical study

Kinship – used in nature and evolutionary computing to refer to the relative similarity between two individuals genealogy

2 Word Count by Chapters

Introduction: 326

Aims: 36

Literature Survey: 2298

Preliminary Simulation: 1185

Cellular Automaton Model: 1139

Simplified Spatial Model: 1524

Conclusions: 440

Total Word Count: 6948

3 Introduction

Altruism is debated as an emergent property in nature as it is rarely observed, and it is difficult to discern the cause of the behaviour. Altruistic behaviour takes several different forms and can occur between kin, unrelated individuals and even between species. Studies have been conducted to investigate the emergence of altruism using evolutionary programming techniques. The initial aim of this project was to create a multi-agent system and study the development of altruistic behaviours in multi species predator-prey populations. First, I would try to create a stable model, reproducing the Lotka-Volterra boom-bust limit cycles typically used to model predator-prey relationships [Goel. N. S., et al, 1971], then I would design some altruistic parameters and begin running experiments. Most of the previous studies on the subject seem to have focused on altruism in the predator population describing them as the higher life form. I intended on using my simulation to study altruism in the prey population, such as the case of vervet monkeys that give alarm calls to warn fellow monkeys of the presence of predators [Cheney. D. L., Seyfarth. R. M., 1990]. The aim of my experimentation was to build upon the work that has already been done on the subject and to better understand the phenomenon and the factors that enable or disable its emergence. I decided to use an agent-based model as the emergence of altruism is fairly complex and I think it is important to try and reproduce the process of natural selection as accurately as possible. A multi-agent system will allow for interactions to occur naturally and generations to evolve dynamically.

Unfortunately, due to the current situation caused by the COVID-19 outbreak, the university was forced to cease all ongoing project work. Therefore, I was unable to complete any studies on altruistic behaviour. I did, however, manage to construct three simulations using different techniques which I will discuss in detail in this report. My adjusted project aims are given below.

4 Aims

- Create three distinct simulations to model predator-prey populations
- Discuss the different experimental methods and their results and evaluate their respective merits for this task
- Explain how each simulation could be adapted to incorporate altruistic behaviour

5 Literature Survey

5.1 Natural Selection and Altruistic Behaviour

The theory of evolution by natural selection was conceived in the 19th century independently by Charles Darwin and Alfred Russel Wallace. They worked together to produce several scientific journals on the subject. The process of natural selection was detailed in Darwin's book, 'On the Origin of Species' [Darwin. C., 1859]. The fundamental ideas are as follows: Individuals of a species have variable traits with respect to their physiology, morphology and behaviour. This variation affects their survival and reproduction rates. If these traits can be inherited, the more favourable traits will become more common through successive generations. Our understanding of the process has increased greatly since the work of Darwin and Wallace, with considerable developments in biochemistry and genetic science. One of the more difficult aspects to study, however, is the evolution of behavioural traits as it is only really possible to observe the behaviour of creatures that are alive today.

One behavioural trait that has been heavily debated in past decades is the phenomenon of altruism [Scogings. C., Hawick. K., 2008]. Altruism can be defined as a selfless behaviour/action that will provide benefit to another at no gain to the actor himself, and possibly even to his detriment. Some theories suggest that altruism can develop with the influence of kin selection and similar discriminatory factors [Maynard Smith. J., 1964], while others hold on to the 'selfish gene' theories put forward by Dawkins [1989], regarding altruism as a negligible occurrence. More recent studies have shown that altruism can even develop in conditions where groups form randomly [Fletcher. J. A., Zwick. M., 2004], this behaviour being termed 'pure altruism'. With the aid of modern computing techniques, it is now possible to simulate natural selection processes. Before, arguments were made with little more than speculation, but with the use of evolutionary programming we can see whether altruistic gene carriers can prosper given the right conditions. If those gene carriers come to dominate the model, we can then evaluate the long-term effects that altruism can have on a population.

5.2 Genetic Algorithms

One of the first evolutionary programming techniques to be developed was the genetic algorithm (GA). Genetic algorithms are a specific form of evolutionary algorithm designed to generate high quality solutions to search and optimization problems [Goldberg. D. E., 1989]. GAs were introduced by John Holland in 1960; the method was inspired by the process of Darwinian evolutionary theory and can be a useful tool to model evolution in artificial life systems [Mitchell. M., Forrest. S., 1994]. Generally, a genetic algorithm has a randomly generated population of individuals or solutions to a problem. The 'fitness' of the population is evaluated as the quantitative representation of the quality of an individual. The fittest individuals from the population are selected to breed a new generation. The 'child' population will be formed using a combination of genetic crossover and mutation. Crossover involves taking 50% of the characteristics from each parent and combining them to create the child.

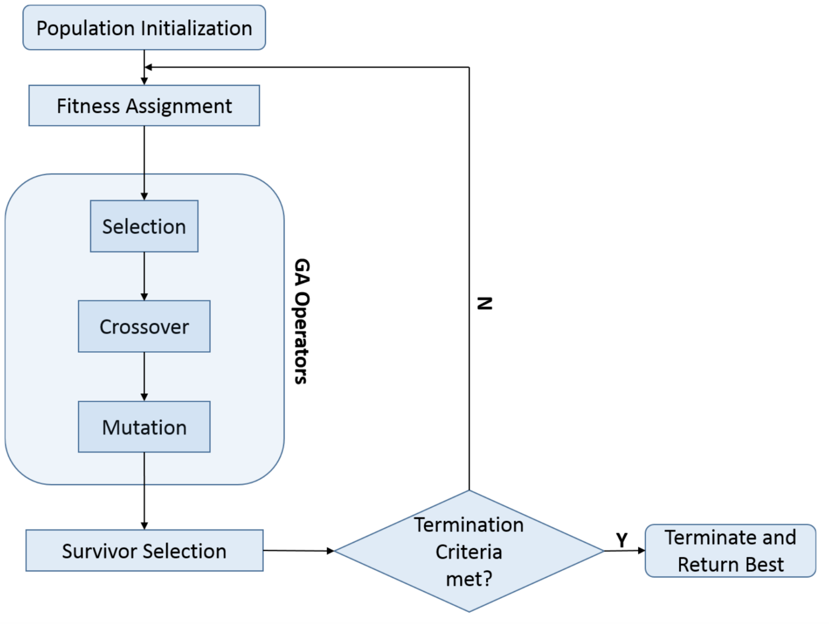

Figure 1: Genetic Algorithms Structure [Deshpande. A., Kumar. M., 2018]

Mutation is a further optional step which involves taking the child DNA code from crossover and applying an additional random change. Whether this occurs to a particular individual is usually determined by a mutation rate, i.e. a percentage chance of occurring [Shiffman. D., 2012]. This process is repeated, as shown in figure 1, so that the fitness of the population will increase over time. In this context, genotype can be considered to describe the encoded 'DNA' of an individual and phenotype might describe how this data is expressed visually. For most genetic algorithm problems there is no phenotype to speak of. GAs are extremely effective for solving optimization problems and though they have often been used to model artificial life systems, they come with some limitations. The standard method has a fixed population size which is replaced each generation. Individuals do not interact and tend to have simple states with coded genotypes but no phenotypes. Though this allows for quick and powerful computation, the lack of interaction can take away from the realism of a simulation.

5.3 Multi-Agent Systems

Multi-agent systems are a more recent computerized system consisting of adaptive, intelligent agents [Alonso. E., Kudenko. D., Kazakov. D., 2003]. This allows for individuals in the system to behave and interact dynamically in an environment. The survival of an individual can be determined by its performance and behaviour based on phenotypes rather than a quantitively defined fitness. This kind of model follows more akin to real life natural selection. Though multi-agent systems bring new useful features for simulating artificial life, it can be desirable to simplify a model in order to produce consistent, verifiable results when conducting scientific studies. Complex multi-agent systems will also be computationally taxing. Some studies, such as the model used by Turner and Kazakov [2003], use a combination

Table 1: MAS *vs*. GA simulation of natural selection

Feature	MAS	GA
Representation of individuals	genotype + phenotype	genotype only
Survival of individuals	deterministic, based on the lifetime interaction with environment	probabilistic, based on genotype's fitness
Population size	unlimited	fixed
Environment resources	limited capacity	use bounded by maximum population size
Preservation of energy	enforced	not considered

Figure 2: Comparative table of MAS and GA methods [Turner. H., Kazakov. D., 2003]

of features from GA and MAS methods. They summarise some of the different features of each method in figure 2.

Simplified MAS models often use 2D mesh grids called cellular automata, greatly simplifying computation. Cellular automata were originally studied in the 1940s and 1950s by mathematicians and computer scientists, but the concept was greatly popularised in 1970 by 'The Game of Life', a creation of the mathematician John Horton Conway [Gardner. M., 1970]. A cellular automaton consists of a discrete grid of cells, each cell having a finite number of states. An initial state is defined for each cell and then subsequent generations are created using a ruleset or mathematical function. The new state for a given cell will be dependent on its current state and the state of the cells in its local 'neighbourhood'. These models are inherently simplistic but can be scaled up to exhibit complex behaviour that allow for detailed mathematical analysis [Wolfram. S., 1983].

5.4 Predictive Models

When designing a biological simulation, it can be useful to compare the results with existing predictive models such as the Lotka-Volterra coupled differential equations [Lotka. A. J., 1925; Volterra. V., 1926]. The non-linear differential equations are often used to describe the dynamics of biological systems, particularly predator-prey relationships. Therefore, they can be used to help validate results from a simulated biological environment. The equations describe the rate of change of the two populations subject to some constant parameters.

$$\frac{dx}{dt} = \alpha x - \beta xy \qquad \frac{dy}{dt} = \delta xy - \gamma y$$

Where x is the number of prey and y is the number of predators. An example of a Lotka-Volterra predator-prey relationship is shown in figure 3. Producing similar boom-bust cycles to these models can help show that there is some realism to a

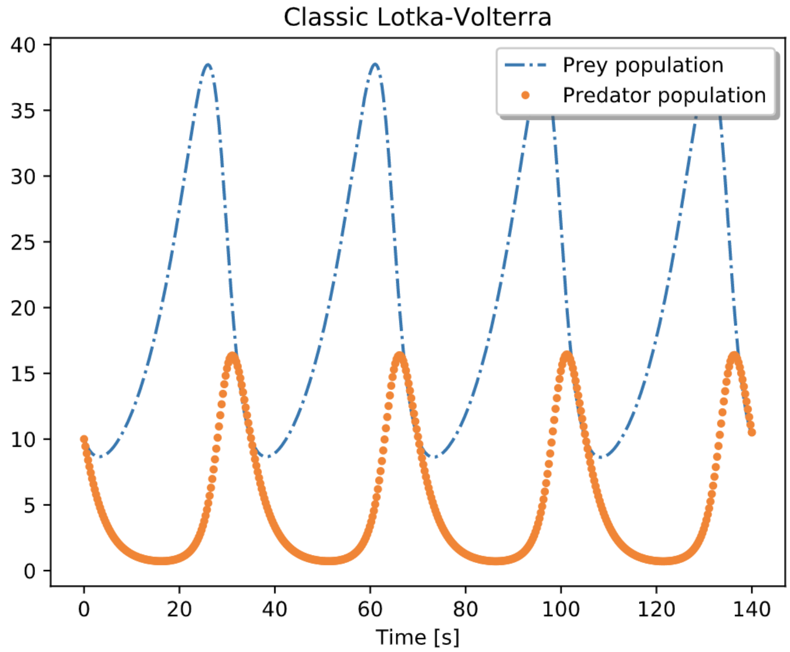

Figure 3: Example of a classic Lotka-Volterra boom-bust cycle [Modelica, 2020]

simulation. The model makes a number of assumptions that may not hold true in nature such as ample food supply for prey, the rate of change of population is proportional to its size and predators have a limitless appetite. However, it is the most widely used model for population dynamics and is frequently used in other fields such as economic theory.

5.5 Altruistic Behavioural Studies

As previously stated, altruism can take many forms and can seem like a fairly abstract concept. But, when conducting a scientific study on the subject, it is important to clearly define how you intend to implement it. Turner and Kazakov's model is a stochastic simulation using kinship-driven sharing functions. Individuals will share energy with one another depending on the degree of kinship between the interacting agents. The model had no spatial dimension and interactions between individuals and their outcomes occur on a probabilistic basis. Each experiment was run with different kinship policies and sharing functions with the aim of evaluating which conditions maintain stable populations of individuals carrying altruist genes. The graphs in figure 4 show the population of altruistic individuals in successive generations.

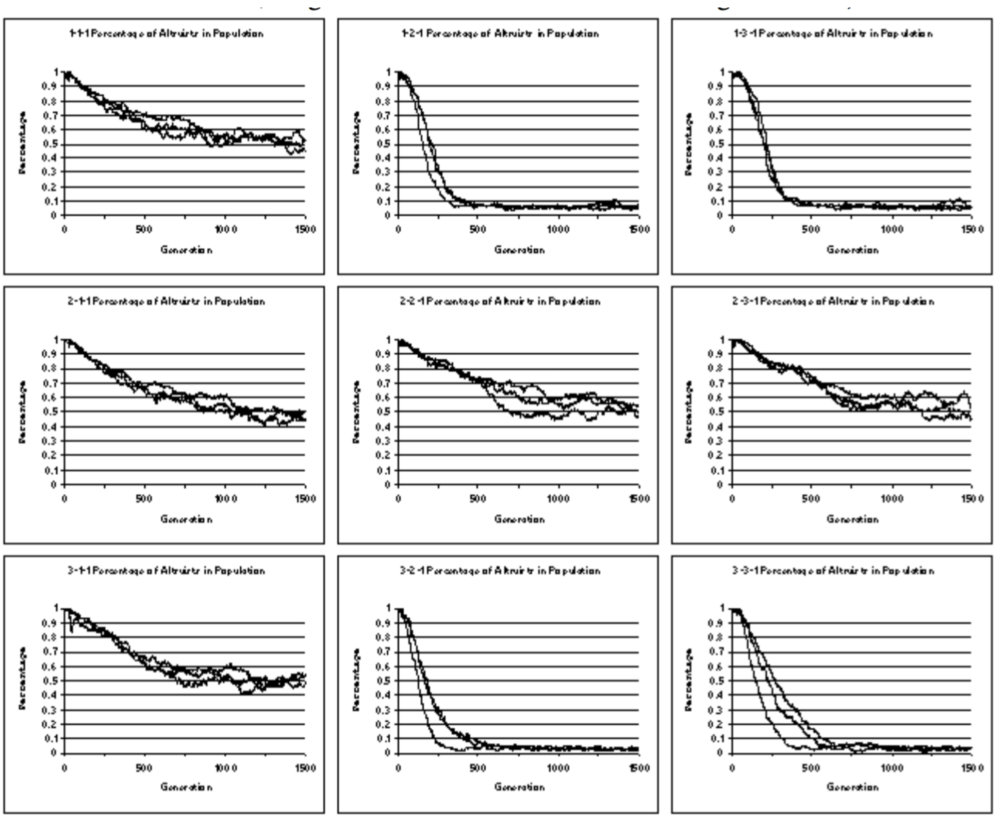

Figure 4: Percentage of altruistic individuals in the population (Columns, from left to right: Royalty, Prediction and Unknown models of kinship recognition. Rows, top to bottom: Communism, Progressive Taxation and Poll Tax sharing functions.)[Turner. H., Kazakov. D., 2003]

The experiments use three different types of kinship policy:

- Royalty model, in which the individuals have a complete knowledge of their genealogy.
- Prediction model, in which they estimate degree of kinship based on the phenotypes of the other.
- Unknown, in which none of this information is available.

They also use three different sharing functions:

- Communism, which equalises the energy levels of individuals with the same genome.
- Poll tax, which defines a fixed amount of energy in the genes of the donor that does not depend on the energy levels of either individual.
- Progressive taxation with a non-taxable allowance, which consists of a simple linear function. $y = \alpha(x - \theta)$ for $x > \theta$; otherwise $y = 0$
  Where y is the energy shared, α is a scaling factor, x is the energy of the donor and θ is the energy of the receiver.

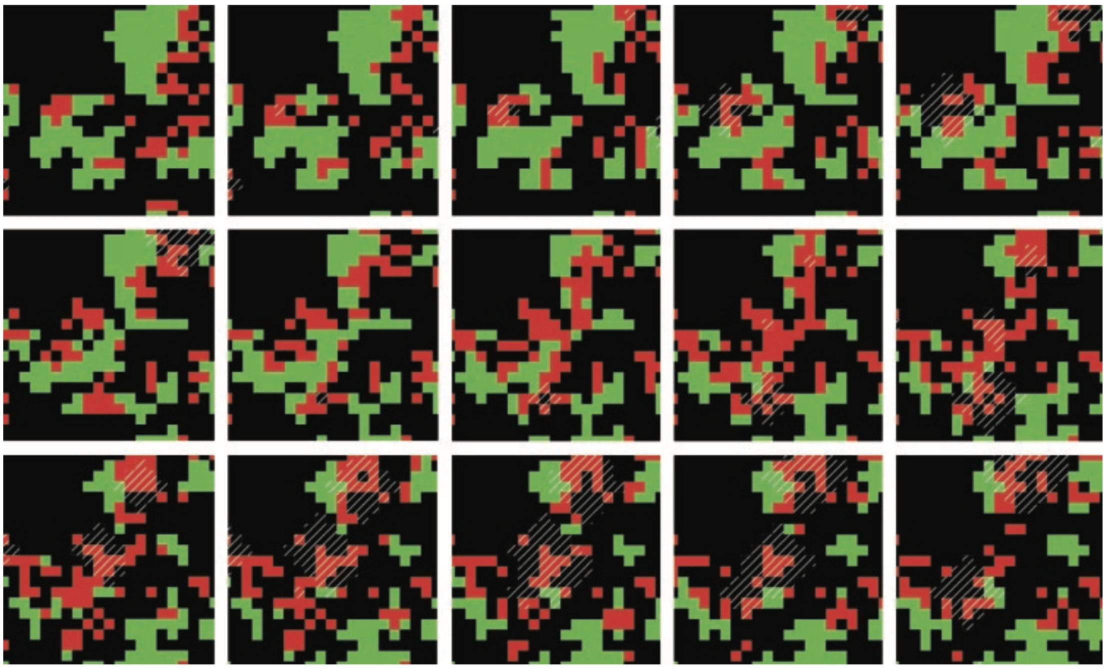

Figure 5: Small area of the lattice at successive time steps (left to right then top to bottom). Black cells are empty, green cells are hosts alone, red cells are hosts in the presence of consumers, and signal is shown as a striped overlay [Werfel. J., Bar-Yam. Y., 2004].

The results show that royalty models where individuals have a complete knowledge of their genealogy ensure that altruistic genes can be selected and maintained. They also show that a progressive taxation sharing policy will also cause altruistic genes to prosper, even when individuals have no knowledge of kinship.

Although this model runs on a stochastic basis, similar studies have been conducted with spatial variants maintaining simplicity by using cellular automaton like environments. One such study, by Werfel and Bar-Yam [2004], models predator-prey populations in which predators can communicate with signals. They use the model, shown in figure 5, to experiment with the evolution of reproductive restraint through social communication. They refer to their predator-prey populations more generally as consumers and hosts respectively. Each square in the mesh can be inhabited by hosts alone, by both hosts and consumers, or by neither. Consumers cannot inhabit a space in the absence of a host. With each time step, the spread and demise of hosts and consumers is decided stochastically. If consumers are surrounded on all sides by more consumers, they will release a signal that travels one space per time step up to a maximum range. The signal implies overpopulation, but the way other consumers react to the signal and to what extent is subject to mutation.

The results of this study support theories that suggest communication-based cooperation is an evolutionary successful strategy. This form of signal-based cooperation is not vulnerable to invasion by noncooperators and communicating individuals are much more likely to become the common ancestor of the entire population.

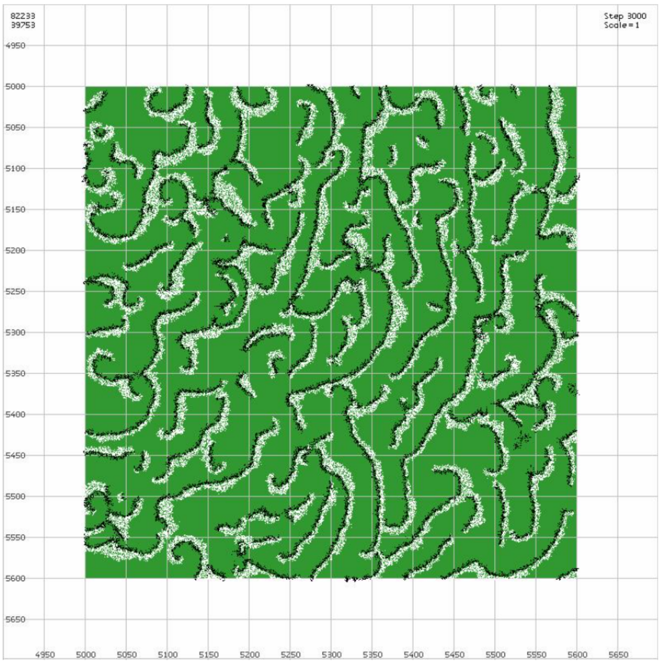

Figure 6: A typical run at step 3000. Predators are black and prey are white. [Scogings. C., Hawick. K., 2008]

Scogings and Hawick [2008] use a different spatial model to study altruism in predator-prey animats. They use the term 'animat' to describe an individual in the simulation. Each animat has a simple state with variables for health, age and position. The energy system is open with the food source for prey being replenished at a given rate defined as the grass value. The simulation runs as a series of discrete time-steps where each animat will check its condition and its surroundings before executing a decision. Similarly, the focus of the study is on altruistic behaviour in the predator population. The method includes no mutation or gene sharing between parents, offspring are simply identical clones of their mothers. There is also no variability in behaviour, simply altruistic or selfish. Altruistic predators will share energy indiscriminately with their neighbours and selfish predators will not. A typical run with only selfish predators is shown in figure 6.

Using the model, they conducted a series of experiments with two different sets of environmental conditions, 'good times' and 'bad times'. The 'good times' experiments had a high grass value, so food resources were plentiful, and in the 'bad times' experiments, food was scarce. They found that, given plentiful food resources, a simulation starting with equal populations of selfish and altruistic predators would always result in the demise of the altruist population. But, in scarce food conditions, altruistic predators were able to prosper and came to dominate the model. This is another example of altruism proving a successful strategy when kinship is not taken into account.

Considering the results of these studies, it is clear that there is a strong case for altruism to evolve naturally given the right conditions. However, altruistic behaviour can take many forms and there is still a lot of room to increase our understanding of how it can be selected as a successful strategy. The nature of the phenomenon requires each study to use very specific fixed parameters in order to obtain meaningful results. Therefore, by using combinations of these methodologies and new methods entirely, the new data will likely produce more significant results. This research can then be accumulated to help build a bigger picture of altruism and its merits as a genetic strategy. The main drive for the animats in the previous studies has been finding food and conserving energy as starvation is the only cause of death other than old age in some examples. By switching the focus to altruistic behaviour in the prey population, the main drive will become the evasion of predators so the simulations may produce very different results.

6 Preliminary Simulation

The first simulation served as an adaptable model in which, I could build up some of the object-oriented framework that could be used in subsequent simulations. The encoded behaviour of the animat class was more complex in this model. Complexity is less desirable for a reliable behavioural study, but it meant that it was easier to visually track what was happening through each generation.

6.1 Method

The rules of the simulation follow closely to the example shown in the Primer video series [Helps. J., 2018]. A single-species population of animats compete for limited food and the traits of their offspring can randomly mutate. At the start of the simulation, an initial population of identical animats spawn in random locations around the edge of the environment. The simulation then runs as a series of day cycles, each day lasting 400 frames. At the start of each day a fixed number of food objects spawn in random locations. To survive the day, an animat must eat at least one food object and return to its starting location. If they eat two food objects they will survive and also produce one offspring. The offspring will have a 10% chance to mutate, in which case, one trait will randomly change by a small amount; otherwise, they will have identical traits to their parent. 10% is an extremely high mutation rate with regard to evolutionary programming standards, but for the purposes of designing these functions, it was beneficial to have the system evolving quickly. Animats have a finite amount of energy, a portion of which is replenished by eating food objects. If an animat runs out of energy before returning home they will stop in place and hence, die at the end of the day. The two traits subject to mutate are the animats maximum speed and their size. Greater maximum speed improves the chances of getting food and returning home, but movement has an energy cost proportional to the square of the current speed. Increased size enables an animat to eat other animats as long as they are 20% larger than their prey (measured in diameter). Eating other animats provides more energy than a food object and eating one animat is sufficient to reproduce at the end of the day. However, size also comes with an energy cost proportional to the cube of the animats diameter.

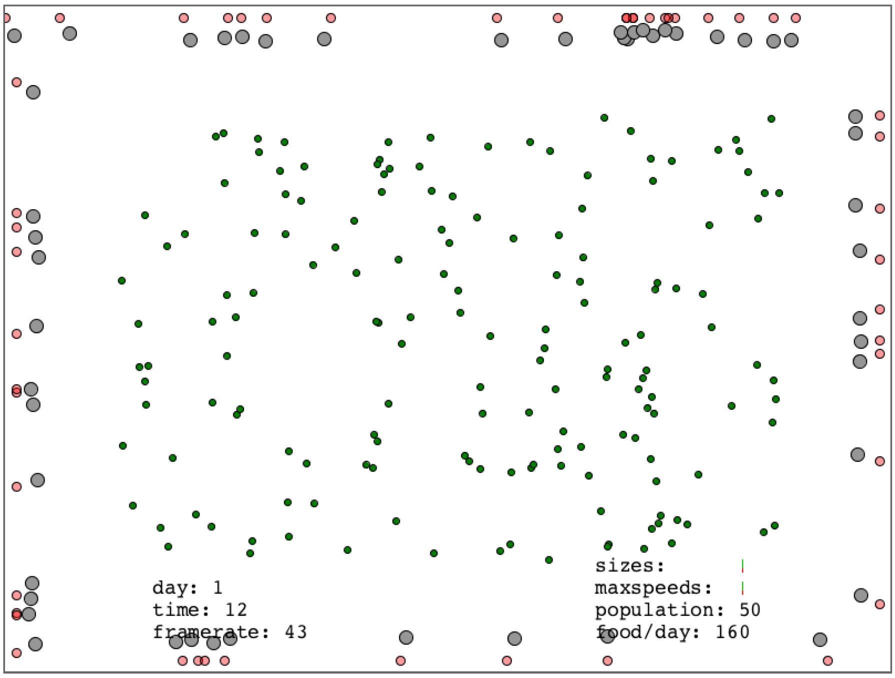

Figure 7: Start of the simulation. The animats are represented by the grey circles, their homes are shown as red circles and the green circles show the food objects. The 'time' displayed shows the number of frames of that particular day.

The animats movements are calculated using velocity and acceleration vectors and similar steering algorithms used in the work of Craig Reynolds [1987]. Figure 8 shows the basic mechanics of the steering algorithms. Each animat will have a desired location, be it a food object, a smaller animat or their home location. They will steer towards this target and accelerate until they reach their specific max speed. There is also a separation algorithm that will cause them to move away from other animats if they are too close. This prevents them from clumping up and occupying the same space.

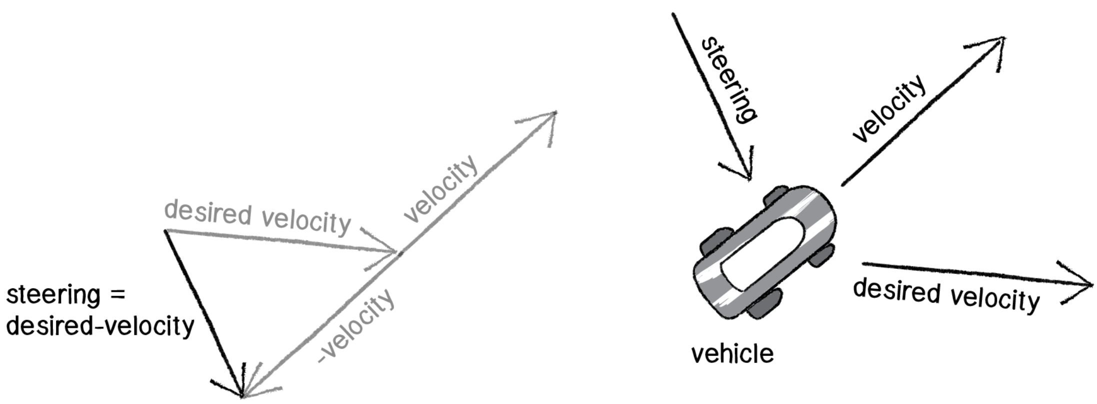

Figure 8: Diagram showing how steering forces are calculated [Shiffman. D., 2012]

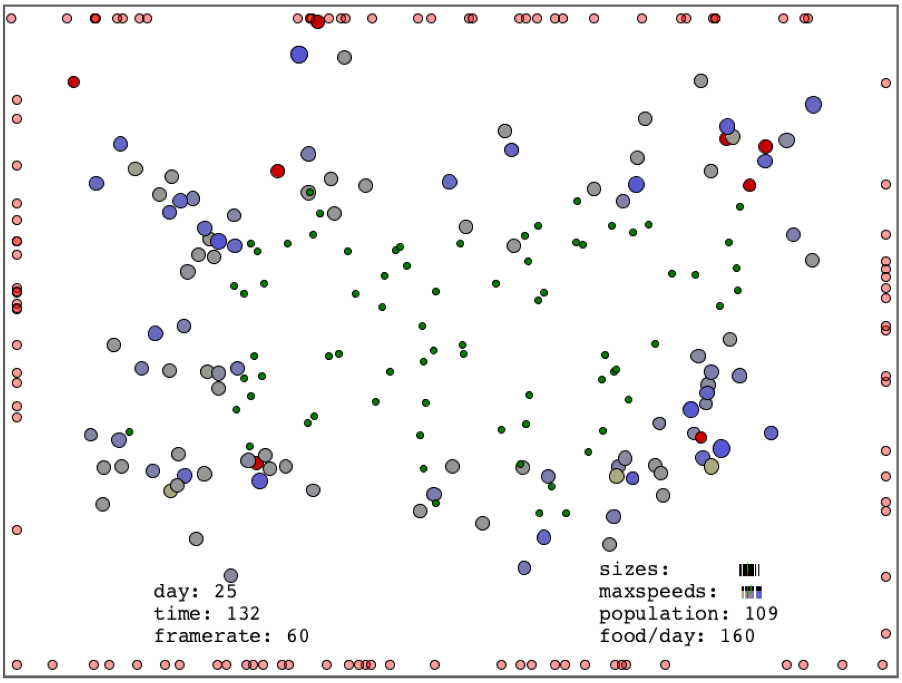

Figure 9: Later stage of the evolving system. The speed of each animat is depicted by its colour (faster animats appear more blue and slower animats appear more green). Animats that have been eaten are shown red.

6.2 Results

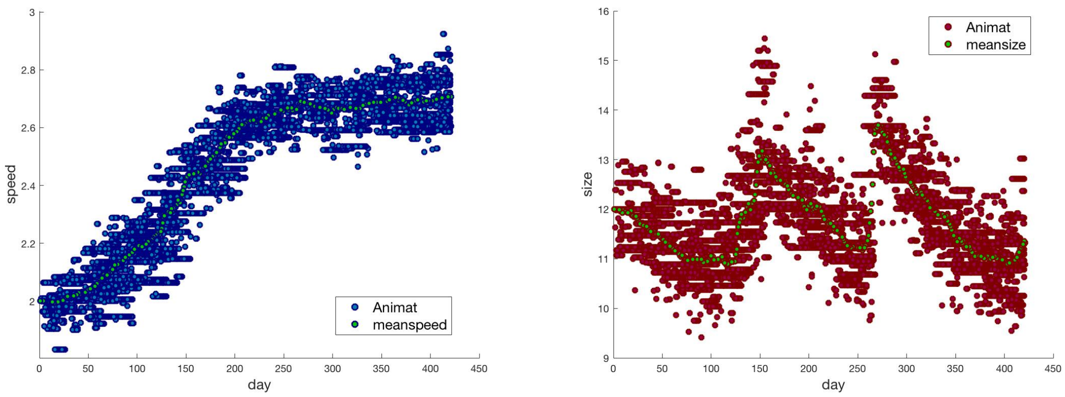

Figure 10: Graphs showing changing speed and size traits in successive generations of animats.

The graphs in figure 10 show how traits can evolve over time. In this case, it is clear that the optimum speed for these conditions is higher than the starting value of 2. As faster animats are selected, the average speed increases until it stabilises at a value of approximately 2.7 after 300 generations. The graph of the animats size produces a fairly chaotic pattern. One explanation is that the average size initially decreases as it is more energy efficient to be small. But when the difference in size

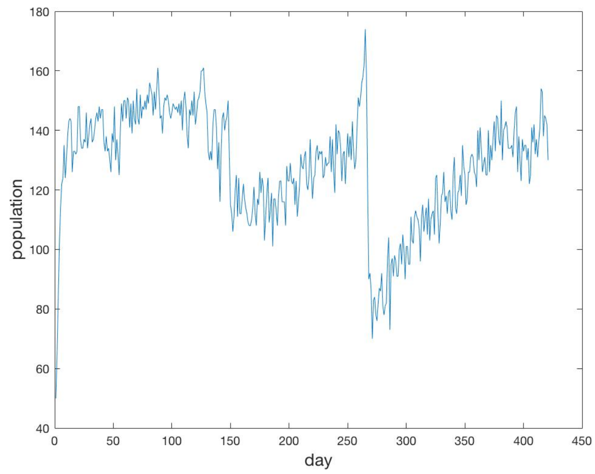

Figure 11: Graph showing the total population in each generation

becomes large enough, the smaller animats are quickly eaten, causing rapid change to the average size. This can also be seen in the graph in figure 11 where the population drops quickly at day 260 as the smaller animats are eaten.

Running the simulation without rendering any of the objects allowed for a higher frame rate and larger populations. The simulation was run for 1500 generations in these new conditions. This actually led to a more unstable population as shown in figure 12. With larger populations and an increased number of food objects per day, the optimum speed seemed to go down with an average speed value closer to 2.3. Between generation 200 and 500, two distinct strategies developed where one group was large and slow and the other was small and quick. Later in the simulation there were often two distinct size groups, but their speeds were similar.

Although it is interesting to see how the simulation reacts to varying conditions, with this method, there are far too many factors that could affect the outcome. It is, therefore, difficult to determine the reasoning behind any trends observed in the behaviour of the system. The rules of the system are quite arbitrary from the perspective of an altruism study as that is not what they were designed for. This setup is better suited for designing mutation functions. The day cycle system made it easier to test these functions as all the offspring were spawned at the same time. However, going forward, I think it would be better for the simulations to run continuously, instead of as a series of discrete days. As the spawn locations were located around the edge of the environment, the animats would get crowded as the population increased. Not only did this make it impossible for some of them to make it home for lack of space, but smaller animats would often be immediately eaten at the start each day. The environment was rectangular which meant that animats spawning in the corners would be less likely to reach food objects. The vectoral movement system is visually realistic and allowed for speed to be used as a variable trait, but it is far too computationally taxing to calculate the velocity and acceleration vectors for each animat. Although, some of these issues could be resolved by adapting the design of the model, it is clear that this system is wholly unsuitable for producing any kind of reliable results. Although this model

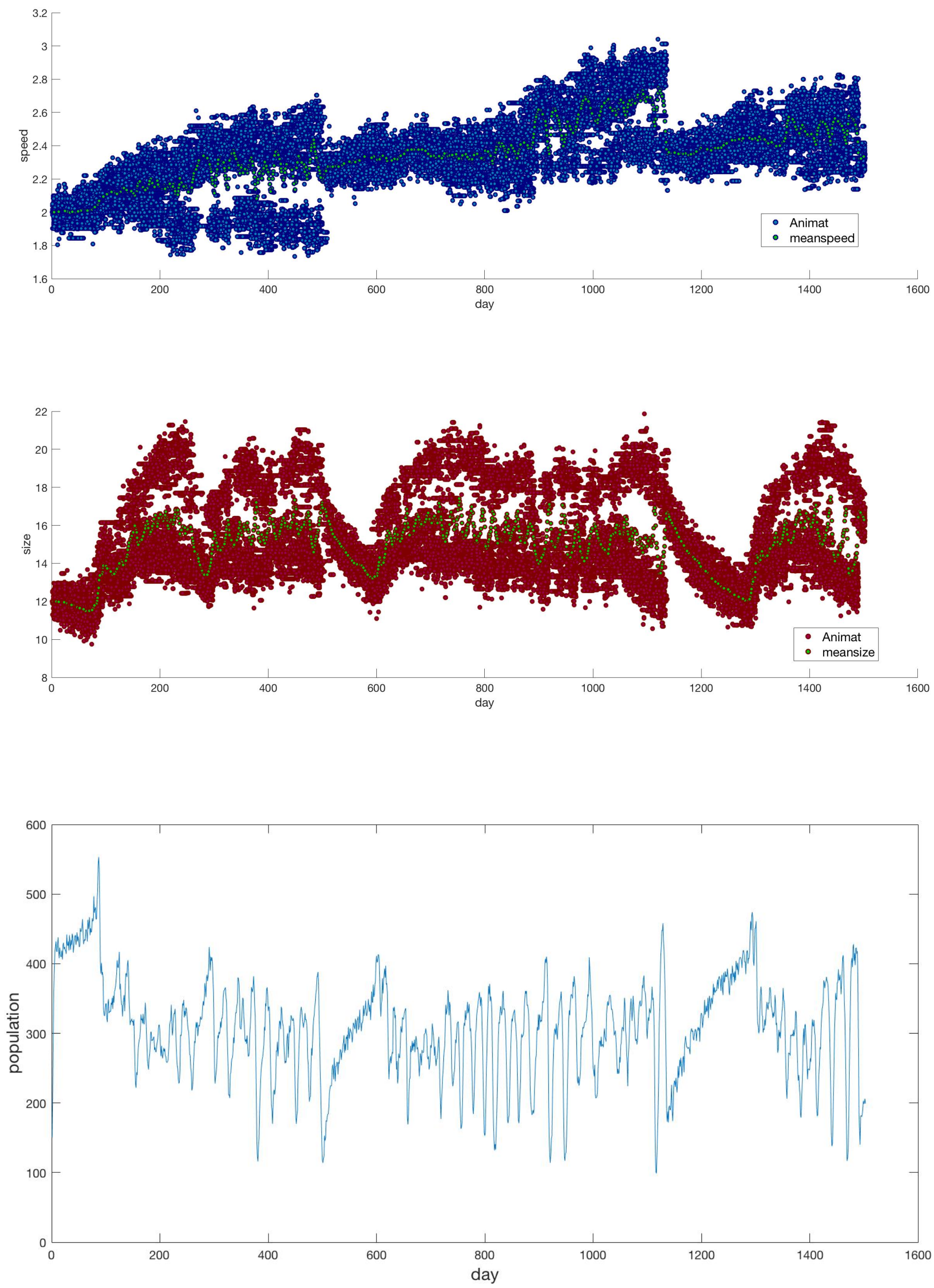

Figure 12: Speed, size and population graphs from the high population run

is improperly designed to conduct a study on altruistic behaviour, it is possible to create a more suitable spatial model, as we have seen in the work of Scogings and Hawick [2008]. Their model consists of a continuous system of pixel sized animats that move in steps along the x and y axes depending on their surroundings. I will attempt to use this method in my next spatial variant.

7 Cellular Automaton Model

7.1 Method

This simulation was based on the model used by Werfel and Bar-Yam [2004] in the study of the evolution of reproductive restraint through social communication. Instead of using a population of animats that can move around the environment, this simulation consists of a lattice of fixed cells. Each cell can be in one of three possible states; for simplicity, I used the same state classifications and colour coding as in the reproductive restraint study. State 0 is an empty cell, state 1 is a cell with only a host and state 2 is a cell with both a host and a consumer. The cells change between states on a stochastic basis. At each new time step a lone host cell will have the chance to spread into neighbouring empty cells with a fixed probability, g, for each empty cell. Similarly, cells with consumers have a chance to spread into neighbouring lone host cells with a fixed probability, T, for each cell. Finally, any given consumer cell has a fixed probability, v, of changing to an empty cell; simulating the consumer killing its host and starving. These simple rules are applied to every cell each time step and the edge cells will consider cells at the opposite edge as their neighbours so that the environment will wrap around. Figure 13 shows 12 successive time steps of a small segment of the lattice. This framework allows the behaviour of the simulation to be changed drastically by simply changing the values of the three probability variables.

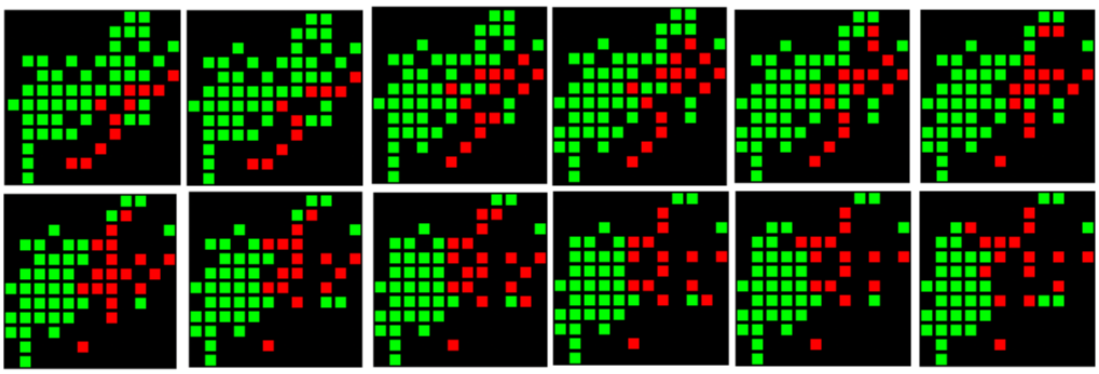

Figure 13: 12 consecutive time steps of a 12x12 selection of the simulation. They are placed in sequence from left to right and then top to bottom. Cells that contain only hosts are green, cells with both a host and a consumer are red and empty cells are black.

Using a cellular automaton structure is much less computationally taxing than the spatial variants. The simulation was able to run smoothly with a lattice containing 30,000 individual cells as shown in figure 14.

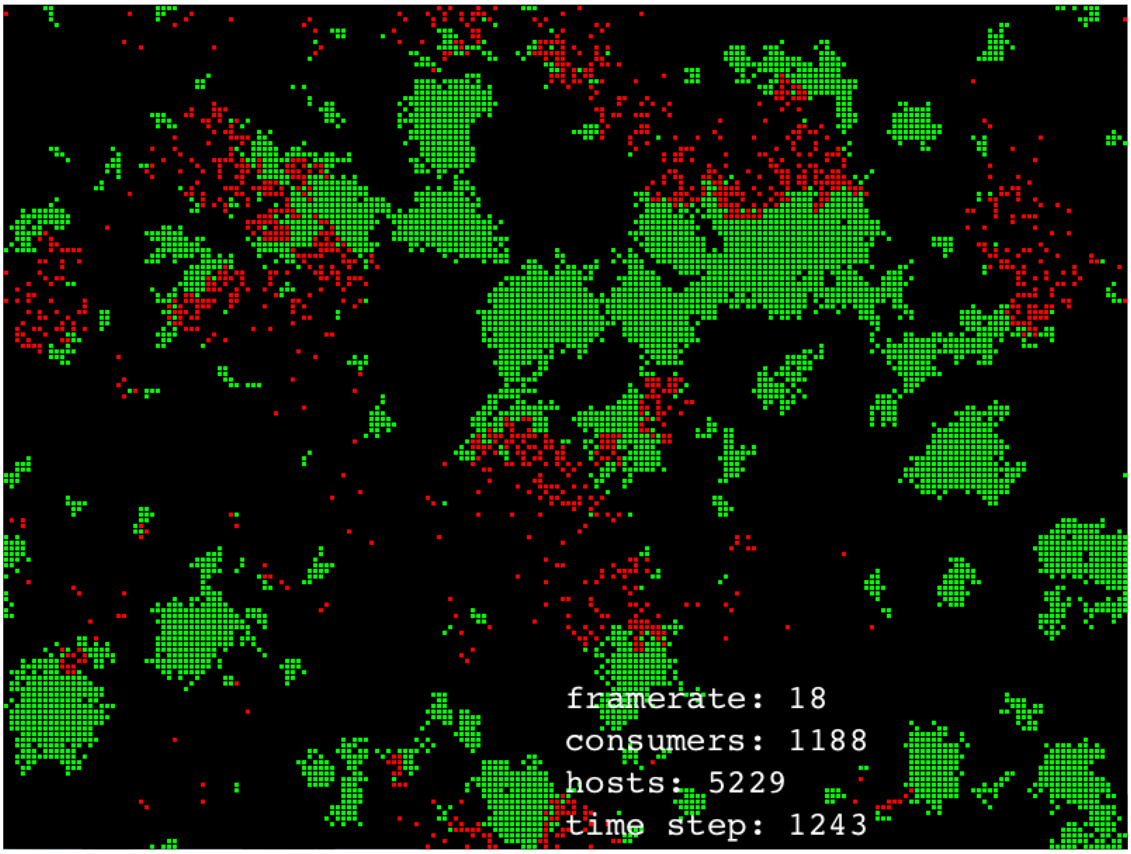

Figure 14: A single time step of the entire lattice with probability values: g = 0.012, T = 0.13, v = 0.12

7.2 Results

Although there are only three variables to define before a run, each variable has a large impact on the behaviour of the system, and they are sensitive to small changes. This can make it quite difficult to find the appropriate combination of probabilities to produce the desired effect. To start, I chose values that were similar to those stated in the reproductive restraint study conducted by Werfel and Bar-Yam [2004]. I found that these values produced a stable model, but the environment was heavily dominated by hosts as shown in population graph A in figure 15. The consumers would spread through the environment, but the cells in their wake would be quickly filled with hosts again so that approximately 50% of the cells were hosts at all times. More suitable conditions may be achieved by decreasing the host growth rate, g, and increasing the consumer transmissibility, T. Graph B shows the system behaviour that results from reducing the consumer demise probability, v, to a much smaller value. As the consumers remain in place for much longer before dying and becoming empty cells, most of the hosts are invaded and killed early in the simulation. The environment is then mostly empty with small groups of consumers and hosts slowly moving through the space. In these conditions, the consumers are able to dominate the model without eliminating all of the hosts.

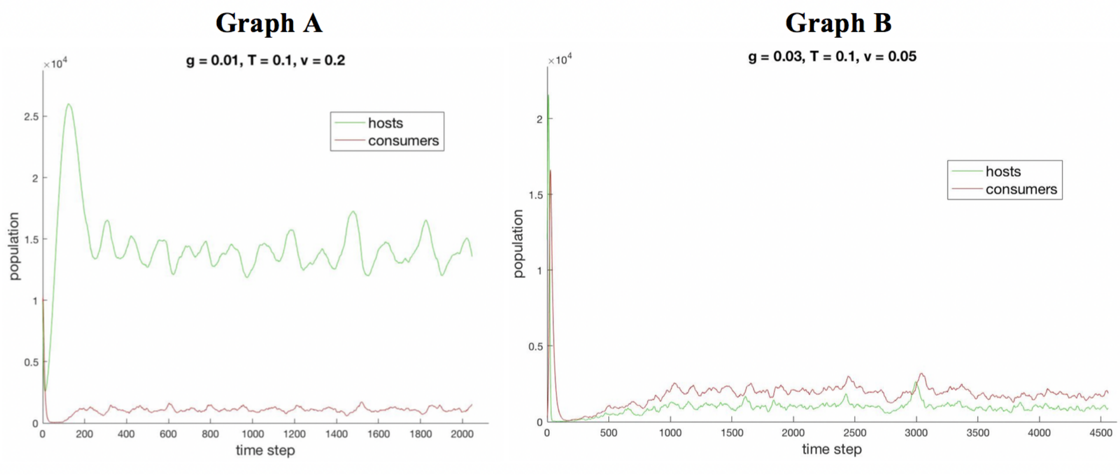

Figure 15: Population graphs from early runs.

The probability values shown in figure 16 produced a system behaviour that was visually very similar to the videos of the model used in the reproductive restraint study. The hosts would form small clusters around the environment and groups of consumers would sweep through them quite quickly. However, as can be seen in the graph, the host population fluctuates with an amplitude of over 2000. The reproductive restraint study focused on the consumers as altruists, so, the behaviour of the hosts would be of less concern as long as they provide a stable food supply for the consumers. As the focus of this project is on the prey animats as altruists, it may be more desirable to have a more stable host population.

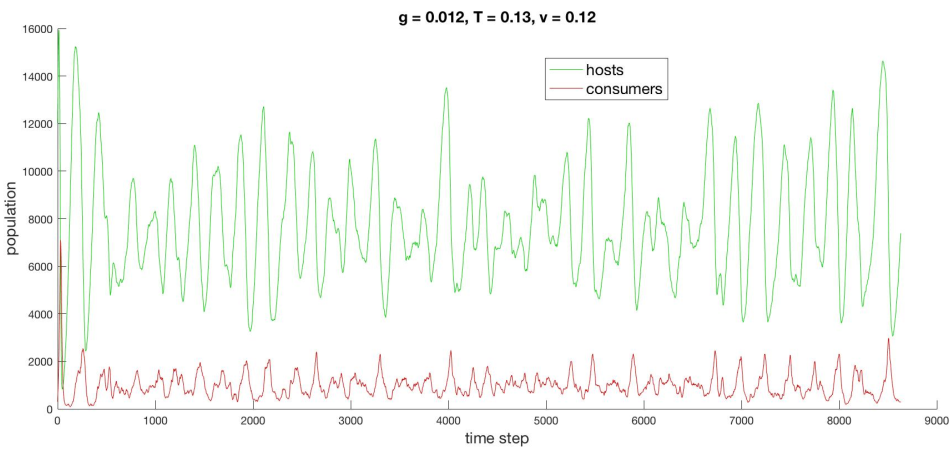

Figure 16: Population graph showing similar behaviour to the reproductive restraint study.

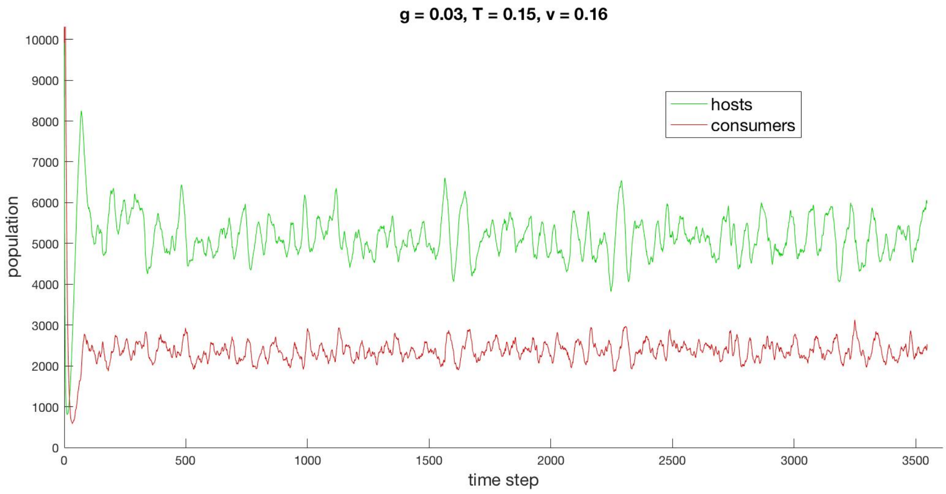

Figure 17: Population graphs showing a more stable system behaviour.

The probability values shown in figure 17 produce a very different system behaviour. Rather than having small groups of consumers sweeping through large clusters of hosts, the consumers are spread much more evenly through the environment with both, hosts and consumers, quickly spreading and dying continuously. This behaviour produces much more stable population curves as can be seen in the graph.

This model is well-suited for simulating predator prey populations as the simple mesh structure allows for very large populations without slowing the frame rate too much. As the behaviour of the system is determined stochastically, the results of runs with the same starting parameters tend to be quite consistent. Consistent behaviour of the base simulation would be extremely beneficial for a study on altruistic behaviour as it will help ensure the reliability of the results.

7.3 Altruism

In the reproductive restraint study, the altruistic consumers would signal their neighbours if they were overcrowded by releasing a signal that would travel outwards from their position over the next few time steps. Other consumers would then react to the signal by changing their transmissivity probability. Whether they change their transmissivity and by how much was subject to mutation. This method could be simply adapted to simulate altruistic hosts. Instead of releasing a signal in response to overcrowding, they could release a signal when a consumer is adjacent or nearby. Releasing the signal would make consumers more likely to spread into the altruist host cell, but neighbouring hosts receiving the signal could become less likely to be invaded by consumers or they could even move into adjacent empty cells in an effort to evade the consumer. This would effectively simulate an alarm call system in which altruist hosts would put themselves at increased risk to increase the survival chance of their neighbours.

It is clear that the host population would be more successful if all the hosts used this alarm system as they would have a decreased chance of consumer invasion on average because more hosts would be receiving the signal than sending it out. But, as with the reproductive restraint study, the test case would involve the introduction of a small population of altruists to see how they perform over time. Either, the altruist hosts come to dominate the model due to the positive feedback or they die out entirely due to their increased vulnerability.

8 Simplified Spatial Model

8.1 Method

This simulation was based on the model used by Scogings and Hawick [2008] for their altruism study. Instead of using vectors to model velocity and acceleration, the animats simply move in small steps along the x and y axes. The model consists of a 2-dimensional environment, in which, the animats can move around and interact with each other. Animats have simple logic rulesets which dictate what direction they will move in depending on their current state variables and the positions of neighbouring animats. They each have variables to define their x and y positions, their age and their current energy value. Prey animats eat grass which is endlessly available in this environment. Predators can only eat prey. The edges of this mesh world do not wrap around as they did in the cellular automaton model as it would require a more complex system to calculate the distances between animats. Instead, the prey are forced to move away from the edges if they come too close, essentially, boxing them in the environment as shown in figure 18. Predators do not need edge logic as they will be continuously seeking prey. No limits were set on population size in either predators or prey, however, animats will only produce offspring if they are not overcrowded. So, there is a theoretical limit for the prey as the environment can fill up and they will not reproduce until there is enough space.

The prey logic is as follows:

- If well fed and not overcrowded – mate with adjacent prey (or move towards suitable mate)
- If hungry and not overcrowded – eat grass
- If overcrowded – move away from nearest prey
- If predator is nearby – move away from predator (This is only executed some of the time, depending on a fixed flee chance)
- Move randomly (or move away from edge if too close)

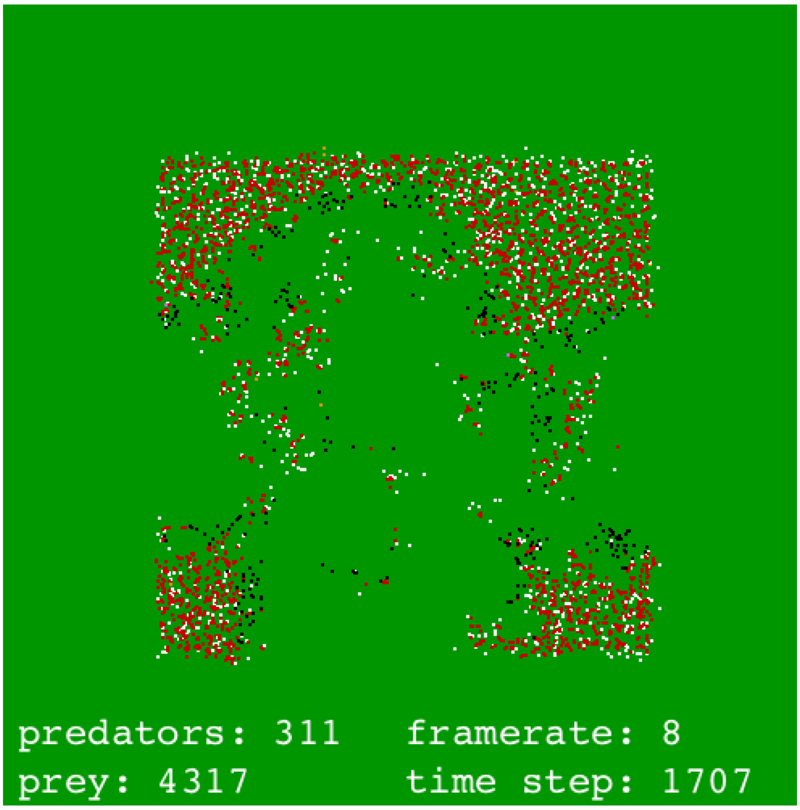

Figure 18: A single time step of the model. Predators are black and prey are white (hungry) and red (full).

The predator logic is as follows:

- If well fed and not overcrowded – mate with adjacent predator (or move towards suitable mate)
- If hungry and not overcrowded – eat adjacent prey (or move towards nearest prey)
- If overcrowded – move away from nearest predator
- Move randomly

The overcrowding conditions prevent the animats from reproducing at an exponential rate, especially in the case of the prey.

8.2 Results

As there are significantly more variables in this model than in the cellular automaton model, the system is more complex, and it is quite difficult to create a stable predator prey population. Some of the early runs are shown in figure 19. The graphs produced do show a typical Lotka-Volterra boom-bust pattern, but the amplitude of the prey curve is too high. This is problematic because the prey population falls from around 6000-8000 down to sub 1000, meaning that a huge proportion of the prey animats

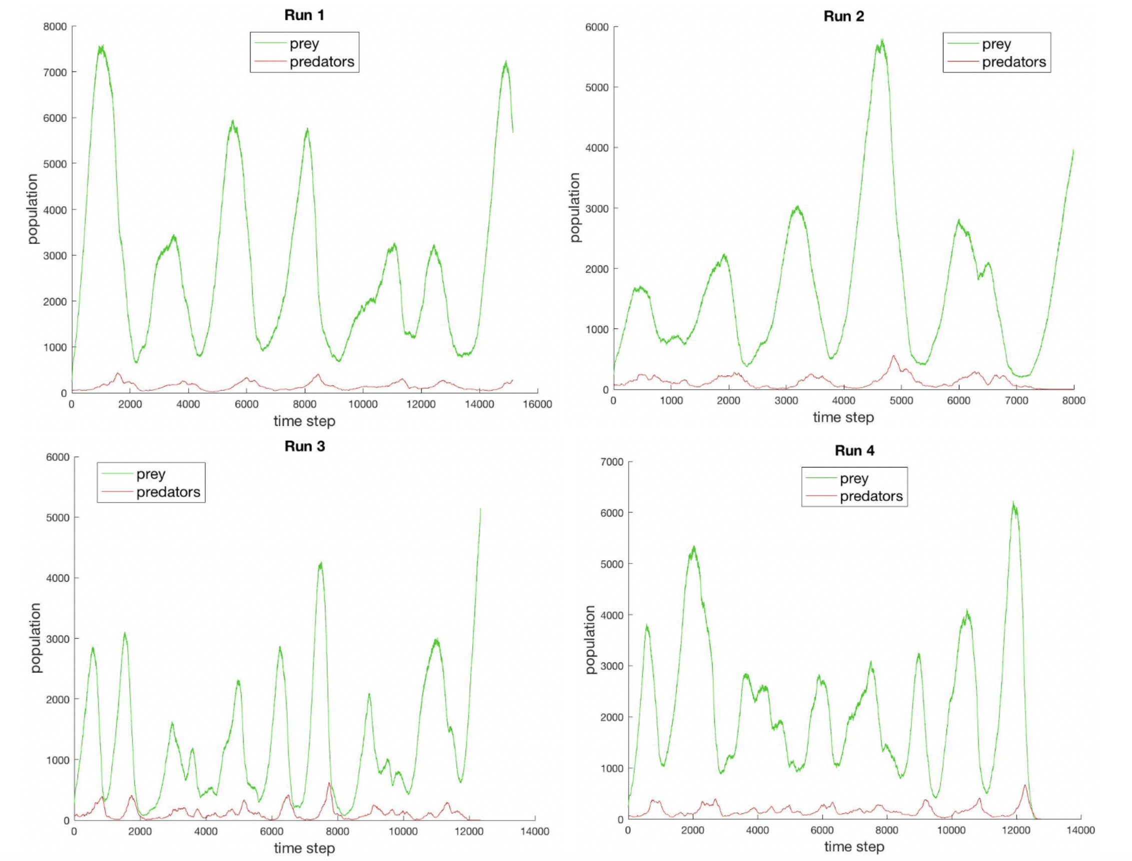

Figure 19: Examples of population graphs from early runs.

die each cycle. This happens because the prey animats initially reproduce much faster than the predators and begin to fill up the environment. Then, with ample food supply, the predators reproduce rapidly and proceed to eat the vast majority of prey animats before starving and dying themselves. In order to study altruistic behaviour with this model, it would be much more suitable to have a more stable prey population. This instability can also cause the simulation to end if the predators eat the prey too quickly and spread themselves out too thin causing them to starve or die of old age without being able to reproduce as can be seen in run 3. With this current setup, the predator population nears zero during most cycles; the model must be adapted so that the predator population minimum values are higher. In some cases, such as run 4, the predators eat the entire population of prey animats which of course will also lead to demise of the predators. The high peaks of the prey population also cause the frame rate of the simulation to slow significantly. Keeping the populations under control will enable the simulation to run much quicker.

The behaviour of the prey in this environment is quite simple compared to that of the predator. I decided that, as long as they were spreading through the environment consistently and not too quickly, their movement logic and reproduction functions were suitable to create a stable model. The focus, therefore, falls upon the predator animats. By adjusting the values of their defining variables and the structure of their logic, it should be possible to produce a more stable model. To achieve the desired system behaviour, the predators would need to reproduce more often when

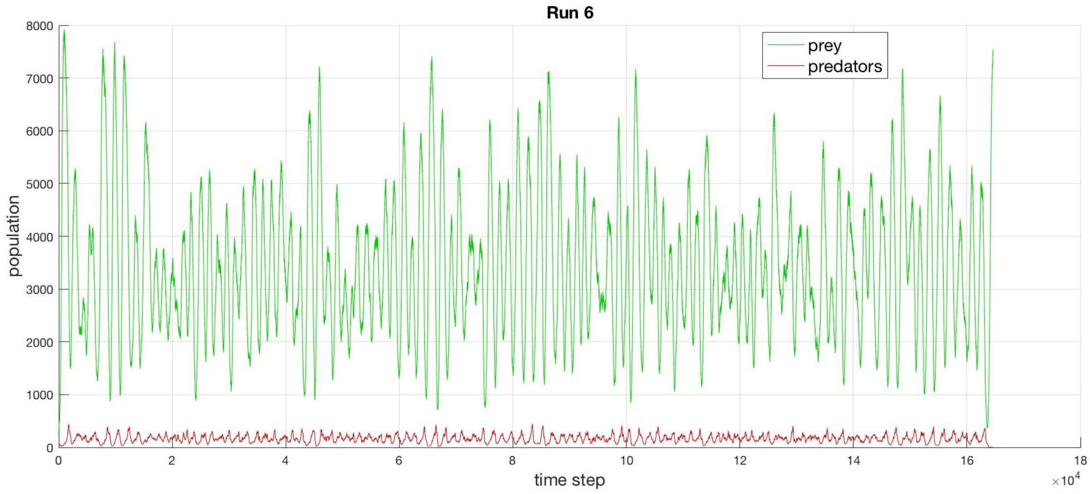

Figure 20: Population graph from an extended run.

they are vastly outnumbered by prey animats but reproduce less as their numbers increase so that they do not exhaust their food supply. Figure 20 shows a later run. At this point the system is stable enough to persist for many cycles, however, some of the issues from early runs are still present, primarily, the large fluctuations of the prey curve.

This model allows a great deal of freedom to the user, as the animats exist as individual objects in the environment. The variables and functions that define their behaviour can be easily changed and rewritten to produce different results. This method is also the closest to real-life natural selection processes as it incorporates many real-life factors. However, the fairly complex class structures of the animats require considerably more computation each time step then an equivalent cell in the cellular model. When the total population goes above four or five thousand the frame rate drops significantly making each run take much longer to compute. The complexity of the animat logic structure and defining variables also make it quite difficult to control the system behaviour. There are many factors that can influence the outcome; that combined with the long run times when the population gets out of control, make it quite difficult to produce a stable model.

8.3 Altruism

Similar to the case in the cellular automaton model, altruism could be introduced into the prey population with the use of signalling. With this model, there are numerous ways that it could be implemented. One method could be, when altruistic prey detect a nearby predator, they release a signal to nearby prey animats. This signal could contain the position data of the predator. The prey receiving the signal would then move in the opposite direction of that predator making them more likely to escape from it. A condition could be added that prey that are giving off a signal must remain static making them less likely to evade the predators. An additional condition could be added so that predators in the signal range will automatically target that prey animat.

A much simpler method would be to utilize the flee chance variable already used in the prey logic. The second to last step in the prey logic path is to check where the nearest predator is, and if that predator is within a certain radius (the maximum visual range of the prey), the prey will move in the opposite direction of that predator. However, this step is only executed some of the time, dependent on a fixed probability variable, the flee chance. This was originally added so that the prey weren't constantly running from the predators making them near impossible to catch. As the flee chance variable is defined in the prey class, it can be changed independently for each prey animat. In this case, when an altruistic prey animat identifies a nearby predator, it will release a signal to other prey within a certain radius. In doing so, it will decrease its own flee chance for a number of time steps, making it more vulnerable to predators for that time. However, the prey receiving the signal will increase their own flee chance so that they will be more likely to evade the predators. This method is very simple to implement and adds very little computation to the existing logic path. Not only that, but it is fairly realistic when compared to the real-life example of vervet monkeys [Cheney. D. L., Seyfarth. R. M., 1990]. When a vervet monkey detects a predator and gives off an alarm call, the other monkeys don't know the exact location of the predators, but they are aware that they are present. They are therefore much more likely to escape as they are alert to the danger and cannot be caught off guard. The monkey giving off the alarm is less likely to escape as it draws a great deal of attention to itself.

Many of the previous studies that focus on the predator population use energy sharing as their altruist condition. As this model also has an energy system, a similar altruistic energy sharing behaviour could be incorporated into the prey population. The current model has an endless food supply for prey, but this could be simply adapted to add food scarcity. This way, the prey animats will be vulnerable to starvation as well as predators, and the results could be quite different from the previous studies.

9 Conclusions

Two of the three simulations created for this project would be suitable to model altruistic behaviour. The preliminary simulation served as a useful tool to write and test functions that would be applicable in all of the models, but the system design and computationally intensive movement algorithms are not well suited for the project aim. An effective model for studying altruistic behaviour should have simple logic for the individual animats and allow for large stable populations. The other two simulations conform to these specifications, while using very different methodologies. The cellular automaton model can produce a surprisingly wide variety of system behaviours by simply adjusting the values of the probability variables. Although the rigid cell structure doesn't allow for the same freedom of design as a spatial model with moving objects, it is possible to simulate a wide variety of situations by adapting the cell rules. As there are a fixed number of cells that simply change states, the framerate stays fairly constant no matter the size of the population. The stochastic nature of the cell interactions causes this simulation to produce the most consistent results.

The simplified spatial model has an unparalleled adaptability as the animats exist in the environment as objects with a wide range of variable traits and logic structures that define their behaviour. As the animats have energy and age variables and have to mate to produce offspring, the model provides more realism than the cellular model. However, the animat classes, containing many variables and functions, make the system comparatively much more complex. Not only does this make it difficult to produce stable behaviour, but it also adds a lot more computation for each time step. The calculations necessary to find distances between animats and locate neighbours require much more computation then the equivalent cell calculations in the cellular model. This means that there is a tighter limit on the maximum population, as the framerate will slow to a standstill if there are too many animats in the environment. There are many factors that can influence the behaviour and decision making of the animats in this model, such as hunger, desire to reproduce and the proximity of the other species. Although these factors are true to life, they can make the system quite chaotic and hard to control. Therefore, it may have been difficult to produce reliable results in the project timeframe.

Due to the scope of this project and the time constraint, I think the cellular automaton model would have been the best choice to take forward and introduce altruistic parameters as it is simple to programme, and it would likely produce reliable results.

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