Rudimentary Evolution Simulation using a Genetic Algorithm

MComp Honours Computer Science (G405)

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May 2021

Word Count: 15087

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Abstract

This dissertation explores the structure of genetic algorithms and how they can be used for purpose of evolution amongst a population of artificial organisms. Genetic algorithms are made up of many parameters, all serving to edit a population’s genetic composition in a variety of ways. This project will provide an interface in which users can alter this algorithm to study its effects on the evolution of the population. Research into real-time physics simulation, as well as collision detection and resolution, will take place to construct a system capable of displaying the population in a constructed environment as it evolves.

Declaration

“I declare that this dissertation represents my own work except where otherwise stated.”

Acknowledgements

Firstly, I would like to thank my supervisor, Dr Phillip Lord, for allowing me to partake in this project. Their guidance in the early stages of this dissertation was crucial and shaped the project into what it has become. I would also like to thank Dr Jaume Bacardit as it was their lecture on evolutionary computation that inspired the project in the first place. Finally, I want to thank my partner Charlie whose support throughout the last year has been invaluable.

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1 Introduction

1.1 Topic

To understand genetic algorithms, you need to take a step back and first look at evolutionary computing. Evolutionary computing is a research area within computer science, inspired by the process of natural evolution. Although you probably have a solid grasp on the concept of evolution, the Introduction to Evolutionary Computing describes it as follows:

> A given environment is filled with a population of individuals that strive for survival and reproduction. The fitness of these individuals is determined by the environment, and relates to how well they succeed in achieving their goals. In other words, it represents their chances of survival and of multiplying. [1]

This style of problem-solving is known as trial-and-error or generate-and-test, where you have a collection of possible solutions of varying qualities that establish how close they are to the ideal solution of a particular problem. Depending on their quality, they are then used as a basis for creating new solutions. This step is repeated until, ideally, a perfect solution is found. Most of the time it is more likely to be a very good solution, rather than perfect. There is a clear link between evolution and this method of problem-solving.

Environment ←→ Problem   Individual ←→ Possible Solution   Fitness ←→ Quality

Genetic algorithms in particular follow a very specific structure. The algorithm starts by generating the initial population of individuals. These individuals each possess a chromosome, which in turn contains a selection of genes. As these terms will be used frequently throughout this paper, here is a diagram to aid in understanding. In this context, A1 to A5 are the individuals/organisms.

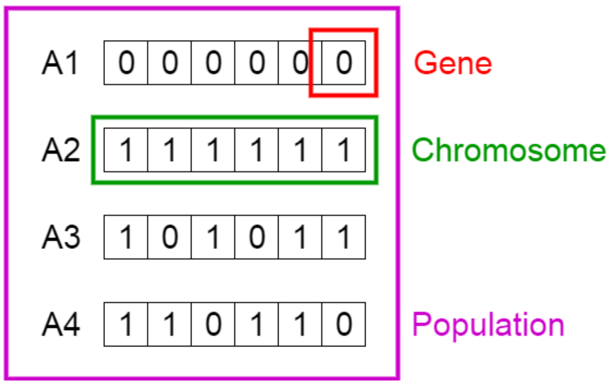


Figure 1-1 Population, Chromosomes and Genes [2]

Next, each individual has their fitness calculated which ranks them depending on their ability to solve the given problem. The selection phase is next which selects the fittest individuals to have their genes passed on to the next generation. This process places the selected individuals into pairs, which then become parents.

The next two stages in the algorithm are the reproduction stages, the first being crossover. Crossover takes each pair of parents and creates offspring by combining their genes to create new chromosomes. It is called crossover as this switching of genes normally takes place at different places, dependent on one or many crossover points. This concept and its different variations will be discussed later. Mutation is the next step in the algorithm. For each new offspring, there is a low probability for each of its genes to be mutated.

This new population of individuals will then have their fitness values calculated and the evolution cycle continues. The algorithm will have a termination criterion that is activated when either a suitable solution is converged upon, the population has not improved for X generations or a specified generation limit has been reached.

1.2 Motivation

The motivation for this project began after I took a module at Newcastle University, titled Biologically Inspired Computing. The lecture notes for genetic algorithms [3] went in-depth into the history of genetic algorithms (GA) as well as information on different selection methods, mutation/crossover methods and many different use cases. I wanted to see the algorithm used in the context of natural evolution. At this point, I had no idea of the extent and reach of evolutionary algorithms and just found the subject interesting. Around this same time, I was still struggling to come up with a topic for my third-year dissertation. This is when the idea of creating an evolution simulation came about. I then had the idea of making it interactive to showcase what a genetic algorithm does and make the program enjoyable to use for others who are interested in genetic algorithms. I know that the project is possible due to similar concepts being achieved by others such as Nathan Rooy [4] who managed to achieve a similar result, with the use of neural networks. Below is a look at Rooy's simulation.

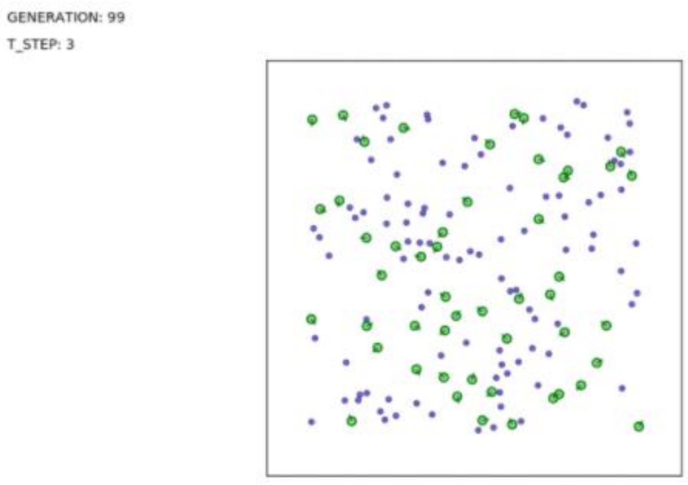


Figure 1-2 Nathan Rooy's Solution [4]

Similar projects, such as one by Nathan Rooy, tend to ignore negative factors in an organism's environment such as predators or poison. This project will, at the very least, include poison in the environment to add another factor for the organism to adapt to. My project will also be interactive, allowing the user to alter the genetic algorithm to produce vastly different results. This could be used in teaching to provide a more exciting approach to genetic algorithm optimisation.

1.3 Aims & Objectives

1.3.1 Aim

Explore how a genetic algorithm can be manufactured to simulate evolution amongst artificial organisms, providing an interactive interface where parameters can be altered to adjust the effectiveness of evolution.

1.3.2 Objectives

1. Theorize and create a genetic algorithm that increases the calculated fitness of an organism, effectively evolving it.

The algorithm will need to be extensive, containing numerous methods which can be changed by a user to alter the effectiveness of the algorithm.

2. Implement a GUI which displays organisms, other entities, and the current statistics of the genetic algorithm.

The interface is needed to display the organisms moving in the environment, finding food, and avoiding poison. The program would work without it but is needed for the user to see the evolution in action.

3. Create a movement system whereby organisms choose where to move based on their size, quality of their vision, and nearby food and poison positions.

The movement system will require the creation of a physics engine that can accurately determine the position of organisms based on numerous factors and will take a lot of research. How the population moves will be partly based on their genes.

4. Create a collision detection system that allows organisms to interact with food/poison entities and have their health affected accordingly. This will be visible in the program.

Without a collision system, there is no way to keep organisms within the confines of the environment, able to consume food, and able to avoid poison. The organisms would also be able to travel through each other without it.

5. Program a death and reproduction cycle which will remove the previous organisms, reproduce them using the genetic algorithm and create a new set of organisms with new chromosome values.

This is key for the actual evolution to occur as there will need to be many generations for the organisms to evolve and become more suited to the environment. The genetic algorithm will manage the reproduction.

6. Introduce an interactive component to the GUI that would allow a user to modify the algorithm's specific parameters to change how fast or effective the evolution of organisms is.

This is another crucial objective as it makes up the entire interactive portion of the project. This will most likely consist of sliders for mutation/crossover chance and the option to change the selection method the algorithm uses.

2 Background

This section will explore the different research sources used to build the knowledge needed to create the simulation. I will research different methods of displaying the entities on the screen along with information about the algorithm. I will be using a collection of external resources as well as University lecture material to detect and handle collisions between organisms and food/poison, affecting the organism's health accordingly.

2.1.1 Algorithm Selection

Population Management

There are two key population management models for genetic algorithms, the generational model, and the steady state model. In the generational model, the entire population is replaced by offspring at the end of each generation. Most simple genetic algorithms use this model, keeping the population size, mating pool size and offspring size the same, to make replacing the entire population simple.

With the steady state model, only part of the population is replaced by its offspring, each generation. The proportion of the population that gets replaced is known as the generational gap. As these models are performed based on a population's fitness, either can be used independently of what the chosen problem is.

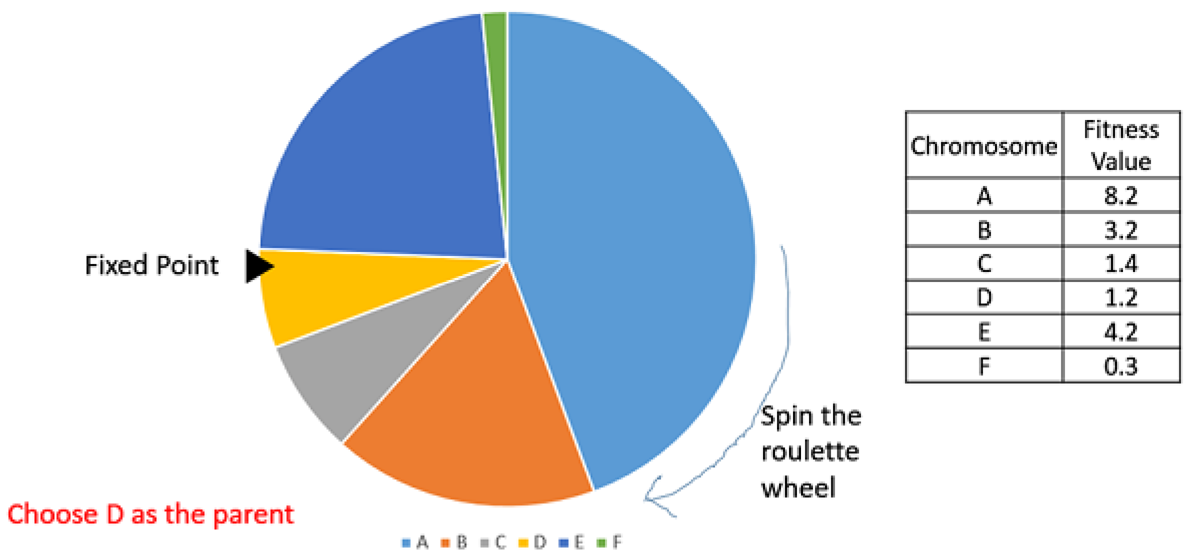
Parent Selection

There are also two types of parent selection, fitness proportional selection (FPS) and ranking selection. FPS is where the probability of an individual being selected for mating depends on its fitness compared to that of the rest of the population. This is the most common method used but has some drawbacks. Individuals with particularly high fitness values, especially early in the algorithm tend to take over the population as they are overly selected. This reduces the chance that the algorithm will search through a large space of possible solutions and is known as premature convergence. There also exists another issue that if fitness values are very close throughout the population, selection pressure is lacking, resulting in almost random selection. This has been shown to slow the improvement of fitness in later generations of the algorithm. One solution to this issue is called windowing, where the fitness of the least-fit individual is subtracted from the fitness of the rest of the population.

Ranking selection was created due to the drawbacks of FPS. The idea is that it keeps a constant selection pressure by ranking the population, based on fitness and then assigning selection probability based on rank, rather than the fitness value itself. This fixes both key concerns with the FPS approach.

Selection Methods

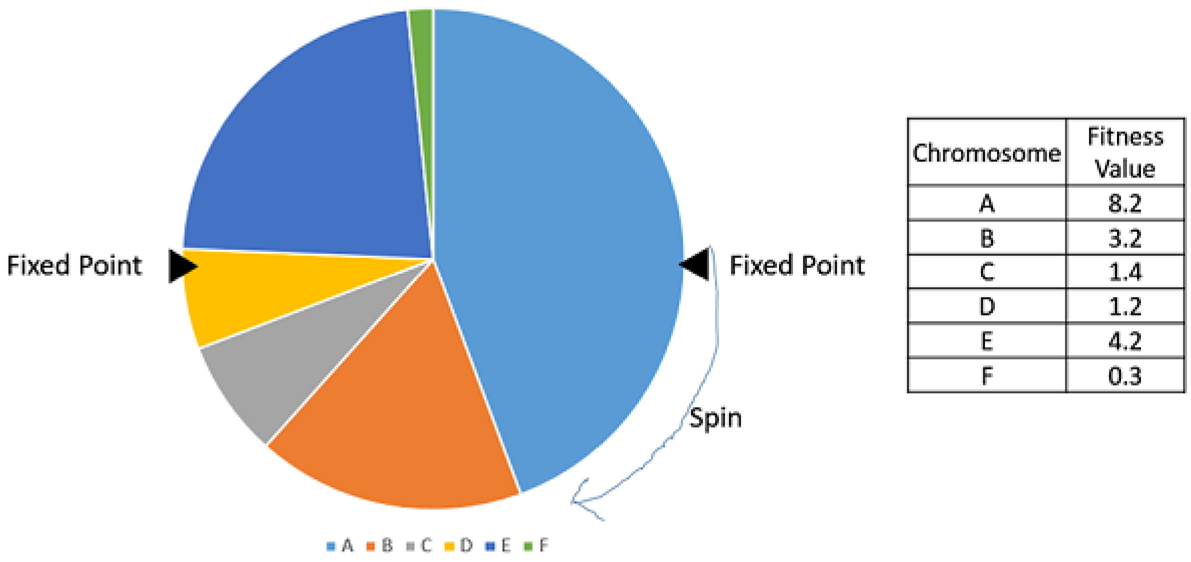
There are many selection methods for genetic algorithms which carry out the actual selecting process. One of these and perhaps the simplest method is roulette wheel sampling. The idea is you spin a wheel with the population on, the size of each individual's section dependent on their fitness or rank. Whatever individual the wheel lands on, will become a parent. Below is a diagram demonstrating this.



Chromosome	Fitness Value
A	8.2
B	3.2
C	1.4
D	1.2
E	4.2
F	0.3

Figure 2-1 Roulette Wheel Selection [5]

Stochastic universal sampling (SUS) is also a wheel but has multiple fixed points, allowing multiple parents to be selected at once and increasing the chance of an individual with high fitness being selected. SUS is demonstrated below.



Chromosome	Fitness Value
A	8.2
B	3.2
C	1.4
D	1.2
E	4.2
F	0.3

Figure 2-2 Stochastic Universal Sampling [5]

Another commonly used selection method is tournament selection. N number of individuals are chosen from the population randomly. These N individuals are then compared against each other, based on fitness, and the fittest individual is selected to become a parent. This is then repeated for each parent. In an alternative version, there can be multiple tournament survivors.

There is also random selection where parents are selected from the population completely randomly. As there is no selection pressure this method is mostly avoided but still available as an option.

2.1.2 Algorithm Crossover

Crossover is directly related to biological reproduction where two parents are selected, and offspring are produced using the genetic material of the parents. Crossover is usually applied with a very high probability and in many cases, the probability is one. There are many crossover methods, with some being more suited to this project than others. Two simple operators are single-point crossover and multiple-point crossover.

One point crossover involves taking a random index within the chromosome and creating a splitting point at that index. From there both parents are split, and the children are created by swapping the tails of the two parents from that index onwards. Multiple point crossover is very similar but this time the parents are split at multiple points along the chromosome. The children are then creating by alternating the segments of the parent chromosomes in each child. The following diagram explains this quite well.

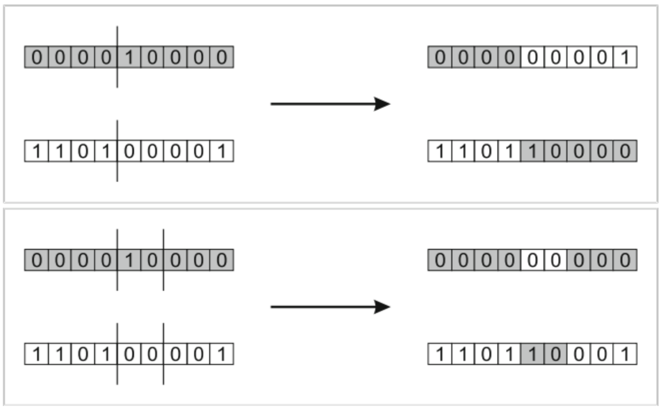


Figure 2-3 Point Crossovers [6]

Uniform crossover is another method commonly used. For this method, each gene in the first offspring has an equal chance of being inherited from either parent. This happens for each gene in the first offspring and then the second offspring is created from the inverse of the first. Once again here is a diagram.

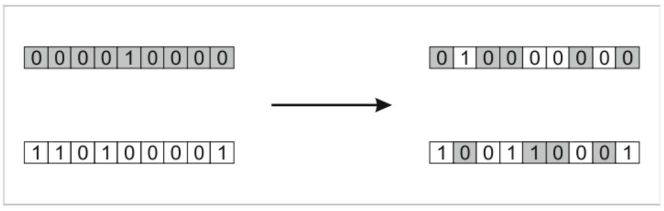


Figure 2-4 Uniform Crossover [6]

2.1.3 Algorithm Mutation

Mutation in genetic algorithms is used to keep diversity in the population and is essential for convergence. Mutation is also applied with a low probability to ensure that the algorithm does not just become a random search. Once again many mutation methods can be used.

Bit flip mutation is the simplest form of mutation and is used for chromosomes encoded in binary. It is as simple as it is named, with genes being flipped between one and zero. This would not be applicable for this project as the chromosomes are encoded with real values. Random resetting is similar but meant for other encoding methods. In this method, the gene is swapped with a random value created from a set of possible, defined values.

Creep mutation works by adding a small positive or negative value to a gene. The size of the step is dependent on the size of the fitness values as you only want to make small steps. The distribution should be symmetric, centred around zero, to ensure the value can move the same amount positively or negatively.

Scramble mutation and inversion mutation are very similar mutation in the sense that they would be implemented similarly. Scramble mutation takes a subset of the chromosome and shuffles the genes within the subset. Inversion mutation also takes place on a random subset of the chromosome but instead reverses the order of the subset. Swap mutation involves swapping two genes in the chromosome randomly. The problem with these methods is that they do not introduce new values into the chromosome and if used exclusively, the entire population will keep recycling the same genes. It could be effective to combine one of these methods with random resetting or creep mutation.

2.1.4 Algorithm Survivors

Genetic Algorithm: A Tutorial Review [7]. This short paper outlines the features of a genetic algorithm as well as the basic pseudocode for a functioning algorithm. Each component of a GA is described in detail, such as the selection methods and crossover/mutation methods for reproduction. It also outlines the different GA expressions and explains each one. I used this resource for my early research but still come back to it occasionally as a reminder of certain aspects.

Evolving Simple Organisms using Deep Learning from Scratch [4]. This blog post which I found quite recently tries to solve a similar problem in scratch using a neural network. This was helpful as it showed, at the very least, that the problem is solvable. It also led me to an interesting question. How am I going to make an organism better or worse at navigating to the food? The author used a neural network and used a normalized value representing the direction to the nearest food as an input. The direction the organism turns is then calculated within the neural network. Reading his blog, I ended learning about neural networks and their usefulness in a situation like this. Although I do not plan on using neural networks, I believe I can create a similar result for determining the angle that the organisms rotate. I can use a simple function to determine the angle from where the organism is facing to the food/poison, then calculate a turning angle based on the values stored in the organism’s chromosomes.

The next section will look at the simulation of physics within the program to create organisms that can move within an environment accurately.

2.2 Physics Simulation

As this project is supposed to simulate organisms in an environment, I felt it was important to incorporate real physics into the simulation. This will make the organisms more realistic and make the movement of each one look more natural. One way of achieving this is by implementing, and forcing organism to abide by, Newtonian physics. Newton's three laws of motion are as follows.

2.2.1 First Law

"When viewed in an inertial reference frame, an object either remains at rest or continues to move at a constant velocity, unless acted upon by a force." [8]

This first law introduces the idea that an object moves after forces are applied to it. A force has a direction and a magnitude, which is measured in Newtons. Newton's first law is also known as the law of inertia, inertia being the resistance of any physical object to any change in its velocity. A still object resists any force trying to move it and a moving object resists any force trying to change its velocity. Any object in a simulation displays inertia based on its mass, the higher the mass, the harder it is to move with a force.

2.2.2 Second Law

"The vector sum of the forces F on an object is equal to the mass m of that object multiplied by the acceleration vector a of the object: $F = ma$." [8]

It makes more sense in this simulation to rearrange the equation as ($a = \frac{F}{m}$). This is because each organism will have a known weight value as well as a force to be applied based on its decisions and genes. This means the change in velocity for each organism can be calculated from the force applied divided by the mass of itself.

2.2.3 Third Law

"When one body exerts a force on a second body, the second body simultaneously exerts a force equal in magnitude and opposite in direction on the first body." [8]

Essentially and well known as, for every action, there is an equal and opposite reaction. In the context of this project, it means that the objects within the simulation pass force between one another, if two organisms hit each other, they will not just stop but act according to the momentum each one is carrying.

Momentum is represented as $p = mv$. Due to the law of conservation of momentum, the total momentum of a system of objects remains constant. Despite the objects exerting equal and opposite forces onto each other, the velocities do not change by the same amount but instead change proportionally to their mass, conserving their momentum.

2.2.4 Calculating Movement

From here onwards, I will refer to aspects of the simulation in the context of this project. For example, objects are now organisms. The SUVAT equations of motion helped me to understand how motion overtime is calculated and how the positions of organisms within the simulation could be manipulated. SUVAT stands for the five variables of linear acceleration:

- S = Displacement (how much an organism's position has changed by).
- U = Initial velocity.
- V = Final velocity.
- A = Acceleration.
- T = Time.

The SUVAT equations allow you to work out any of the five variables based on the values of the other variables. To demonstrate this, the first equation is as follows, $v = u + at$. This means that if you know the constant acceleration (m/s/s) and time then you can work out how much the acceleration affects the overall velocity of an organism. There is a problem with SUVAT equations in that they are dependent on there being constant acceleration or velocity. In this simulation, organisms move in different ways relative to the current conditions of their environment. This means that these factors are never constant. Calculus is needed to work out how the positions of the organisms should change, starting with derivatives.

- Position is noted as s.
- Velocity is the first derivative of position with respect to time, noted as $\dot{s}$.
- Acceleration is the second derivative of position with respect to time, noted as $\ddot{s}$.

Using these derivates and the equation $\dot{s} = \frac{ds}{dt}$, you can work out the velocity of an organism if you know its positions at two points in time. Here is an example:

Organism position at 0.5 seconds = [5,0]

Organism position at 3.5 seconds = [35,0]

$$\dot{s} = \frac{[35,0] - [5,0]}{3.5s - 0.5s} = \frac{[30,0]}{3.0s} = [10,0] = 10\ units/second$$

This equation does not account for whether the velocity varied between 0.5 seconds and 3.5 seconds, only giving the average velocity. This is solved by repeating the equation many times a second, referred to as the hertz (Hz). Many game physics engines update at anywhere from 60Hz to 240Hz. Even those running at 240Hz may not be perfectly accurate but are enough to simulate physics to a respectable degree. Once again there is a problem with this approach concerning this project. We need to calculate an organism's new position based on its changing velocity, whereas this approach calculates velocity based on positions. The next step to solving the problem is integration.

Integration is used to determine how changes in an organism position's derivatives affect its position over time. The integrals of the position's derivatives are ($\dot{s} = \int \ddot{s}dt$ and $s = \int \dot{s}dt$). dt in this context is the time between each sample (timestep). In a simulation dt is the time between each frame, or $\frac{1}{Hertz\ of\ simulation}$. Several integration methods can be used starting with Euler's Integration.

$$v_{n+1} = v_n + a_n dt$$

$$s_{n+1} = s_n + v_n dt$$

These values are calculated each update cycle, taking the values from the current cycle (n) and adding the derivatives, multiplied by the timestep to calculate the next cycle's values (n+1). The problem with this method is that velocity is treated as a constant value during a timestep whereas the velocity should be constantly changing due to the integration of acceleration. This ultimately results in a loss of accuracy over time. There is an alternate method, known as Backward Euler, which calculates the derivative at the next timestep rather than the current timestep. This is shown below.

$$v_{n+1} = v_n + a_{n+1}dt$$

$$s_{n+1} = s_n + v_{n+1}dt$$

This method has a glaring problem for a real-time simulation in that it needs to know the velocity and acceleration from the next timestep, which is information you do not have. Fortunately, there is a third option that provides more accuracy over time while not forcing you to predict the future. This is known as 'Symplectic Euler'. Here, acceleration is integrated using the current cycle values and velocity can then be integrated more accurately relative to the current state of the organism's motion.

$$v_{n+1} = v_n + a_n dt$$

$$s_{n+1} = s_n + v_{n+1}dt$$

Having a small timestep is very important when using any of these integration methods. The result of the calculation will never be perfect and having a small timestep can help to minimize the inaccuracy of the simulation over longer periods. The following example, provided by Richard Davison's game physics tutorial [9], demonstrates how different timesteps used in Symplectic integration can affect how positions are calculated:

> We know from the SUVAT calculations that after 2.4 seconds; a constant acceleration of 2 m/s should result in an end position of:
>
> $$s = ut + \frac{1}{2}at^2 \quad \rightarrow \quad s = 0 * t + \left(\frac{1}{2}(2 * 2.4)\right)^2 \quad \rightarrow \quad s = 5.76$$
>
> Using Semi-Implicit Euler (Symplectic) integration results in the following positions:
>
> - Position using timestep 0.01 = 5.784
> - Position using timestep 0.1 = 6
> - Position using timestep 0.2 = 6.24
> - Position using timestep 0.4 = 6.72
> - Position using timestep 0.8 = 7.68

Richard then goes on to describe how a 60Hz or 60 frames per second simulation, which equates to a timestep of 0.0166 seconds would be "fairly accurate" but would still lead to the position being inaccurate after a decent amount of time. This suggests that physics engines should aim to run at as many hertz as possible while still maintaining adequate performance.

This content was covered due to the importance of a physics engine as a part of the model, and this is the best simulation technique I found for the context of the project. The next section I will be covering is collision detection and resolution.

2.3 Collision Detection and Resolution

2.3.1 Overview

Collision detection is extremely important in many computer systems, being a "fundamental problem in computer animation, computer graphics, physically-based modelling, and robotics." [10] It is easy to think that if you have two circles on the screen, the computer should know whether or not they are touching or not but instead a series of equations is needed, as well as different types and phases of collision detection for accuracy and efficiency. Anytime the mouse is moved in a program or webpage there is most likely a function in the background tracking exactly where the mouse is and whether it is within the bounds of another element.

Just as important is collision resolution. As an example, if you watched a simulation of two cars colliding at high speed you could easily tell at what point the cars collided. However, there is a good chance that you would not be able to tell exactly how the cars would act afterwards. Many factors need to be considered. How fast was each car going? What direction was each car travelling? What material are they driving on? How much does each car weigh? The job of the simulation, in this case, would be to consider all these factors and calculate the trajectory of each car after the collision.

There are three types of collision detection needed for the project, rectangle to rectangle, circle to circle and rectangle to circle. There are multiple methods for collision detection and for each, I would need to also get the penetration distance between the two objects and the direction of least penetration.

While my 'Programming for Games' lecture [11] gave me a solid starting point for learning about collision detection, Jeffrey Thompson's collision detection website [12] provided me with an extensive resource for detection between different basic shapes. Each example is well explained, and easy to understand. He explains that there are "more efficient ways to detect collisions" and that the principles are taught with minimal math. This was a great starting point and provided samples with each section.

2.3.2 Circle/Circle

To calculate whether two circles are colliding you need to first get the distance between the centres of both circles. This is achieved by the following calculation, with circle A and circle B.

- DistanceX = A Centre X – B Centre X.
- DistanceY = A Centre Y – B Centre Y.
- Distance = Square Root (DistanceX^2 + DistanceY^2).

You then check whether 'Distance' is less than or equal to the sum of the radii of the circles. If this is true, then they are colliding.

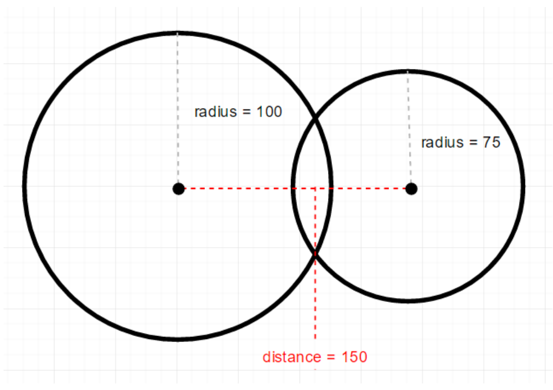


Figure 2-5 Circle/Circle Collision [13]

To resolve a collision you need some more information, chiefly, the penetration distance of the collision and the direction of least penetration (collision normal vector). For circle-to-circle collisions finding the penetration distance is easy. It is the radii of the two circles, minus the distance between the two centres at the time of the collision. To get collision normal you need the direction vector between the two circles by subtracting the position of the second circle from the first. You then normalise this value.

2.3.3 Rectangle/Rectangle

If you have two rectangles A and B, here are the checks you must do to detect whether they are colliding.

1. Is the right side of A to the right of the left side of B?
2. Is the left side of A to the left of the right side of B?
3. Is the bottom side of A below the top side of B?
4. Is the top side of A above the bottom side of B?

If all of these are true, then the two shapes are colliding. Although not easy to follow by reading, it would be easy to implement in C++.

2.3.4 Rectangle/Circle

For this collision method, you need to first work out which side of the rectangle is closest to the circle and then you carry out the following tests.

1. If the circle is to the right, check against the right edge of the rectangle.
2. If the circle is to the left, check against the left edge of the rectangle.
3. If the circle is above, check against the top edge of the rectangle.
4. If the circle is below, check against the bottom edge of the rectangle.

Simple enough. Once you know which side you need to check you use the Pythagorean Theorem to calculate the distance between the centre of the circle and the edge of the rectangle closest to the edge. Here is how this value is found:

- DistanceX = Circle Centre X – Left/Right Edge (dependent on previous tests).
- DistanceY = Circle Centre Y – Top/Bottom Edge (dependent on previous tests).
- Distance = Square Root (DistanceX^2 + DistanceY^2).

You then check whether ‘Distance’ is less than or equal to the radius of the circle. If this is true, then they are colliding.

2.3.5 Collision Resolution

A collision where two objects overlap would be an error in the simulation, however, it is inevitable. The physics engine could move an object after finding no collisions in that frame, right into the position of another. On the next frame this collision would be spotted and only then can it be resolved. There are two stages to collision resolution. The first step is moving the objects out of each other so that they are no longer colliding. The second step is accurately simulating the velocity of the two objects after that have separated, as they would no longer carry on in the same direction or at the same magnitude as they did before the collision.

For the first step, you would need to use the penetration and collision normal values calculated in the detection stage, as well as the inverse mass of each object. The mass is needed to ensure that an organism would not be able to move a wall, or a smaller organism would move more than a larger organism. Everything should be moved proportionally to its mass. Inverse mass is used to create objects with infinite mass, such as the walls of the environment. You would set the inverse mass to 0 and when the position change is calculated, it will be multiplied by 0. This is how the positions would be resolved, where the two objects are A and B:

$$totalMass = m\frac{-1}{A} + m\frac{-1}{B}\ (inverse\ mass\ is\ denoted\ as\ m\frac{-1}{object})$$

$$posA -= normal\ .\ penetration\ .\ (m\frac{-1}{A} /\ totalMass)$$

$$posB += normal\ .\ penetration\ .\ (m\frac{-1}{B} /\ totalMass)$$

For the second stage of collision resolution, the velocity of the colliding objects will be directly manipulated, instead of using integration, to cause an instant change in momentum as bodies bounce off each other. To ensure that the objects move in the correct (and opposite) direction when colliding and momentum is conserved by the engine, an impulse is calculated. The equation for an impulse between two colliding objects is as follows, provided by Rich Davison [14]:

$$\boldsymbol{J} = \frac{-(1+e)v_r.\hat{n}}{totalMass}$$

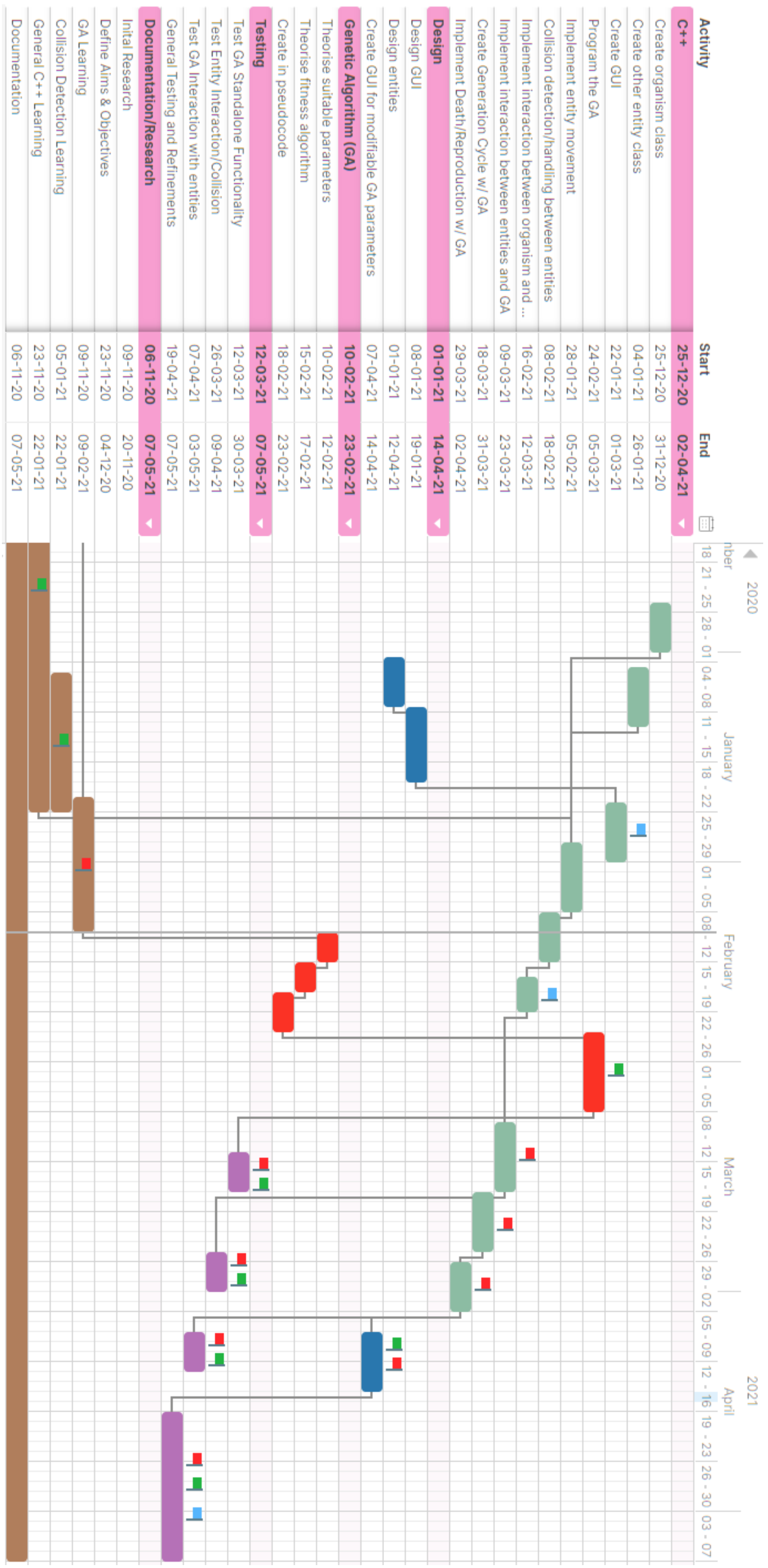
The total mass would be calculated already from separating the two objects which leaves the top half of the equation to understand, starting with v_r. This is the relative velocity between the two objects. To work out how much velocity is travelling in the direction of the collision between the objects, the dot product of the relative velocity and the collision normal, denoted $\hat{n}$, is calculated. This is $v_r.\hat{n}$.

Although not relevant in the context of this project, $-(1+e)$ is mainly used to calculate how objects of different material types behave when colliding with other objects. The coefficient of restitution denoted e, however, is important. This is a value typically between 0 and 1 where a value of 1 would mean that an object loses no velocity when colliding with another object. Conversely, a value of 0 means that an object would completely halt when a collision occurred. These would be known respectively as a perfectly elastic collision and a perfectly inelastic collision.

These collision detection and resolution methods were covered due to the importance of accuracy when it comes to the simulation of the organisms' environment. This concludes the background and research portion of this dissertation. The next section of this document will cover the design and implementation of the system.

3 Design & Implementation

3.1 Project Plan



Activity	Start	End
C++	**25-12-20**	**02-04-21**
Create organism class	25-12-20	31-12-20
Create other entity class	04-01-21	26-01-21
Create GUI	22-01-21	01-03-21
Program the GA	24-02-21	05-03-21
Implement entity movement	28-01-21	05-02-21
Collision detection/handling between entities	08-02-21	18-02-21
Implement interaction between organism and ...	16-02-21	12-03-21
Implement interaction between entities and GA	09-03-21	23-03-21
Create Generation Cycle w/ GA	18-03-21	31-03-21
Implement Death/Reproduction w/ GA	29-03-21	02-04-21
Design	**01-01-21**	**14-04-21**
Design GUI	08-01-21	19-01-21
Design entities	01-01-21	12-04-21
Create GUI for modifiable GA parameters	07-04-21	14-04-21
Genetic Algorithm (GA)	**10-02-21**	**23-02-21**
Theorise suitable parameters	10-02-21	12-02-21
Theorise fitness algorithm	15-02-21	17-02-21
Create in pseudocode	18-02-21	23-02-21
Testing	**12-03-21**	**07-05-21**
Test GA Standalone Functionality	12-03-21	30-03-21
Test Entity Interaction/Collision	26-03-21	09-04-21
Test GA Interaction with entities	07-04-21	03-05-21
General Testing and Refinements	19-04-21	07-05-21
Documentation/Research	**06-11-20**	**07-05-21**
Inital Research	09-11-20	20-11-20
Define Aims & Objectives	23-11-20	04-12-20
GA Learning	09-11-20	09-02-21
Collision Detection Learning	05-01-21	22-01-21
General C++ Learning	23-11-20	22-01-21
Documentation	06-11-20	07-05-21

Figure 3-1 Project Plan Diagram

3.1.1 Plan Explanation

The diagram above details the project plan that I have used throughout the year, beginning in November 2020, and ending in May 2021. The diagram was created using tomsplanner.com [15] in the early stages of the project. It is split into 5 sections:

1. **Programming**

   Any task that involves using Visual Studio and creating the actual simulation in which this project is aiming to produce. This will often have overlap with the genetic algorithm and design section, indicated by a flag of the respective colour of these sections.

2. **Genetic Algorithm**

   This section is for any task related to the genetic algorithm used on the project. The algorithm needed to be built from the ground up, tailored specifically to work hand in hand with the C++ program. This meant careful planning was needed, as well as achieved in a suitable time for the rest of the project to run according to plan.

3. **Design**

   These tasks relate to the general designing of aspects of the project. This ended up being a very small part of the project in the end as I kept the visual front of the program very simple to spend more time on the complicated backend.

4. **Testing**

   Any task related to ensuring correct functionality of the program and algorithm. This was a long and important part of the project as every single algorithm method and aspect of the physics engine had to be tested. Although a lot of testing was done at the tail end of the project, testing was continuous throughout due to adopting an Agile development methodology.

5. **Research/Documentation**

   Constant research and documentation have taken place throughout the lifespan of the project. Despite there being start and end dates for each of the learning tasks, I have been continually learning new things since beginning this dissertation. Documentation has been frequent, with me writing down how I am implementing features as I create them and keeping the aims and objectives noted down ready for the final writeup.

As you can see from the dependency arrows in Figure 3.1, nearly every piece of the project had to be completed in a set order, or else continuing would become impossible. Later I will discuss how this affected the rate at which the project was completed and whether I would change my approach in the future.

3.2 System Design

3.2.1 System Requirements

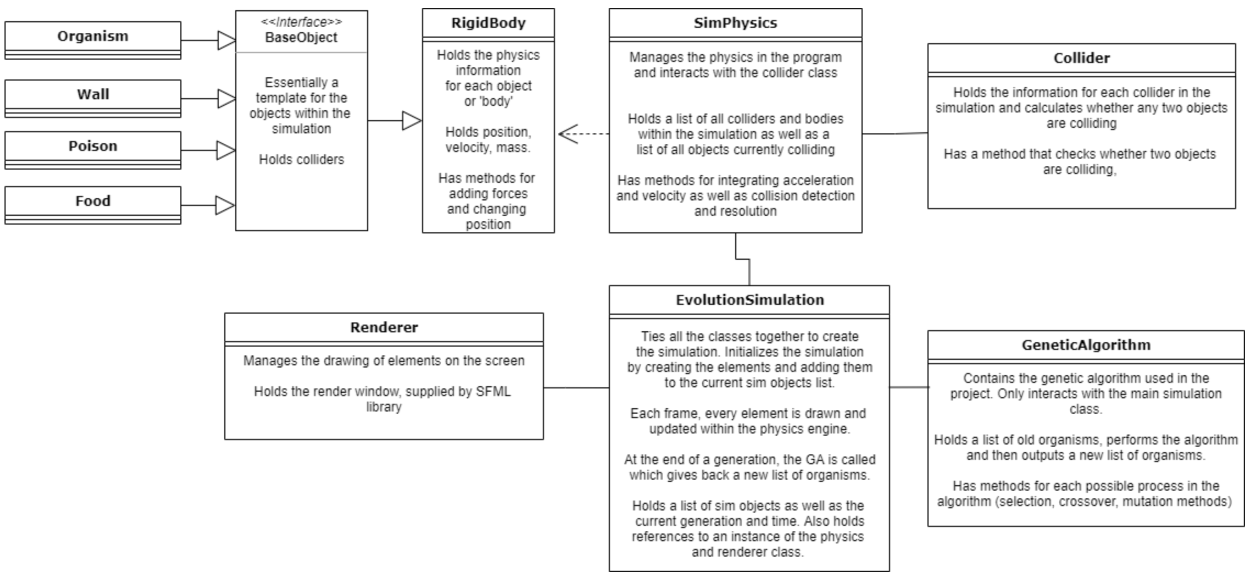
Functional Requirements

1. At program launch, the system must provide the user with a list of options regarding altering the GA and the number of elements in the environment.
2. The system must display all organisms, food elements, poison elements and the current generation number in a window, all in the correct positions according to the physics engine.
3. The console should output the current statistics of the genetic algorithm during, and after each generation.
4. At the end of each generation, all elements in the scene should be replaced with the new elements created by the GA.
5. The system should detect collisions between elements and pass this information to the physics engine for resolution.
6. When a collision is detected, the velocity and position of affected elements should be handled accurately by the physics engine and displayed to the user.
7. The GA should be able to carry out multiple operations for each of the following: population selection, chromosome crossover, and gene mutation.

Non-Functional Requirements

1. The GA should receive the old population and return the next generation in less than 1 second.
2. The system should run on the following operating systems:
    - Windows 10 64-bit/32-bit: Home, Professional, Education, Enterprise.
    - Windows 7 SP1: Home Premium, Professional, Enterprise, Ultimate.
3. The system should support the following hardware:
    - A video card that supports a minimum resolution of 1280x720. Ideally, a resolution of (1366x768) should be in use.
    - At least 50MB free disk space.
    - 4GB of RAM, ideally 8GB.

3.2.2 Simple Class Diagram



BaseObject: Essentially a template for the objects within the simulation. Holds colliders

RigidBody: Holds the physics information for each object or 'body'. Holds position, velocity, mass. Has methods for adding forces and changing position

SimPhysics: Manages the physics in the program and interacts with the collider class. Holds a list of all colliders and bodies within the simulation as well as a list of all objects currently colliding. Has methods for integrating acceleration and velocity as well as collision detection and resolution

Collider: Holds the information for each collider in the simulation and calculates whether any two objects are colliding. Has a method that checks whether two objects are colliding,

EvolutionSimulation: Ties all the classes together to create the simulation. Initializes the simulation by creating the elements and adding them to the current sim objects list. Each frame, every element is drawn and updated within the physics engine. At the end of a generation, the GA is called which gives back a new list of organisms. Holds a list of sim objects as well as the current generation and time. Also holds references to an instance of the physics and renderer class.

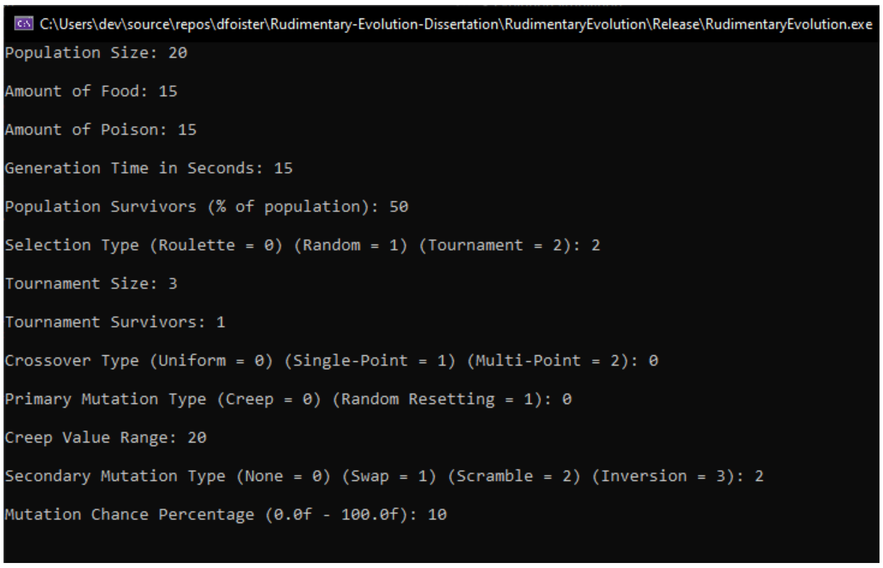
Renderer: Manages the drawing of elements on the screen. Holds the render window, supplied by SFML library

GeneticAlgorithm: Contains the genetic algorithm used in the project. Only interacts with the main simulation class. Holds a list of old organisms, performs the algorithm and then outputs a new list of organisms. Has methods for each possible process in the algorithm (selection, crossover, mutation methods)

Figure 3-2 Simplified Class Diagram

3.3 GUI Design

I made a deliberate choice to keep the UI and its elements simple to focus more on the backend algorithm and physics engine. For this reason, I used a simple console input/output system for user input. Trying to include all parameters in the simulation window seemed unnecessary and convoluted and would only serve to make the project more difficult. Below is a figure showing the console at the program launch.



```
C:\Users\dev\source\repos\dfoister\Rudimentary-Evolution-Dissertation\RudimentaryEvolution\Release\RudimentaryEvolution.exe
Population Size: 20

Amount of Food: 15

Amount of Poison: 15

Generation Time in Seconds: 15

Population Survivors (% of population): 50

Selection Type (Roulette = 0) (Random = 1) (Tournament = 2): 2

Tournament Size: 3

Tournament Survivors: 1

Crossover Type (Uniform = 0) (Single-Point = 1) (Multi-Point = 2): 0

Primary Mutation Type (Creep = 0) (Random Resetting = 1): 0

Creep Value Range: 20

Secondary Mutation Type (None = 0) (Swap = 1) (Scramble = 2) (Inversion = 3): 2

Mutation Chance Percentage (0.0f - 100.0f): 10
```

Figure 3-3 Console at Program Launch

The simulation window was kept simple, with a plain grey background and black walls to display the organisms' environment. The organisms themselves I displayed as hollow purple circles, with small green and red dots to show food and poison, respectively. I also display the generation number in the top left for the user's convenience. This is displayed below.

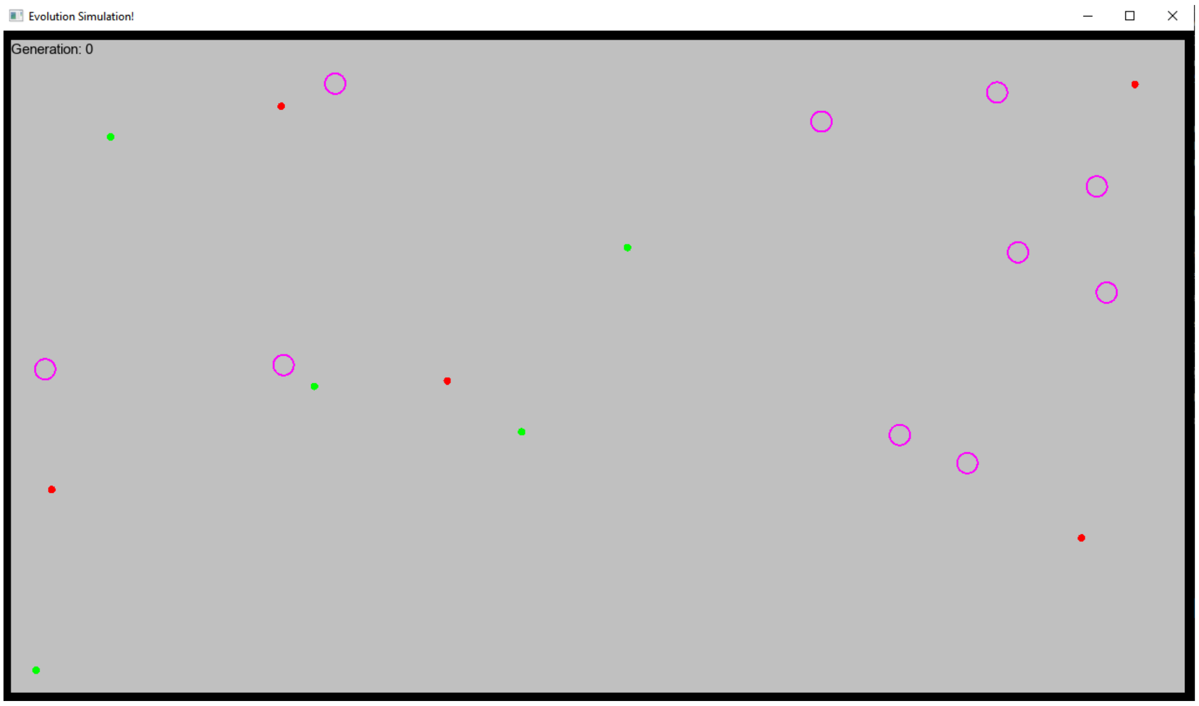


Figure 3-4 Program GUI

3.4 Tools & Technologies

3.4.1 C++17

Before I began this project, I was not sure which language I was going to use. Java was my preferred and most used language, but I had recently started using C++, and there were a few things I liked compared to Java.

C++ is a compiled language, meaning it is much faster than other languages and offers much greater control due to being a strongly-typed unsafe language. As cplusplus.com forum user, Albatross states:

> C++ is a language that expects the programmer to know what he or she is doing, but allows for incredible amounts of control as a result. [16]

The language also supports dynamic type checking, which has helped create the collision classes.

Java's garbage collection system constantly checks whether memory is still in use, whereas C++ trusts the programmer only to allocate and use what they need to. In a simulation where there are many calculations taking place every frame, this is rather important.

SFML, which provides the GUI for the project, was also primarily created for the C and .NET languages, which helped in the decision-making process.

3.4.2 Visual Studio 2019

Visual Studio (VS) was my IDE of choice as I have used it many times for previous projects I have undertaken. The inbuilt IntelliSense feature has saved hours that would have been spent searching through class documentation by providing a robust code-completion aid. The debugger is also the best I have used and has been very useful to me throughout the year. Git integration out of the box has also made source control and backing up the project a swift process.

3.4.3 Eigen

The Eigen header library was used for Vector2 representation and calculations. This was needed for representing positions and the forces used on elements of the simulation. I was tempted to create my own vector class; however, it seemed more sensible to use a simple header library and fill in the blanks where needed as the time would be better spent elsewhere.

3.4.4 SFML

Simple and Fast Multimedia Library provides the ability to apply a simple interface to Windows applications to help with the development of games. There are five modules within the library, of which I used three. These three were the system, window, and graphic modules. The alternative option I had was Simple DirectMedia Layer (SDL) which is a library that provides low-level access to graphics using Direct3D and OpenGL. SDL had a couple of problems which made me go with SFML. SDL is not very beginner-friendly and learning to use it effectively would take more time than what would be worth for the project. SDL can also require extra external libraries depending on what you want to do, whereas SFML is completely self-contained for the purpose I required it for.

3.5 Application Development Methodology

I had the choice of a couple of methodologies I could have used for the project, chiefly agile or waterfall. I ended up choosing waterfall for a couple of reasons. I had a good idea of what I wanted to develop from the very beginning of the project. Since then, the aim and objectives for the project have stayed the same and I am using the same requirements I created around that time. I have also stayed true to my original plan, created back in November. This resulted in me falling into a waterfall-styled development methodology quite naturally as the project progressed. The implementation stage of the project was structured and followed the project plan, rarely needing me to go back to alter past code. Although I did investigate agile and its benefits, I felt that a more structured overall plan would help me to complete the project on time and to the specification I had created.

3.6 Algorithm Development

3.6.1 Planning

Although I wanted the algorithm to be customisable by the user, there were a couple of factors that either could not be changeable or I felt were not necessary for the project. One of these factors was population initialisation. The two main methods for this were random initialisation and heuristic initialisation.

The problem with the heuristic approach was that there is not a known heuristic for the problem I am trying to solve. I also did not want a fully random approach as I soon found out while experimenting with the early stages of the simulation, extreme values can ruin the entire simulation. For example, if one organism has an incredibly high speed and size it will hit other organisms, in turn, pushing them towards or away from food and poison they otherwise would have found. Although realistically this could happen, this population is specifically designed to ignore each other. The approach I went with was to use a mixture of both. I experimented with a reasonable range of values that a gene could have to begin with and then the population was initialized with a range of these semi-random values.

The other factor I addressed before the project took place was the population model for the algorithm. The two most popular approaches are the steady state model whereby just a couple of organisms are replaced in each generation with new offspring and the generation model where the entire population is replaced each generation. I found that the difference between the choices was too drastic, with steady state being too slow for a problem where generations can last over a minute long. Meanwhile, generational runs the risk of deviating away from the best solution by removing potentially perfect organisms. Once again, I compromised on a solution I believed would be better. By default, each generation would keep 50% of its population through the selection process and new offspring will be created from this 50% through crossover and mutation.

I had to also decide on a fitness function suitable for this problem. Initially, it would just take the populations current health values when the generation ends and use that, however, I ran into an issue. What if the entire population died before the generation ended? Slightly less drastically, what if any 10% of the population died before the generation ended. It would not make sense that two organisms that died at different times would have the same fitness value. So, I decided to track each organism’s lifetime and current health, combining these to create the fitness value. This means that dead organisms will be ranked by the time they stayed alive and living organisms will be ranked by their current health.

3.6.2 Algorithm Overview

The algorithm is called at the end of a generation within the main evolution simulation class. These are the steps it takes to produce a new population of organisms:

- Fitness values for each organism calculated.
- Selection process is carried out.
- Crossover is performed to create offspring.
- Mutation alters the populations' chromosomes.
- The new population is prepared for insertion into the simulation and passed back into the main simulation class.

The parameters for the algorithm are selected at runtime by the user which can then be directly accessed by the genetic algorithm class. Below is the implementation for the general methods listed above.

Selection Process -> Crossover Process -> Mutation Process

Each of these methods check which parameters the user has chosen at runtime and picks the correct function. Below is a code snippet from the mutation process showing how this is achieved.

```
void GeneticAlgorithm::mutationProcess()
{
	std::random_device rdMutation;

	engine.seed(rdMutation());

	if (mutationFirst_ == 2) mutationScramble();
	if (mutationFirst_ == 1) mutationSwap();
	if (mutationFirst_ == 3) mutationInversion();

	if (mutationSecond_ == 0) mutationCreep();
	if (mutationSecond_ == 1) mutationRandomResetting();

}
```

Figure 3-5 Mutation Process Code

The crossover process method also randomises the selected population and pairs them, in preparation for mating via crossover.

Create New Population

This method goes through the list of organisms and places their chromosome into a new organism. This is to ensure any previous data held on an organism from the last generation is removed and the simulation can have a completely fresh set of organisms. This list of organisms is then returned to the simulation class, ready to be placed into the simulation.

3.6.3 Selection Implementation

Roulette Wheel Selection & Stochastic Universal Sampling (SUS)

Roulette wheel selection keeps a variable that contains the total of all fitness values from the population. A random value between zero and the total fitness is then created. Next, a loop goes through the population, adding their fitness value to a temporary variable and comparing this temporary variable against the random value. If the random value is less than or equal to the temporary variable, this organism is added to the list of organisms to be mated and placed in the next generation.

```
for (int i = 0; i < GLOBAL::SURVIVORS; i++) {

	float wheelValue = static_cast <float> (distrWheel(engine));
	float tempFitness = 0;

	for (Organism* i : population_) {
		tempFitness += getFitness(i);
		if (wheelValue <= tempFitness) {
			fittestPopulation_.emplace_back(i);
			break;
		}
	}
}
```

Figure 3-6 Roulette Wheel Selection Code

SUS is implemented similarly to roulette wheel selection, except two random values are pulled from the 'wheel' instead of just one. The loop searches for the first value first and then it is repeated for the second value.

Random Selection

This is quite a simple method. It calculates 10 random, unique numbers between 0 and the population size. These are used as indexes for the population list. N number of organisms from the population are then added to the new list of organisms, based on the random indexes. N in this case would be the pre-determined size of organisms to be selected for crossover and mutation.

Tournament Selection

This function first loops through the number of participants in a tournament (the tournament size) and adds that number of random organisms from the population to a list of competitors. This list is then sorted by the fitness values of the organisms within. Finally, the N fittest organisms from that list are added to the list of organisms to be mated and placed in the next generation, where N is the number of survivors. Both the tournament size and tournament survivor amount can be modified.

```
for (int i = 0; i < GLOBAL::SURVIVORS; i++) {

	std::vector<Organism*> competitors;

	// Adds N random competitors to list, where N is GLOBAL::TOURNAMENT_SIZE
	for (int j = 0; j < GLOBAL::TOURNAMENT_SIZE; i++) {
		competitors.emplace_back(population_[distrPopulation(engine)]);
	}

	// Sorts the competitors based on their fitness.
	std::sort(competitors.begin(), competitors.end(), [](Organism* o1,
	Organism* o2) { return o1->getHealth() + o1->getLifetime() < o2-
	>getHealth() + o2->getLifetime(); });

	// Adds N survivors to new population, where N is
	GLOBAL::TOURNAMENT_SURVIVORS.
	for (int i = 0; i < GLOBAL::TOURNAMENT_SURVIVORS; i++) {
		fittestPopulation_.emplace_back(competitors.at(i));
	}
}
```

Figure 3-7 Tournament Selection Code

3.6.4 Crossover Implementation

Uniform Crossover

The chromosomes from both organisms in a mating pair are looped through. For each gene, in both chromosomes, there is a 50% chance they are swapped in the offspring. A diagram detailing from tutorialspoint.com is below. These offspring are then placed, with the parents, in a list ready to be passed to the mutation function. This process is repeated for each mating pair.

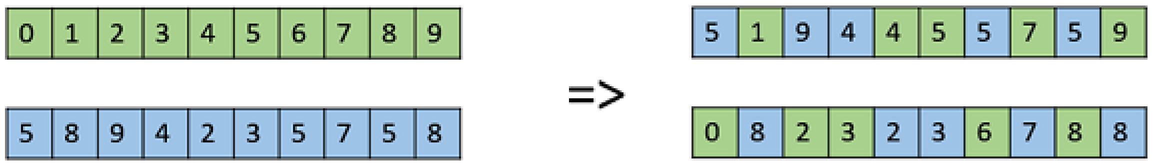


Figure 3-8 Uniform Crossover [17]

Single-Point Crossover

For single-point crossover, a random point along the chromosomes of the parents is chosen using the program's random engine. The tail end of each chromosome is then swapped in the offspring. Both new organisms and the parents are then moved to a list to be passed to the mutation function. This process is repeated for each mating pair.

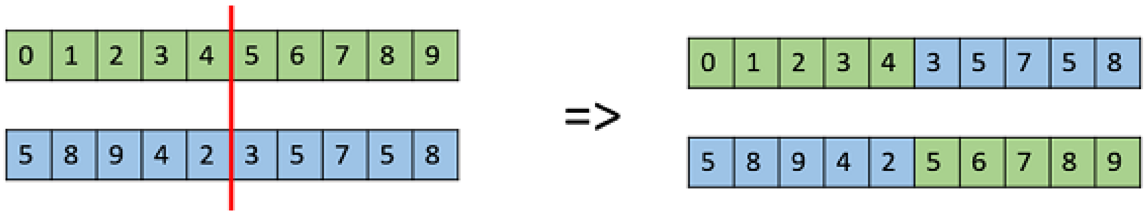


Figure 3-9 Single Point Crossover [17]

Multi-Point Crossover

The multiple point crossover function is very similar to the one above, except this time there are two dividing points on a chromosome. To get these separate points, I created a list containing all indexes in a chromosome. The list is then shuffled, and all but the first two values are removed. This remaining list would now contain the two dividing points.

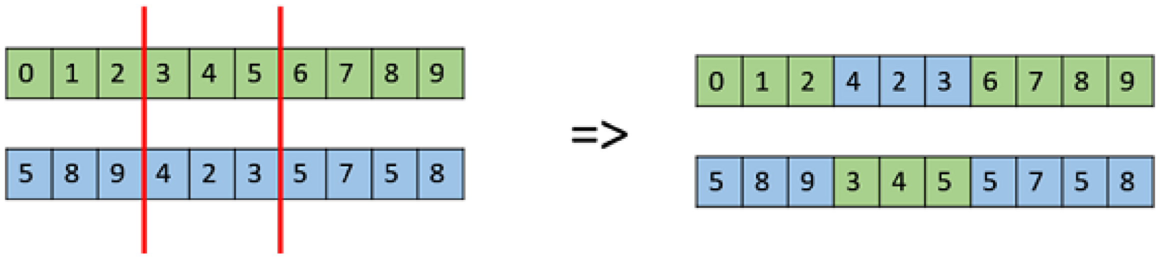


Figure 3-10 Multiple Point Crossover [17]

3.6.5 Mutation Implementation

I have split mutation into two sections. Section one is compulsory and consists of creep mutation and random resetting. These methods introduce new genes into the gene pool and are key to evolving the population beyond the first few generations. The second section of mutation is optional and contains position swapping mutation methods such as scramble, inversion, and swap mutation. These methods do alter the chromosomes but do not introduce new gene values into the population. This limits the extent to which the population's overall fitness can improve, but does add variation between generations, especially when two or more of the same organisms have made it into the new population.

Scramble & Inversion Mutation

The mutation methods start by doing a probability check to see if the mutation chance condition is met. For scramble mutation, a list containing all indexes in a chromosome is created. This list is shuffled, and the first two values are sorted and placed into a separate list. These two values act as a subset of the chromosome. The genes within the subset are also randomly shuffled and replace the values previously in the subset of the chromosome. This is then repeated for each organism in the population. Inversion mutation is the same as scramble in the sense that a random subset of each chromosome is altered. The difference is, instead of scrambling the subset, it is instead inverted. Below I have included a code snippet demonstrating how scramble mutation is carried out.

```
for (Organism* o : fittestPopulation_) {
	// If mutation chance condition successful.
	if (distrPopulation(engine) <= GLOBAL::MUTATION_CHANCE) {

		// A list of the possible indexes is created and shuffled.
		std::vector<int> possibleIndexes{ 0,1,2,3,4,5 };

		std::shuffle(possibleIndexes.begin(), possibleIndexes.end(),
		std::default_random_engine(rdNumbers()));

		// Picks two of the shuffled index values and stores them in a list.
		std::vector<int> indexList;
		indexList.emplace_back(possibleIndexes.at(0));
		indexList.emplace_back(possibleIndexes.at(1));
		// This list is sorted so the indexes are in the correct order.
		std::sort(indexList.begin(), indexList.end());

		// Adds in gene in the subset to a list.
		for (int i = indexList[0]; i <= indexList[1]; i++) {
			tempArray.emplace_back(o->chromosome_[i]);
		}
		// The list is shuffled.
		std::shuffle(tempArray.begin(), tempArray.end(),
		std::default_random_engine(rdNumbers()));
		// Shuffled subset added back to the chromosome.
		for (int i = possibleIndexes[0]; i <= possibleIndexes[1]; i++) {
			o->chromosome_[i] = tempArray.back();
			tempArray.pop_back();
		}
	}
}
```

Figure 3-11 Scramble Mutation Code

Swap Mutation

Swap mutation is quite simple. If the mutation probability check is successful, then a gene in the chromosome is swapped with another gene. This is then repeated as if it is only done once, the other mutation methods are more likely and more capable of having a larger impact on the population.

```
for (Organism* o : fittestPopulation_) {

	// If mutation chance condition successful.
	if (distrPopulation(engine) <= GLOBAL::MUTATION_CHANCE) {

		// Swap Mutation is carried out twice.
		for (int i = 0; i < 2; i++) {

			// Two random indexes chosen.
			std::uniform_int_distribution<> distrSwap(0,5);
			int index = distrSwap(engine);
			int index2 = distrSwap(engine);

			// Values in the two indexes are swapped.
			float temp = o->chromosome_[index];

			o->chromosome_[index] = o->chromosome_[index2];
			o->chromosome_[index2] = temp;
		}
	}
}
```

Figure 3-12 Swap Mutation Code

Creep Mutation

Creep mutation occurs per each gene rather than against the whole chromosome. For each gene, there is a chance that a value between -X and +X is added to that gene’s current value. The X is chosen by the user when the program begins if the user selects creep mutation.

```
for (Organism* o : fittestPopulation_) {

    // For each gene in the organism's chromosome
    for (size_t i = 0; i < o->chromosome_.size(); i++) {

       // If mutation chance condition successful.
       if (distrPopulation(engine) <= GLOBAL::MUTATION_CHANCE) {

               // Random value between -X and X added to gene.
               uniform_real_distribution<> distrCreep
                                      (-GLOBAL::CREEP_RANGE, GLOBAL::CREEP_RANGE);
               float creep = distrCreep(engine);
               o->chromosome_[i] += creep;
       }
    }
}
```

Figure 3-13 Creep Mutation Code

Random Resetting Mutation

Random resetting is also computed per gene, like creep mutation above. The only difference between the two is that creep mutation adds a value onto the current gene whereas random resetting completely replaces this gene's value with another value. The bounds for this value are chosen by the user when the program begins. This is the code that sits within the for loop for each organism.

```
// For each gene in the organism's chromosome
for (size_t i = 0; i < o->chromosome_.size(); i++) {

       // If mutation chance condition successful.
       if (distrPopulation(engine) <= GLOBAL::MUTATION_CHANCE) {

              // Random value between chosen lower and upper bound assigned to gene.
              uniform_real_distribution<> distrRandom
                                            (GLOBAL::RAND_LOWER, GLOBAL::RAND_UPPER);
              o->chromosome_[i] = distrRandom(engine);
       }
}
```

Figure 3-14 Random Resetting Code

3.6.6 Algorithm Output

At the start of the algorithm where the fitness values are calculated the algorithm outputs each organism's chromosome, as well as its calculated fitness. This also includes the best fitness within the population as well as the average fitness for that generation.

```
=================================================================
Organism 1:  101.451,97.3173,110.828,83.5512,113.796,92.25. Fitness:  73.6265
Organism 2:  98.99,107.964,116.27,113.053,99.3706,105.428. Fitness:  88.1274
Organism 3:  118.773,104.376,105.37,102.315,101.508,116.776. Fitness:  52.3903
Organism 4:  91.0335,96.4703,102.846,106.456,91.3404,85.0398. Fitness:  96.5316
Organism 5:  118.773,104.376,105.37,96.9707,101.508,116.776. Fitness:  117.39
Organism 6:  112.196,80.5409,100.3,108.22,89.3244,103.173. Fitness:  98.295
Organism 7:  112.196,67.1359,92.3687,108.22,89.3244,103.173. Fitness:  123.295
Organism 8:  112.196,80.5409,109.407,108.22,89.3244,103.173. Fitness:  98.295
Organism 9:  87.5399,72.2619,112.482,113.619,83.6673,84.1707. Fitness:  103.694
Organism 10:  112.196,80.5409,99.1613,108.22,89.3244,103.173. Fitness:  98.295
Organism 11:  92.5941,107.964,110.828,83.5512,99.3706,92.25. Fitness:  98.6265
Organism 12:  101.451,97.3173,116.27,113.053,113.796,99.5354. Fitness:  128.128
Organism 13:  118.773,104.376,102.484,102.315,91.3404,85.0398. Fitness:  117.39
Organism 14:  91.0335,96.4703,102.846,106.456,101.508,116.776. Fitness:  96.5316
Organism 15:  112.196,80.5409,92.3687,108.22,89.3244,116.776. Fitness:  98.295
Organism 16:  118.773,104.376,105.37,102.315,113.112,103.173. Fitness:  52.3903
Organism 17:  112.196,80.5409,92.3687,108.22,89.3244,103.173. Fitness:  98.295
Organism 18:  100.299,80.5409,92.3687,108.22,97.5008,103.173. Fitness:  83.295
Organism 19:  87.5399,82.3472,92.3687,113.619,83.6673,103.173. Fitness:  63.6945
Organism 20:  112.196,80.5409,112.482,108.22,73.5875,84.1707. Fitness:  123.295
Best Fitness:   128.128
Avg. Fitness:   95.4941
=================================================================
```

Figure 3-15 Algorithm Output

3.7 Organism Development

3.7.1 The Chromosome

Despite being a crucial aspect of the project, an organism's chromosome is represented simply as a list of floating-point values, each corresponding to a gene. The default values for these genes fall between 80 and 120.

Position	0	1	2	3	4	5
Gene	Normal Speed	Food/Poison Impulse	Body Size (Mass)	Base Health	Food Radius	Poison Radius

Figure 3-16 Chromosome Representation

Normal Speed – Controls the speed at which the organisms travel with no other influences.

Food/Poison Impulse – The impulse speed applied to an organism when in range of food/poison.

Body Size (Mass) – The size of the organism, which also correlates to its mass. Heavier organisms also move slower due to their mass. This means an organism with a high normal speed could be slower than a lighter organism with a lower normal speed.

Base Health – The health which the organisms are 'born' with. Each frame decreases this by 0.10.

Food Radius & Poison Radius – The visual radius in which organisms can detect food or poison.

3.7.2 Normal Movement

As shown below, the standard movement for organisms is quite simple. A random direction is chosen each frame and a force is added to the organism in that direction, the strength correlating to its normal speed gene.

```
// Random engine seeded.
std::random_device rdMove;
engine_.seed(rdMove());
// Random X and Y direction.
std::uniform_real_distribution<> distrX(-2.5f, 2.5f);
std::uniform_real_distribution<> distrY(-2.5f, 2.5f);
float randomX = static_cast <float> (distrX(engine_));
float randomY = static_cast <float> (distrY(engine_));
// Add force in the random chosen direction at a speed related to its genes.
addForce((Eigen::Vector2f(randomX, randomY).normalized() * (normalSpeed_*2.5f) ));
```

Figure 3-17 Organism Movement Code

3.7.3 Food and Poison

Each frame, the organism loses 0.10 from its current health, or 3 health a second. The only way for the organism to gain health is through consuming food in the environment, restoring 25 health. However, if the organism consumes poison, it loses 40 health. Considering base health in generation 1 starts between 80 and 120, there is a great incentive for organisms to learn to avoid poison.

Each organism has a visual radius in which they can see food and poison. If they see food, then they will start to move towards it at a speed relative to their food/poison impulse gene. Alternatively, if they are in the range of poison, they will have a chance each frame to move away from the poison. Both their chance to move away and the speed at which they do so is relative to the food/poison impulse gene.

3.8 Physics Engine Development

3.8.1 High-Level Explanation

1. The main simulation loop calls the physics engine update method, passing the timestep.

2. The physics engine calculates the result of the accumulated forces on each body. (Acceleration Integration)

3. Forces calculated from any collisions are accounted for by the physics engine. (Collision Detection & Collision Resolution)

4. New positions for each body in the simulation are integrated for the next frame. (Velocity Integration)

3.8.2 Rigid Bodies

Rigid bodies are the objects that the simulation is made up of. As none of the elements in the simulation change shape over time, soft bodies are not needed so that leaves us with rigid bodies. Each of these bodies holds a position, a mass, and a volume in which the mass is spread across.

The mass for these bodies is stored as inverse mass, or $\frac{1}{m}$. This is done for a couple of reasons. Instead of dividing, the CPU can multiply instead, which is slightly faster. Although this does not have a huge impact, it can be noticeable in larger systems with several thousand bodies. A more important reason is that it allows the simulation to have bodies with infinite mass. If a body has an inverse mass of zero, it is infinitely heavy. This is useful for walls as I do not want organisms to be able to push the boundaries of the environment away from the screen.

3.8.3 Integrating Acceleration

Each frame, each body holds all the accumulative forces that have been applied to it. When the physics engine updates, it takes all the forces and calculates the resulting acceleration. The formula used for this is $a = \frac{\boldsymbol{F}}{m}$. A temporary velocity variable is then calculated using this acceleration and the timestep passed from the main loop.

```
void SimPhysics::integrateAcceleration(float dt) {

	for (RigidBody* body : allBodies_) {
		Vector2f acceleration = body->force_ * body->inverseMass_;
		body->velocity_ += acceleration * dt;
		body->velocity_ *= body->damp_;
	}

}
```

Figure 3-18 Acceleration Integration Code

This velocity cannot be used yet as it has not considered collisions and how they might have affected the organism's movement. You can see in the figure above that the bodies store a variable named 'damp_'. This variable stores a value just below 1 (0.999) and ensures that objects slow down over time. This is to simulate air resistance and friction without the need to calculate these values. Although this slightly disobeys Newton's first law, it is adequate for the simulation I am creating.

3.8.4 Collision Detection/Resolution Within the Physics Engine

It was difficult to decide where to talk about the following implementation of collision detection and resolution. I decided that because the velocity integration is first dependent on collisions being resolved I would talk about resolution here and the information the physics engine needs to resolve collisions from the collision detection class. Below you can see code from within the SimPhysics class which loops through each pair of colliders in the system and checks whether they are colliding. Specifics on how collisions are detected will be covered in chapter 3.9. The result from this method returns three values; true or false depending on whether they are colliding, the penetration distance of one collider into another, and the normal vector which in this case is the direction of least penetration. If they are colliding, both colliders are passed into a collision pair object, which is then added to a list of collisions.

```
FOR EACH COLLIDER
       FOR EACH COLLIDER
       // isCollided returns true/false, penetration amount and normal vector.
       std::tie(result, penetration, normal) = allColliders_[i]->
       isCollided(allColliders_[j]);

              if (result == true) {  // If collided

                     CollisionPair* temp = new CollisionPair
                     (allColliders_[i], allColliders_[j], penetration, normal);

                     // Adds the collision pair to a list
                     collisionList_.push_back(temp);
              }
```

Figure 3-19 (Physics Engine) Collision Detection Code

I have split the resolution into two halves, penetration resolution and velocity resolution. Penetration resolution is moving the two objects out of each other. This may sound as simple as just moving each object an equal distance away from each other but then I would run into the problem of a wall moving whenever an organism collides with it. To solve this, I needed to make each object move proportionally to its mass. The bottom two lines show how this is achieved. If the object has an infinite mass, as the wall would, their position change is multiplied by ($\frac{inverse\ mass}{totalMass}$). If the inverse mass is 0, this means the wall would not move at all, while the other collider will move out of the wall.

```
RigidBody* a = pair->getCollisionA()->getObject();
RigidBody* b = pair->getCollisionB()->getObject();

float massA = a->inverseMass_;
float massB = b->inverseMass_;
float totalMass = massA + massB;

a->pos_ -= pair->getNormal() * pair->getPenetration() * (massA / totalMass);
b->pos_ += pair->getNormal() * pair->getPenetration() * (massB / totalMass);
```

Figure 3-20 Collision Penetration Resolution

The second half of the resolution needs to calculate the movement change over time caused by the collision as organisms bounce off each other or a wall. This is achieved by directly manipulating the velocity through an impulse.

```
velocity_ += impulse * inverseMass_;
```

The impulse is a vector as it is a derivative of force. The complicated part is now working out the impulse vector, referred to as ‘j’ in the code below. The impulse needs to both get the bodies travelling in the correct direction (which is opposite to each other due to Newton’s Third Law) as well as conserving the momentum of the bodies. This is achieved in a few steps.

As seen above in the research portion of the project, the equation for the impulse is as follows:

$$\boldsymbol{J} = \frac{-(1+e)v_r.\hat{n}}{m\frac{-1}{a} + m\frac{-1}{b}}$$

The bottom half of the equation is simply the total mass which I have already saved as a variable from above. This leaves me with e, which is the coefficient of restitution and $v_r.\hat{n}$, which is the dot product of the relative velocity, and the collision normal. You can see the dot product of relative velocity and the normal calculated below, but the coefficient of restitution is simply 0.8. This value was chosen as a somewhat middle ground between 1, where the objects would lose no magnitude on collision and 0, where the objects would come to a complete halt.

```
// Relative velocity calculation
Vector2f relativeVelocity = a->velocity_ - b->velocity_;
// Dot product of relative velocity and the collision normal.
float dotRelativeVelocityNormal = relativeVelocity.dot(pair->getNormal());
float coefficientOfRestitution = 0.8f;

// Impulse calculation
float j = (-(1 + coefficientOfRestitution) * dotRelativeVelocityNormal) / totalMass;

a->velocity_ += massA * j * pair->getNormal();
b->velocity_ -= massB * j * pair->getNormal();
```

Figure 3-21 Collision Velocity Resolution

3.8.5 Integrating Velocity

Once all collisions have been resolved and all previously applied forces have been accumulated and integrated, the new position of each body a be determined by integrating the velocity. This marks the end of the current frame and will set the positions for the next frame. This is the physics engine loop in its entirety.

```
void SimPhysics::integrateVelocity(float dt)
{
	for (RigidBody* body : allBodies_) {
		body->pos_ += body->velocity_ * dt;
	}
}
```

Figure 3-22 Velocity Integration Code

3.9 Collision Detection Development

Each simulation object stores its own collider object. Colliders have several properties and methods which aid in detecting collisions between objects. The properties include:

- Collider area.
- Position of the collider.
- Radius / Width / Height.
- Colour.
- Collider Type (Organism, food, wall, etc...).
- Collider Shape (Rectangle/Circle).
- minExtentX & maxExtentX (used for calculations)

3.9.1 Circle/Circle Collision

Perhaps the simplest of the collision detection methods, circle to circle collision simply checks whether the distance between the centres of two circles is less than the sum of their radii. If this is true, the circles must be colliding. This leaves the penetration distance and collision normal to be calculated.

The penetration distance is just the radii of the circles, minus the distance between their centres. The collision normal is the line vector (variable 'delta'), normalized. This leaves you with a unit vector, giving the direction between the two circles.

```
float radii = radius_ + collider->getRadius();

// Line between the centres of the two circles.
Vector2f delta = (collider->getPosition() - position_);
// The distance between the two centres
float deltaLength = Vec2Operations::length(delta);

// If the distance between the two centres is less than the combined radii.
if (deltaLength < radii) {

	// The difference between the radii and distance is the penetration distance
	float pen = (radii - deltaLength);
	// The normal is the direction of the line between the two centres.
	Vector2f normal_ = Vec2Operations::normalized(delta);
	return std::make_tuple(true, pen, normal_);
}
else {
	return std::make_tuple(false, 0.0f, Vector2f(0, 0));
}
```

Figure 3-23 Circle/Circle Collision Code

3.9.2 Rectangle/Circle

Collisions between circles and rectangles can be detected by clamping the sphere’s position to the minimum and maximum extent of the rectangle on both axes. This gives you the closest point on the rectangle to the circle. If the closest point is less than the radius of the circle away from the centre of the circle, then the two objects are colliding. Luckily, C++ has a built-in clamp function as of recently.

Finding the normal vector and penetration distance is now an easy task. The normal vector is found by normalizing the line vector between the circle’s centre and the closest point on the rectangle. This gives you the direction vector between the two points. The penetration distance is just the difference between the radius and the distance between the closest point and the circle’s centre.

```cpp
Vector2f halfBox = Vector2f(width_ / 2, height_ / 2);
// Line vector between centre of both shapes.
Vector2f delta = col->getPosition() - position_;

// Clamp circle axes to min/max extent of the rectangle.
float closestX = std::clamp(delta.x(), -halfBox.x(), halfBox.x());
float closestY = std::clamp(delta.y(), -halfBox.y(), halfBox.y());
Vector2f closestPoint = Vector2f(closestX, closestY);

// Line between closest point on rectangle and the circle’s centre.
Vector2f localPoint = delta - closestPoint;

// Distance between the closest point on the rectangle and the circle’s centre.
float distance = Vec2Operations::length(localPoint);

if (distance < col->getRadius()) {
	// Direction vector between closest point and circle centre.
	Vector2f normal_ = Vec2Operations::normalized(localPoint);
	// Difference between radius and distance.
	float penetration = (col->getRadius() - distance);

	return std::make_tuple(true, penetration, -normal_);
}

return std::make_tuple(false, 0.0f, Vector2f(0, 0));
```

Figure 3-24 Rectangle/Circle Collision Code

3.9.3 Rectangle/Rectangle

Although I had already implemented it by the time I realised it, I did not need to check for collisions between rectangle objects in the simulation. As the moving elements within the simulations all use circle colliders, only the walls of the environment are rectangular and do not move throughout the program’s runtime. It is a shame that this was the case as working out the penetration distance and normal vector for rectangle-to-rectangle collisions was the most complicated and took more time than the others. I will include the code for this collision detection method in Appendix 4.

3.10 Renderer Development

The rendering on the project is mostly managed by the SFML graphics library, this class just takes advantage of the capabilities of the library and provides a way to draw the elements I need efficiently. The class contains all the drawing functions needed for the program as well as holding the window object itself. The four drawing functions included are:

- DrawCircle: used for drawing food and poison elements.
- DrawBox: used for drawing the outer walls of the environment.
- DrawOrganism: used for drawing the population.
- DrawHealth: used for drawing the organism’s current health above it.

Main.cpp is where the program begins, creating a new renderer object. Using the SFML library, a window is then created at a resolution of 1280 by 720 and a framerate limit is set. I chose 720p as 16:9 is the most common aspect ratio for modern computer monitors and laptop. Also, even cheaper laptops tend to have a resolution no smaller than 1366 by 768. In the worst case where the resolution is smaller than this, the program can be resized, only altering the simulation for a few frames.

At this point, a new EvolutionSimulation object is created, with the window object passed into its constructor, allowing elements to be drawn outside of main.cpp. Next, the main game loop begins.

3.11 Global Header

This file holds all global variables used throughout the program. Throughout the development of the project, it would store variables that I had not yet decided how to use or where to use them. Some of the variables it holds include:

- Population size.
- The number of food pieces.
- The number of poison pieces.
- Generation time.
- The framerate limit.
- Mutation chance.
- Selection/Crossover/Mutation1/Mutation2 methods.
- Tournament size/survivors.
- Creep range.
- Survivors.
- Random Resetting upper and lower bounds.

When the user is prompted for the properties of the algorithm, the answers are stored in the global header for use throughout the runtime.

3.12 Completed System UML Diagram

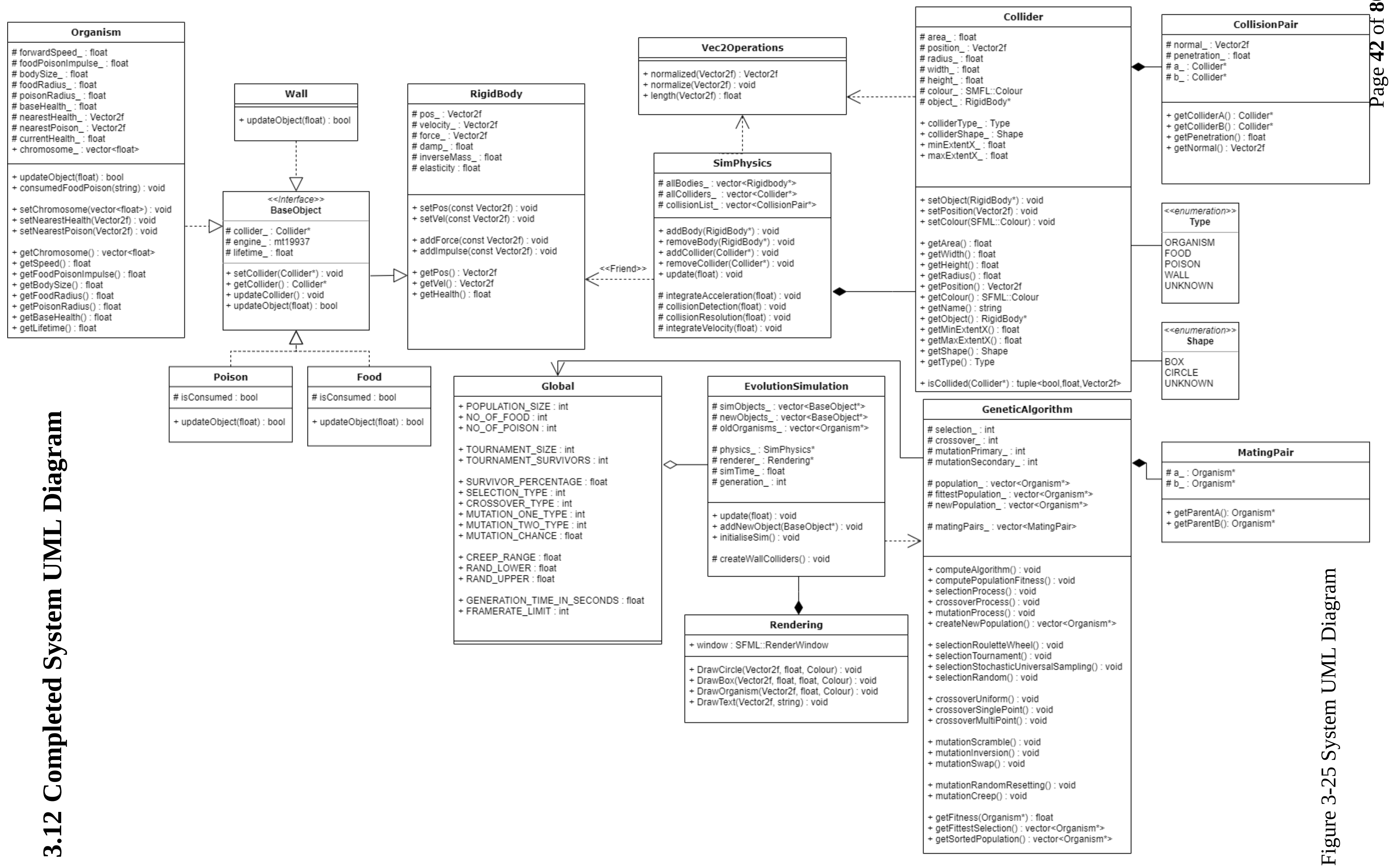

Organism
# forwardSpeed_ : float
# foodPoisonImpulse_ : float
# bodySize_ : float
# foodRadius_ : float
# poisonRadius_ : float
# baseHealth_ : float
# nearestHealth_ : Vector2f
# nearestPoison_ : Vector2f
# currentHealth_ : float
+ chromosome_ : vector<float>
+ updateObject(float) : bool
+ consumedFoodPoison(string) : void
+ setChromosome(vector<float>) : void
+ setNearestHealth(Vector2f) : void
+ setNearestPoison(Vector2f) : void
+ getChromosome() : vector<float>
+ getSpeed() : float
+ getFoodPoisonImpulse() : float
+ getBodySize() : float
+ getFoodRadius() : float
+ getPoisonRadius() : float
+ getBaseHealth() : float
+ getLifetime() : float
Wall
+ updateObject(float) : bool
<<Interface>>
BaseObject
# collider_ : Collider*
# engine_ : mt19937
# lifetime_ : float
+ setCollider(Collider*) : void
+ getCollider() : Collider*
+ updateCollider() : void
+ updateObject(float) : bool
Poison
# isConsumed : bool
+ updateObject(float) : bool
Food
# isConsumed : bool
+ updateObject(float) : bool
RigidBody
# pos_ : Vector2f
# velocity_ : Vector2f
# force_ : Vector2f
# damp_ : float
# inverseMass_ : float
# elasticity : float
+ setPos(const Vector2f) : void
+ setVel(const Vector2f) : void
+ addForce(const Vector2f) : void
+ addImpulse(const Vector2f) : void
+ getPos() : Vector2f
+ getVel() : Vector2f
+ getHealth() : float
<<Friend>>
Vec2Operations
+ normalized(Vector2f) : Vector2f
+ normalize(Vector2f) : void
+ length(Vector2f) : float
SimPhysics
# allBodies_ : vector<Rigidbody*>
# allColliders_ : vector<Collider*>
# collisionList_ : vector<CollisionPair*>
+ addBody(RigidBody*) : void
+ removeBody(RigidBody*) : void
+ addCollider(Collider*) : void
+ removeCollider(Collider*) : void
+ update(float) : void
# integrateAcceleration(float) : void
# collisionDetection(float) : void
# collisionResolution(float) : void
# integrateVelocity(float) : void
Collider
# area_ : float
# position_ : Vector2f
# radius_ : float
# width_ : float
# height_ : float
# colour_ : SMFL::Colour
# object_ : RigidBody*
+ colliderType_ : Type
+ colliderShape_ : Shape
+ minExtentX_ : float
+ maxExtentX_ : float
+ setObject(RigidBody*) : void
+ setPosition(Vector2f) : void
+ setColour(SFML::Colour) : void
+ getArea() : float
+ getWidth() : float
+ getHeight() : float
+ getRadius() : float
+ getPosition() : Vector2f
+ getColour() : SFML::Colour
+ getName() : string
+ getObject() : RigidBody*
+ getMinExtentX() : float
+ getMaxExtentX() : float
+ getShape() : Shape
+ getType() : Type
+ isCollided(Collider*) : tuple<bool,float,Vector2f>
CollisionPair
# normal_ : Vector2f
# penetration_ : float
# a_ : Collider*
# b_ : Collider*
+ getColliderA() : Collider*
+ getColliderB() : Collider*
+ getPenetration() : float
+ getNormal() : Vector2f
<<enumeration>>
Type
ORGANISM
FOOD
POISON
WALL
UNKNOWN
<<enumeration>>
Shape
BOX
CIRCLE
UNKNOWN
Global
+ POPULATION_SIZE : int
+ NO_OF_FOOD : int
+ NO_OF_POISON : int
+ TOURNAMENT_SIZE : int
+ TOURNAMENT_SURVIVORS : int
+ SURVIVOR_PERCENTAGE : float
+ SELECTION_TYPE : int
+ CROSSOVER_TYPE : int
+ MUTATION_ONE_TYPE : int
+ MUTATION_TWO_TYPE : int
+ MUTATION_CHANCE : float
+ CREEP_RANGE : float
+ RAND_LOWER : float
+ RAND_UPPER : float
+ GENERATION_TIME_IN_SECONDS : float
+ FRAMERATE_LIMIT : int
EvolutionSimulation
# simObjects_ : vector<BaseObject*>
# newObjects_ : vector<BaseObject*>
# oldOrganisms_ : vector<Organism*>
# physics_ : SimPhysics*
# renderer_ : Rendering*
# simTime_ : float
# generation_ : int
+ update(float) : void
+ addNewObject(BaseObject*) : void
+ initialiseSim() : void
# createWallColliders() : void
Rendering
+ window : SFML::RenderWindow
+ DrawCircle(Vector2f, float, Colour) : void
+ DrawBox(Vector2f, float, float, Colour) : void
+ DrawOrganism(Vector2f, float, Colour) : void
+ DrawText(Vector2f, string) : void
GeneticAlgorithm
# selection_ : int
# crossover_ : int
# mutationPrimary_ : int
# mutationSecondary_ : int
# population_ : vector<Organism*>
# fittestPopulation_ : vector<Organism*>
# newPopulation_ : vector<Organism*>
# matingPairs_ : vector<MatingPair>
+ computeAlgorithm() : void
+ computePopulationFitness() : void
+ selectionProcess() : void
+ crossoverProcess() : void
+ mutationProcess() : void
+ createNewPopulation() : vector<Organism*>
+ selectionRouletteWheel() : void
+ selectionTournament() : void
+ selectionStochasticUniversalSampling() : void
+ selectionRandom() : void
+ crossoverUniform() : void
+ crossoverSinglePoint() : void
+ crossoverMultiPoint() : void
+ mutationScramble() : void
+ mutationInversion() : void
+ mutationSwap() : void
+ mutationRandomResetting() : void
+ mutationCreep() : void
+ getFitness(Organism*) : float
+ getFittestSelection() : vector<Organism*>
+ getSortedPopulation() : vector<Organism*>
MatingPair
# a_ : Organism*
# b_ : Organism*
+ getParentA(): Organism*
+ getParentB(): Organism*

Figure 3-25 System UML Diagram

4 Evaluation

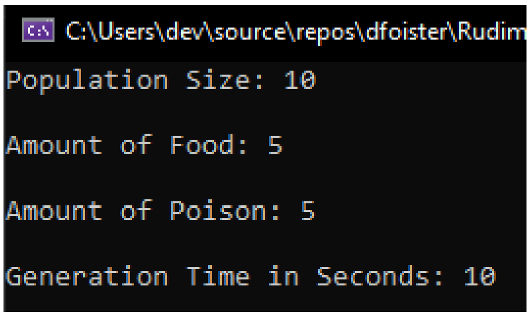
4.1 Overview

A large portion of the program is non-deterministic and there is no exact expected outcome for a lot of functions. Couple with the stochasticity of the genetic algorithm means that visual testing is going to an important factor in testing the solution as well as some manual white box testing. Collision detection and resolution is an aspect of the program that is deterministic and for any two shapes in any two positions, the program should know whether they have collided, how far they have collided and where they have collided.

4.2 Testing Solution

4.2.1 Element Creation

Each time the program begins, the user chooses the number of organisms, food pieces and poison pieces present in the environment. The UI should show the correct number of these elements in different positions across the environment.



```
C:\Users\dev\source\repos\dfoister\Rudim
Population Size: 10

Amount of Food: 5

Amount of Poison: 5

Generation Time in Seconds: 10
```

Figure 4-1 Program Start

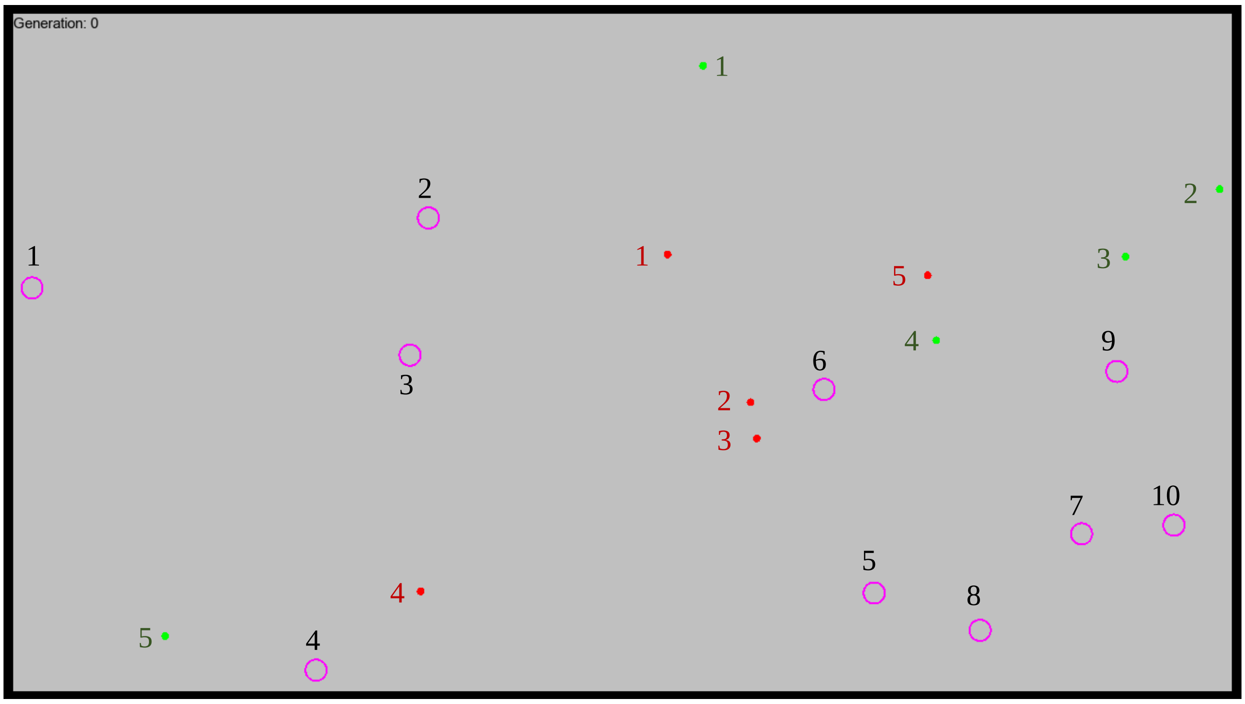


Figure 4-2 Program Running with Numbered Elements

4.2.3 Crossover Methods

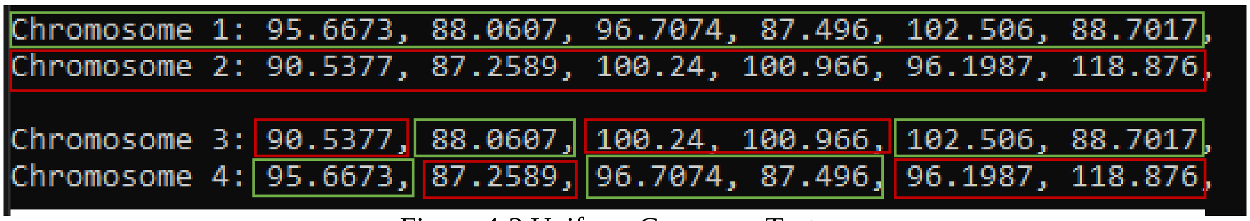
For all crossover testing the same parameters have been used:

- Population: 20.
- Food: 1.
- Poison: 1.
- Generation Time: 1 second.
- Selection Method: Roulette Wheel.
- Mutation: Disabled
- Survivors: 10

As crossover does not take fitness or mutation into account, I was able to disable mutation completely and reduce other factors down to nearly nothing. This means all chromosomes were selected nearly randomly but will not affect the outcome of the crossover procedure.

Uniform Crossover

The figure below is output from the uniform crossover method. Chromosomes 1 and 2 represent the parent chromosomes, whereas three and four represent the children created via uniform crossover. Here you can see that each gene has remained in the same position as it did in the parent chromosome but each child alternates randomly which gene it receives.

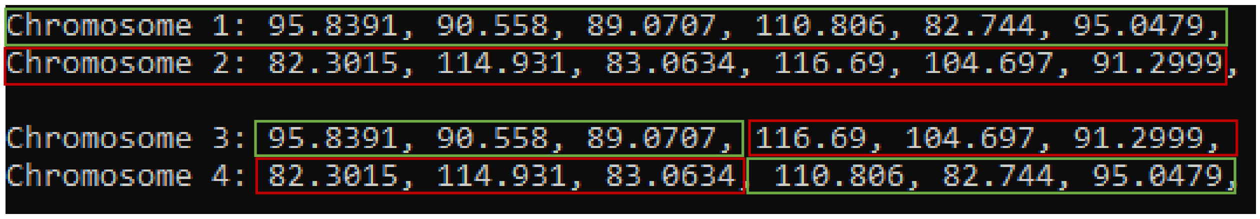


```
Chromosome 1: 95.6673, 88.0607, 96.7074, 87.496, 102.506, 88.7017,
Chromosome 2: 90.5377, 87.2589, 100.24, 100.966, 96.1987, 118.876,

Chromosome 3: 90.5377, 88.0607, 100.24, 100.966, 102.506, 88.7017,
Chromosome 4: 95.6673, 87.2589, 96.7074, 87.496, 96.1987, 118.876,
```

Figure 4-3 Uniform Crossover Test

Single Point Crossover

Like the test above, chromosomes 1 and 2 are the parent chromosomes and the bottom two are the offspring. The output of the function shows that the algorithm is successfully splitting the parent chromosomes at a single point and assigning each split to the correct child chromosomes.

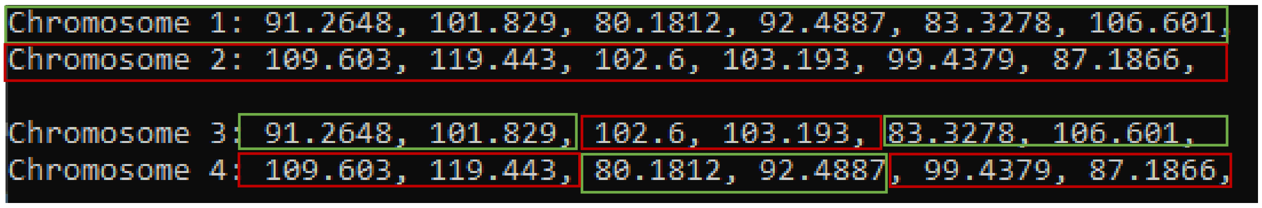


```
Chromosome 1: 95.8391, 90.558, 89.0707, 110.806, 82.744, 95.0479,
Chromosome 2: 82.3015, 114.931, 83.0634, 116.69, 104.697, 91.2999,

Chromosome 3: 95.8391, 90.558, 89.0707, 116.69, 104.697, 91.2999,
Chromosome 4: 82.3015, 114.931, 83.0634, 110.806, 82.744, 95.0479,
```

Figure 4-4 Single Point Crossover Test

Multiple Point Crossover

Multiple-point crossover is almost identical to single point except, as the name suggests, the chromosomes are split at multiple points. In this GA, they are split exactly twice. Although in this test, they are split evenly into three slices, containing two genes each, the two splits can happen anywhere on the chromosomes.



```
Chromosome 1: 91.2648, 101.829, 80.1812, 92.4887, 83.3278, 106.601,
Chromosome 2: 109.603, 119.443, 102.6, 103.193, 99.4379, 87.1866,

Chromosome 3: 91.2648, 101.829, 102.6, 103.193, 83.3278, 106.601,
Chromosome 4: 109.603, 119.443, 80.1812, 92.4887, 99.4379, 87.1866,
```

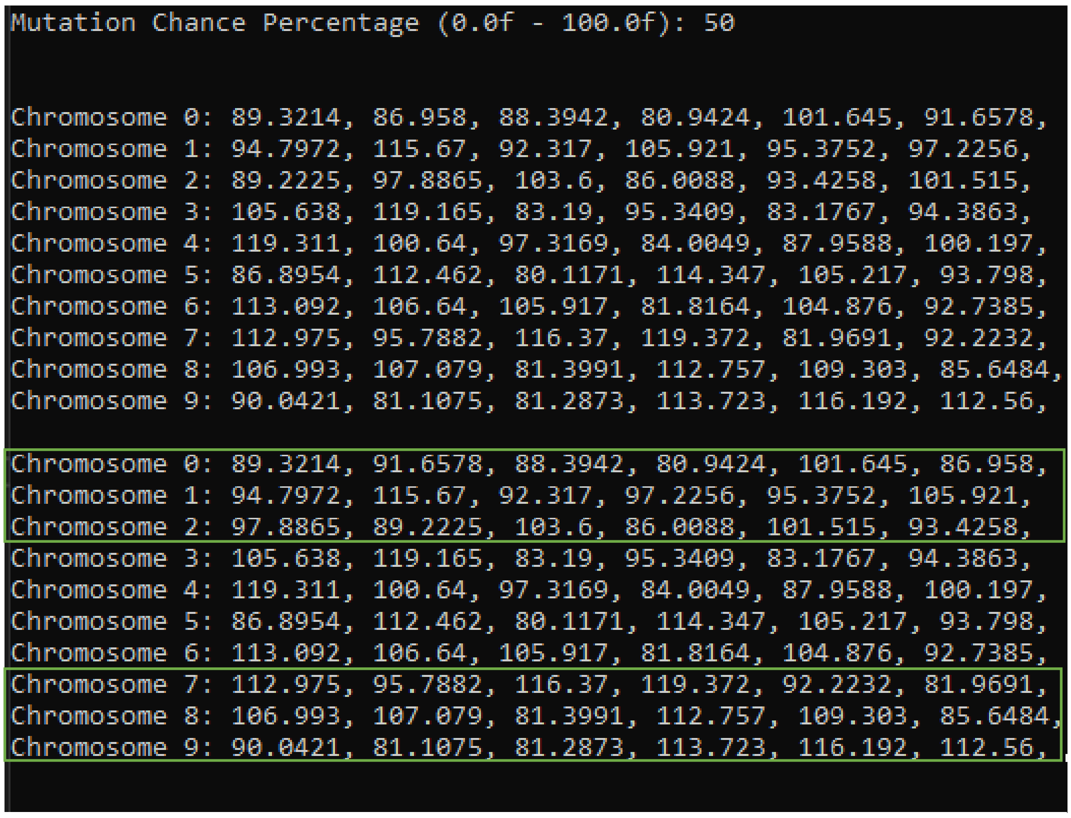
Figure 4-5 Multiple Point Crossover Test

4.2.4 Mutation Methods

For the mutation tests, I printed 10 random chromosomes to the console and then passed them into the function, along with a mutation chance. I then outputted the same chromosomes after the function had completed seeing whether the chromosomes had been mutated correctly.

Swap Mutation

As discussed in section 3, if the swap mutator is called, it will swap one or two random genes on a chromosome with two other random genes on that same chromosome. With a mutation chance of 50%, we should expect around half of the 10 chromosomes to be mutated, with one or two genes swapped. I will highlight the mutated chromosomes in green on the figure below. Once again, the top set of chromosomes are the originals, and the bottom set are the chromosomes after the function has run.

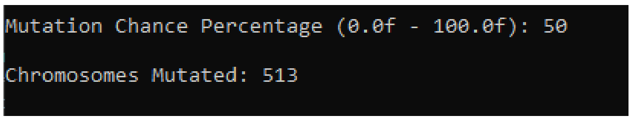


```
Mutation Chance Percentage (0.0f - 100.0f): 50


Chromosome 0: 89.3214, 86.958, 88.3942, 80.9424, 101.645, 91.6578,
Chromosome 1: 94.7972, 115.67, 92.317, 105.921, 95.3752, 97.2256,
Chromosome 2: 89.2225, 97.8865, 103.6, 86.0088, 93.4258, 101.515,
Chromosome 3: 105.638, 119.165, 83.19, 95.3409, 83.1767, 94.3863,
Chromosome 4: 119.311, 100.64, 97.3169, 84.0049, 87.9588, 100.197,
Chromosome 5: 86.8954, 112.462, 80.1171, 114.347, 105.217, 93.798,
Chromosome 6: 113.092, 106.64, 105.917, 81.8164, 104.876, 92.7385,
Chromosome 7: 112.975, 95.7882, 116.37, 119.372, 81.9691, 92.2232,
Chromosome 8: 106.993, 107.079, 81.3991, 112.757, 109.303, 85.6484,
Chromosome 9: 90.0421, 81.1075, 81.2873, 113.723, 116.192, 112.56,

Chromosome 0: 89.3214, 91.6578, 88.3942, 80.9424, 101.645, 86.958,
Chromosome 1: 94.7972, 115.67, 92.317, 97.2256, 95.3752, 105.921,
Chromosome 2: 97.8865, 89.2225, 103.6, 86.0088, 101.515, 93.4258,
Chromosome 3: 105.638, 119.165, 83.19, 95.3409, 83.1767, 94.3863,
Chromosome 4: 119.311, 100.64, 97.3169, 84.0049, 87.9588, 100.197,
Chromosome 5: 86.8954, 112.462, 80.1171, 114.347, 105.217, 93.798,
Chromosome 6: 113.092, 106.64, 105.917, 81.8164, 104.876, 92.7385,
Chromosome 7: 112.975, 95.7882, 116.37, 119.372, 92.2232, 81.9691,
Chromosome 8: 106.993, 107.079, 81.3991, 112.757, 109.303, 85.6484,
Chromosome 9: 90.0421, 81.1075, 81.2873, 113.723, 116.192, 112.56,
```

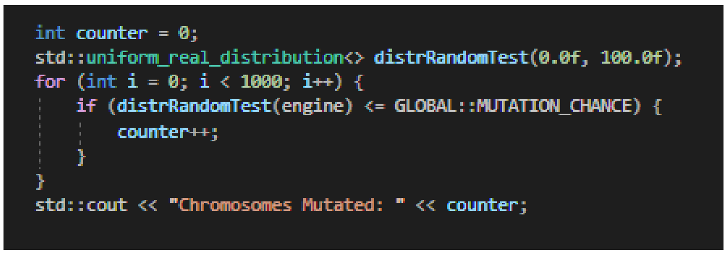
Figure 4-6 Swap Mutation Test

As you can see, I have highlighted six out of the ten chromosomes. With a mutation chance of 50% and only 10 chromosomes, 60% is an acceptable result. To show that the random engine I am using is reliable I also tested whether the mutator would have been activated if called 1000 times with a mutation chance of 50%. The results of this are below.

Essentially, a random number is generated between 0 and 100. If this number is 50 or less, then the mutator would have been called and therefore a counter is incremented. Out of 1000 calls, the counter is incremented 513 times, or 51.3% of the time, which is more than acceptable for the simulation.



```
Mutation Chance Percentage (0.0f - 100.0f): 50

Chromosomes Mutated: 513
```

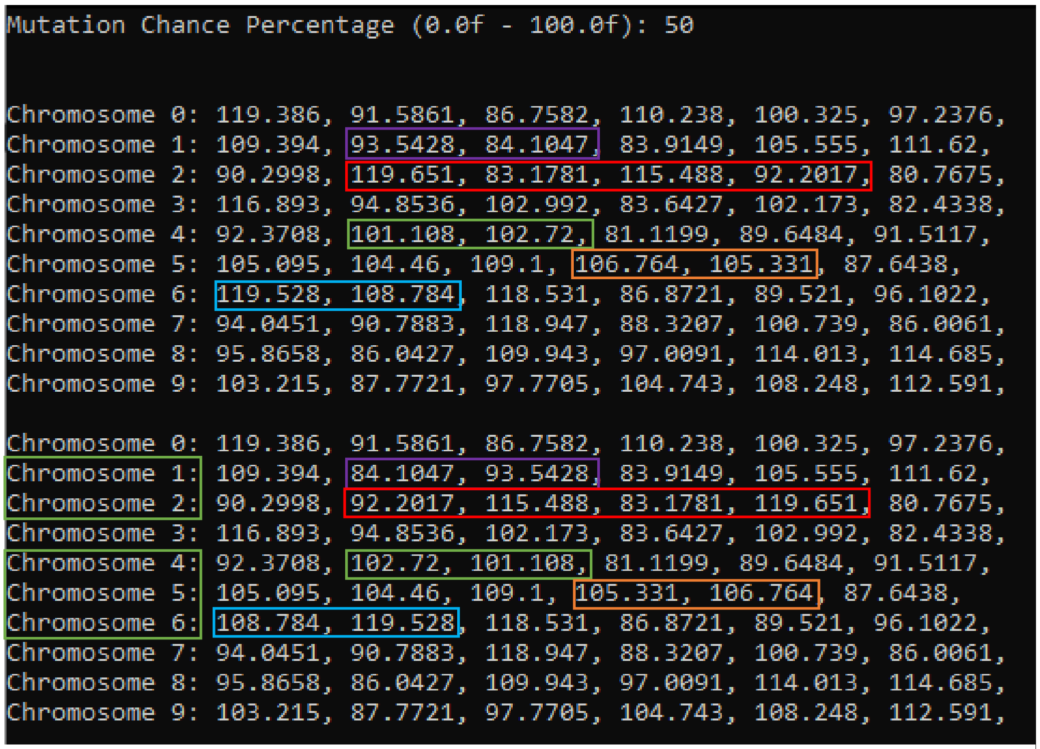


```
int counter = 0;
std::uniform_real_distribution<> distrRandomTest(0.0f, 100.0f);
for (int i = 0; i < 1000; i++) {
    if (distrRandomTest(engine) <= GLOBAL::MUTATION_CHANCE) {
        counter++;
    }
}
std::cout << "Chromosomes Mutated: " << counter;
```

Figure 4-7 Swap Mutation & Random Engine Test

Scramble/Shuffle Mutation

If the scramble mutator is called, a random subset of that chromosome has its genes shuffled. Below is the output from this function when 10 random organisms have been passed to it. A mutation chance of 50% has been used once again. On the left, I will highlight which chromosomes have been mutated and then on the right, I will highlight the subsets which have been scrambled, with colours corresponding to the original chromosome.

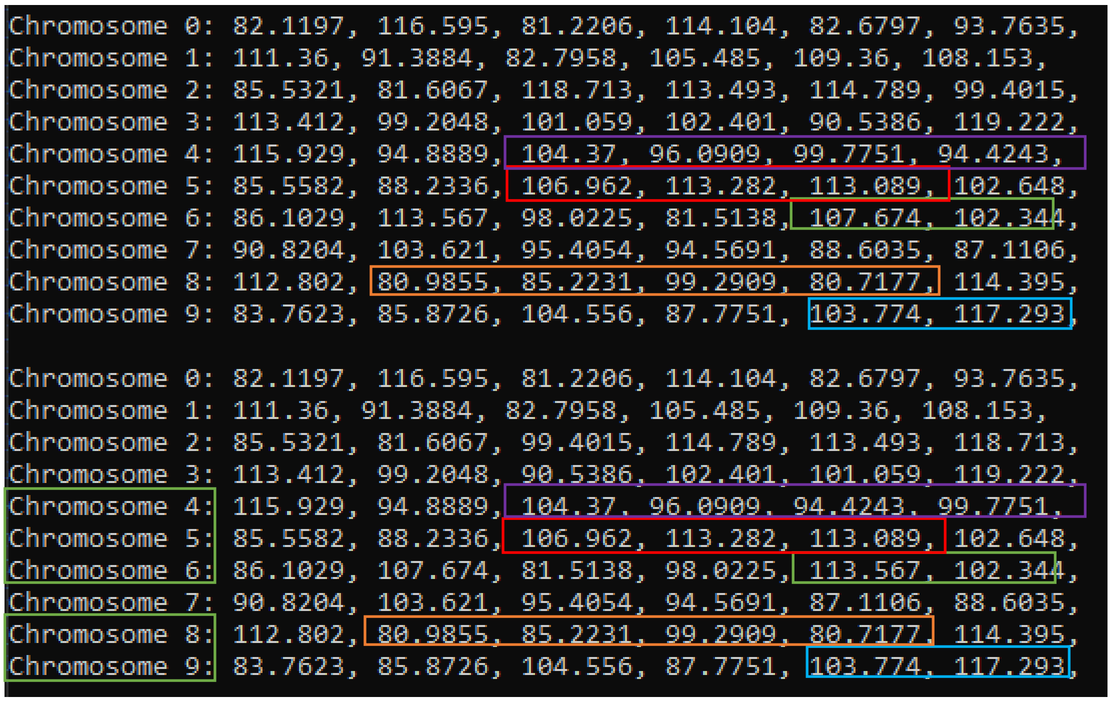


```
Mutation Chance Percentage (0.0f - 100.0f): 50


Chromosome 0: 119.386, 91.5861, 86.7582, 110.238, 100.325, 97.2376,
Chromosome 1: 109.394, 93.5428, 84.1047, 83.9149, 105.555, 111.62,
Chromosome 2: 90.2998, 119.651, 83.1781, 115.488, 92.2017, 80.7675,
Chromosome 3: 116.893, 94.8536, 102.992, 83.6427, 102.173, 82.4338,
Chromosome 4: 92.3708, 101.108, 102.72, 81.1199, 89.6484, 91.5117,
Chromosome 5: 105.095, 104.46, 109.1, 106.764, 105.331, 87.6438,
Chromosome 6: 119.528, 108.784, 118.531, 86.8721, 89.521, 96.1022,
Chromosome 7: 94.0451, 90.7883, 118.947, 88.3207, 100.739, 86.0061,
Chromosome 8: 95.8658, 86.0427, 109.943, 97.0091, 114.013, 114.685,
Chromosome 9: 103.215, 87.7721, 97.7705, 104.743, 108.248, 112.591,

Chromosome 0: 119.386, 91.5861, 86.7582, 110.238, 100.325, 97.2376,
Chromosome 1: 109.394, 84.1047, 93.5428, 83.9149, 105.555, 111.62,
Chromosome 2: 90.2998, 92.2017, 115.488, 83.1781, 119.651, 80.7675,
Chromosome 3: 116.893, 94.8536, 102.173, 83.6427, 102.992, 82.4338,
Chromosome 4: 92.3708, 102.72, 101.108, 81.1199, 89.6484, 91.5117,
Chromosome 5: 105.095, 104.46, 109.1, 105.331, 106.764, 87.6438,
Chromosome 6: 108.784, 119.528, 118.531, 86.8721, 89.521, 96.1022,
Chromosome 7: 94.0451, 90.7883, 118.947, 88.3207, 100.739, 86.0061,
Chromosome 8: 95.8658, 86.0427, 109.943, 97.0091, 114.013, 114.685,
Chromosome 9: 103.215, 87.7721, 97.7705, 104.743, 108.248, 112.591,
```

Figure 4-8 Scramble Mutation Test

Inversion Mutation

This test is almost identical to the last test except instead of scrambling the random subset, it is instead inverted. Here you can see exactly 50% of the chromosomes are mutated and each has a randomly inverted subset.

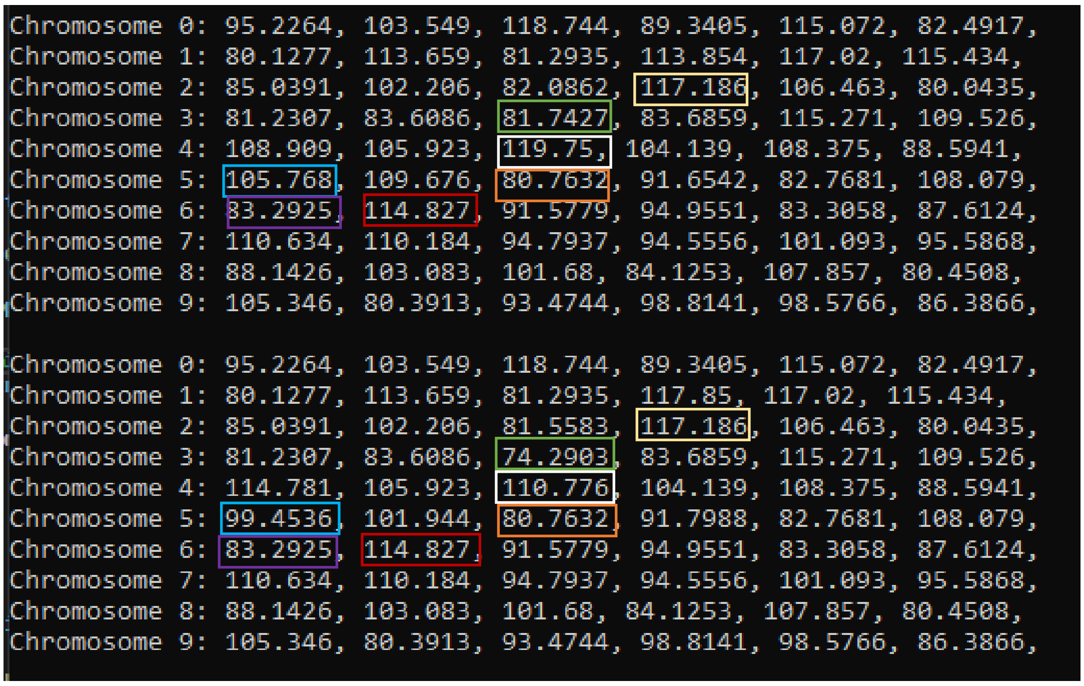


```
Chromosome 0: 82.1197, 116.595, 81.2206, 114.104, 82.6797, 93.7635,
Chromosome 1: 111.36, 91.3884, 82.7958, 105.485, 109.36, 108.153,
Chromosome 2: 85.5321, 81.6067, 118.713, 113.493, 114.789, 99.4015,
Chromosome 3: 113.412, 99.2048, 101.059, 102.401, 90.5386, 119.222,
Chromosome 4: 115.929, 94.8889, 104.37, 96.0909, 99.7751, 94.4243,
Chromosome 5: 85.5582, 88.2336, 106.962, 113.282, 113.089, 102.648,
Chromosome 6: 86.1029, 113.567, 98.0225, 81.5138, 107.674, 102.344,
Chromosome 7: 90.8204, 103.621, 95.4054, 94.5691, 88.6035, 87.1106,
Chromosome 8: 112.802, 80.9855, 85.2231, 99.2909, 80.7177, 114.395,
Chromosome 9: 83.7623, 85.8726, 104.556, 87.7751, 103.774, 117.293,

Chromosome 0: 82.1197, 116.595, 81.2206, 114.104, 82.6797, 93.7635,
Chromosome 1: 111.36, 91.3884, 82.7958, 105.485, 109.36, 108.153,
Chromosome 2: 85.5321, 81.6067, 99.4015, 114.789, 113.493, 118.713,
Chromosome 3: 113.412, 99.2048, 90.5386, 102.401, 101.059, 119.222,
Chromosome 4: 115.929, 94.8889, 104.37, 96.0909, 94.4243, 99.7751,
Chromosome 5: 85.5582, 88.2336, 106.962, 113.282, 113.089, 102.648,
Chromosome 6: 86.1029, 107.674, 81.5138, 98.0225, 113.567, 102.344,
Chromosome 7: 90.8204, 103.621, 95.4054, 94.5691, 87.1106, 88.6035,
Chromosome 8: 112.802, 80.9855, 85.2231, 99.2909, 80.7177, 114.395,
Chromosome 9: 83.7623, 85.8726, 104.556, 87.7751, 103.774, 117.293,
```

Figure 4-9 Inversion Mutation Test

Creep Mutation

Creep mutation carries out mutation on single genes rather than the entire chromosome. For this reason, I lowered the mutation chance to 10% for the test to avoid cluttering the figure below. Once again, I have highlighted the mutated genes and colour coordinated them with the gene from the original chromosome. For this test, the creep value was set between -15 and +15 and as you can see, all mutated genes fall into this range. The percentage of mutated genes in this example was 11.6%, landing very close to the chosen 10% mutation chance.

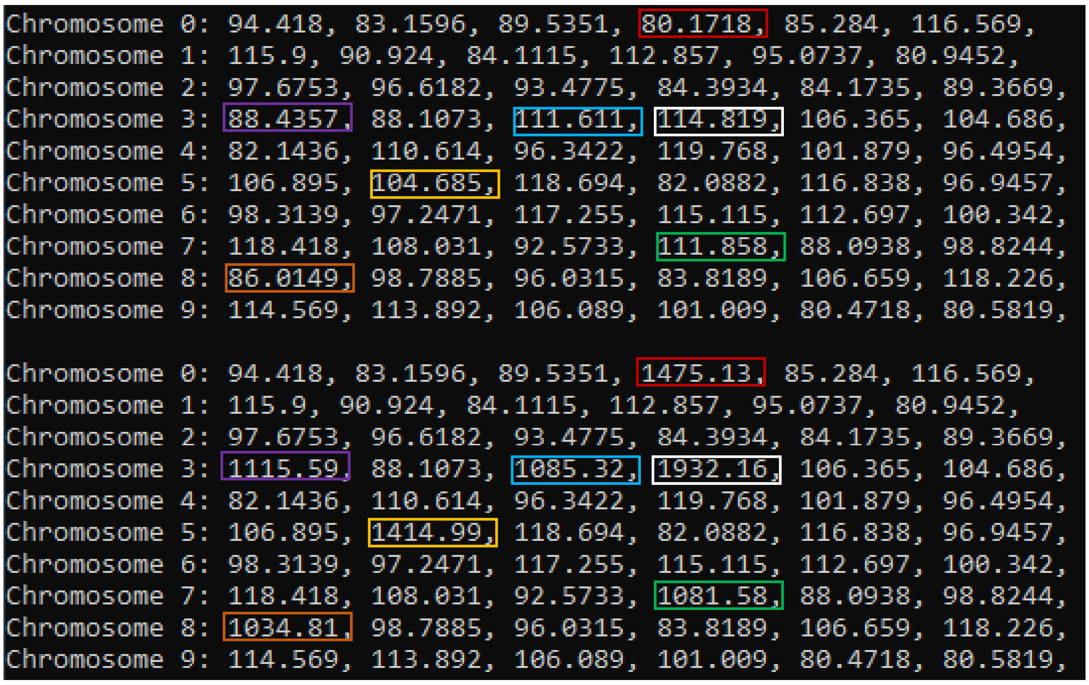


```
Chromosome 0: 95.2264, 103.549, 118.744, 89.3405, 115.072, 82.4917,
Chromosome 1: 80.1277, 113.659, 81.2935, 113.854, 117.02, 115.434,
Chromosome 2: 85.0391, 102.206, 82.0862, 117.186, 106.463, 80.0435,
Chromosome 3: 81.2307, 83.6086, 81.7427, 83.6859, 115.271, 109.526,
Chromosome 4: 108.909, 105.923, 119.75, 104.139, 108.375, 88.5941,
Chromosome 5: 105.768, 109.676, 80.7632, 91.6542, 82.7681, 108.079,
Chromosome 6: 83.2925, 114.827, 91.5779, 94.9551, 83.3058, 87.6124,
Chromosome 7: 110.634, 110.184, 94.7937, 94.5556, 101.093, 95.5868,
Chromosome 8: 88.1426, 103.083, 101.68, 84.1253, 107.857, 80.4508,
Chromosome 9: 105.346, 80.3913, 93.4744, 98.8141, 98.5766, 86.3866,

Chromosome 0: 95.2264, 103.549, 118.744, 89.3405, 115.072, 82.4917,
Chromosome 1: 80.1277, 113.659, 81.2935, 117.85, 117.02, 115.434,
Chromosome 2: 85.0391, 102.206, 81.5583, 117.186, 106.463, 80.0435,
Chromosome 3: 81.2307, 83.6086, 74.2903, 83.6859, 115.271, 109.526,
Chromosome 4: 114.781, 105.923, 110.776, 104.139, 108.375, 88.5941,
Chromosome 5: 99.4536, 101.944, 80.7632, 91.7988, 82.7681, 108.079,
Chromosome 6: 83.2925, 114.827, 91.5779, 94.9551, 83.3058, 87.6124,
Chromosome 7: 110.634, 110.184, 94.7937, 94.5556, 101.093, 95.5868,
Chromosome 8: 88.1426, 103.083, 101.68, 84.1253, 107.857, 80.4508,
Chromosome 9: 105.346, 80.3913, 93.4744, 98.8141, 98.5766, 86.3866,
```

Figure 4-10 Creep Mutation Test

Random Resetting Mutation

As random mutation also performs against single genes rather than the entire chromosome, I kept the mutation chance to 10 for this test. I set the lower bounds of the random value to 1000, and the upper bound to 2000. I did this to make it clearer where mutation had occurred. When attempting to use the program for evolution simulation I would not use bounds as high as these. Once again, the rate of mutation was 11.6% in this iteration, falling close to the 10% target.

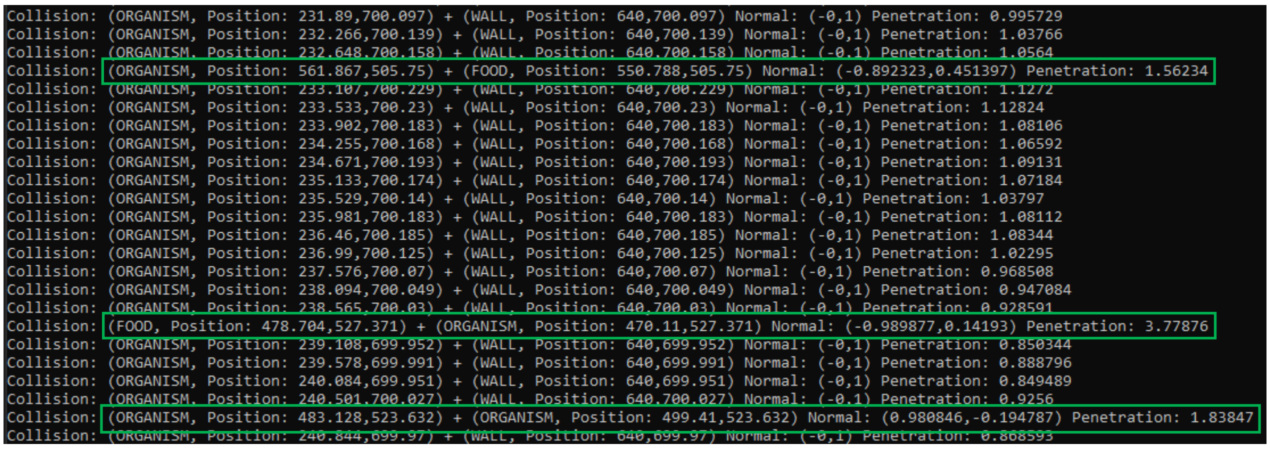


```
Chromosome 0: 94.418, 83.1596, 89.5351, 80.1718, 85.284, 116.569,
Chromosome 1: 115.9, 90.924, 84.1115, 112.857, 95.0737, 80.9452,
Chromosome 2: 97.6753, 96.6182, 93.4775, 84.3934, 84.1735, 89.3669,
Chromosome 3: 88.4357, 88.1073, 111.611, 114.819, 106.365, 104.686,
Chromosome 4: 82.1436, 110.614, 96.3422, 119.768, 101.879, 96.4954,
Chromosome 5: 106.895, 104.685, 118.694, 82.0882, 116.838, 96.9457,
Chromosome 6: 98.3139, 97.2471, 117.255, 115.115, 112.697, 100.342,
Chromosome 7: 118.418, 108.031, 92.5733, 111.858, 88.0938, 98.8244,
Chromosome 8: 86.0149, 98.7885, 96.0315, 83.8189, 106.659, 118.226,
Chromosome 9: 114.569, 113.892, 106.089, 101.009, 80.4718, 80.5819,

Chromosome 0: 94.418, 83.1596, 89.5351, 1475.13, 85.284, 116.569,
Chromosome 1: 115.9, 90.924, 84.1115, 112.857, 95.0737, 80.9452,
Chromosome 2: 97.6753, 96.6182, 93.4775, 84.3934, 84.1735, 89.3669,
Chromosome 3: 1115.59, 88.1073, 1085.32, 1932.16, 106.365, 104.686,
Chromosome 4: 82.1436, 110.614, 96.3422, 119.768, 101.879, 96.4954,
Chromosome 5: 106.895, 1414.99, 118.694, 82.0882, 116.838, 96.9457,
Chromosome 6: 98.3139, 97.2471, 117.255, 115.115, 112.697, 100.342,
Chromosome 7: 118.418, 108.031, 92.5733, 1081.58, 88.0938, 98.8244,
Chromosome 8: 1034.81, 98.7885, 96.0315, 83.8189, 106.659, 118.226,
Chromosome 9: 114.569, 113.892, 106.089, 101.009, 80.4718, 80.5819,
```

Figure 4-11 Random Resetting Test

4.2.5 Collision Detection

The best way to test collision detection and resolution would be to show the simulation in action, however, that will not be possible within this document. The next best thing I could do was output the collisions as they were being resolved, detailing the types of objects, their positions, the collision normal, and the penetration distance. These collisions were outputted within the collision resolution method, as there is a loop that loops through each pair of colliders that had collided that frame. Within the console output, you can see collisions between an organism and a piece of food, two organisms colliding with each other, as well as the same stubborn organism repeatedly headbutting a wall.



```
Collision: (ORGANISM, Position: 231.89,700.097) + (WALL, Position: 640,700.097) Normal: (-0,1) Penetration: 0.995729
Collision: (ORGANISM, Position: 232.266,700.139) + (WALL, Position: 640,700.139) Normal: (-0,1) Penetration: 1.03766
Collision: (ORGANISM, Position: 232.648,700.158) + (WALL, Position: 640,700.158) Normal: (-0,1) Penetration: 1.0564
Collision: (ORGANISM, Position: 561.867,505.75) + (FOOD, Position: 550.788,505.75) Normal: (-0.892323,0.451397) Penetration: 1.56234
Collision: (ORGANISM, Position: 233.107,700.229) + (WALL, Position: 640,700.229) Normal: (-0,1) Penetration: 1.1272
Collision: (ORGANISM, Position: 233.533,700.23) + (WALL, Position: 640,700.23) Normal: (-0,1) Penetration: 1.12824
Collision: (ORGANISM, Position: 233.902,700.183) + (WALL, Position: 640,700.183) Normal: (-0,1) Penetration: 1.08106
Collision: (ORGANISM, Position: 234.255,700.168) + (WALL, Position: 640,700.168) Normal: (-0,1) Penetration: 1.06592
Collision: (ORGANISM, Position: 234.671,700.193) + (WALL, Position: 640,700.193) Normal: (-0,1) Penetration: 1.09131
Collision: (ORGANISM, Position: 235.133,700.174) + (WALL, Position: 640,700.174) Normal: (-0,1) Penetration: 1.07184
Collision: (ORGANISM, Position: 235.529,700.14) + (WALL, Position: 640,700.14) Normal: (-0,1) Penetration: 1.03797
Collision: (ORGANISM, Position: 235.981,700.183) + (WALL, Position: 640,700.183) Normal: (-0,1) Penetration: 1.08112
Collision: (ORGANISM, Position: 236.46,700.185) + (WALL, Position: 640,700.185) Normal: (-0,1) Penetration: 1.08344
Collision: (ORGANISM, Position: 236.99,700.125) + (WALL, Position: 640,700.125) Normal: (-0,1) Penetration: 1.02295
Collision: (ORGANISM, Position: 237.576,700.07) + (WALL, Position: 640,700.07) Normal: (-0,1) Penetration: 0.968508
Collision: (ORGANISM, Position: 238.094,700.049) + (WALL, Position: 640,700.049) Normal: (-0,1) Penetration: 0.947084
Collision: (ORGANISM, Position: 238.565,700.03) + (WALL, Position: 640,700.03) Normal: (-0,1) Penetration: 0.928591
Collision: (FOOD, Position: 478.704,527.371) + (ORGANISM, Position: 470.11,527.371) Normal: (-0.989877,0.14193) Penetration: 3.77876
Collision: (ORGANISM, Position: 239.108,699.952) + (WALL, Position: 640,699.952) Normal: (-0,1) Penetration: 0.850344
Collision: (ORGANISM, Position: 239.578,699.991) + (WALL, Position: 640,699.991) Normal: (-0,1) Penetration: 0.888796
Collision: (ORGANISM, Position: 240.084,699.951) + (WALL, Position: 640,699.951) Normal: (-0,1) Penetration: 0.849489
Collision: (ORGANISM, Position: 240.501,700.027) + (WALL, Position: 640,700.027) Normal: (-0,1) Penetration: 0.9256
Collision: (ORGANISM, Position: 483.128,523.632) + (ORGANISM, Position: 499.41,523.632) Normal: (0.980846,-0.194787) Penetration: 1.83847
Collision: (ORGANISM, Position: 240.844,699.97) + (WALL, Position: 640,699.97) Normal: (-0,1) Penetration: 0.868593
```

Figure 4-12 Collision Detection Test

4.3 Results

I figured that an important part of this dissertation would be demonstrating that the genetic algorithm can allow the organisms' fitness to increase over time through the evolution of their genes. This section of the evaluation will then look at certain parameters that can be used to achieve this result. This also gives a chance to demonstrate all functions in the GA working together to create new populations.

4.3.1 Example One

Full output from the program can be found at the end of the document, Appendix 1.

Parameters

- Population Size: 20
- Amount of Food: 20
- Amount of Poison: 15
- Generation Time (seconds): 25
- Population Survivors: 50% (10)
- Selection: Roulette Wheel
- Crossover: Multiple-Point
- Primary Mutation: Creep
- Creep Value: 25
- Secondary Mutation: Scramble
- Mutation Chance: 15%

Results

Generation	Average Fitness	Best Fitness
1	135.3	197.496
2	136.316	200.08
3	130.65	212.531
4	157.733	223.023
5	155.392	252.843
6	163.34	244.631
7	164.979	262.588
8	158.092	309.657
9	163.951	313.738
10	164.345	332.006
11	173.789	311.109
12	175.209	325.14
13	173.018	319.547
14	171.242	324.109
15	177.129	357.613

Figure 4-13 Result One Table

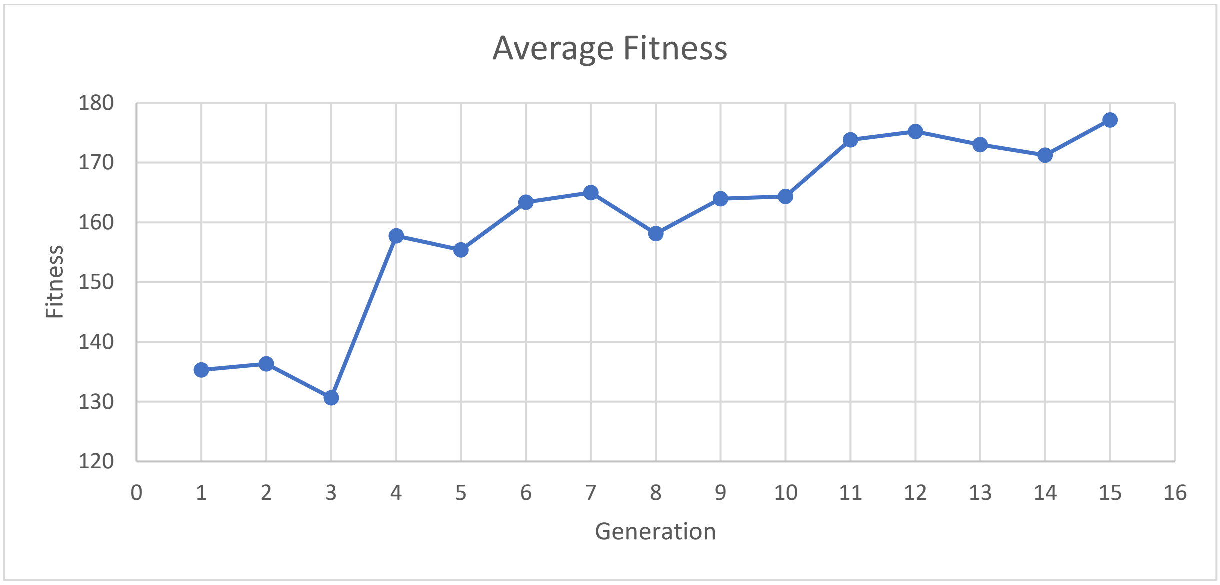


Figure 4-14 Result One Average Fitness

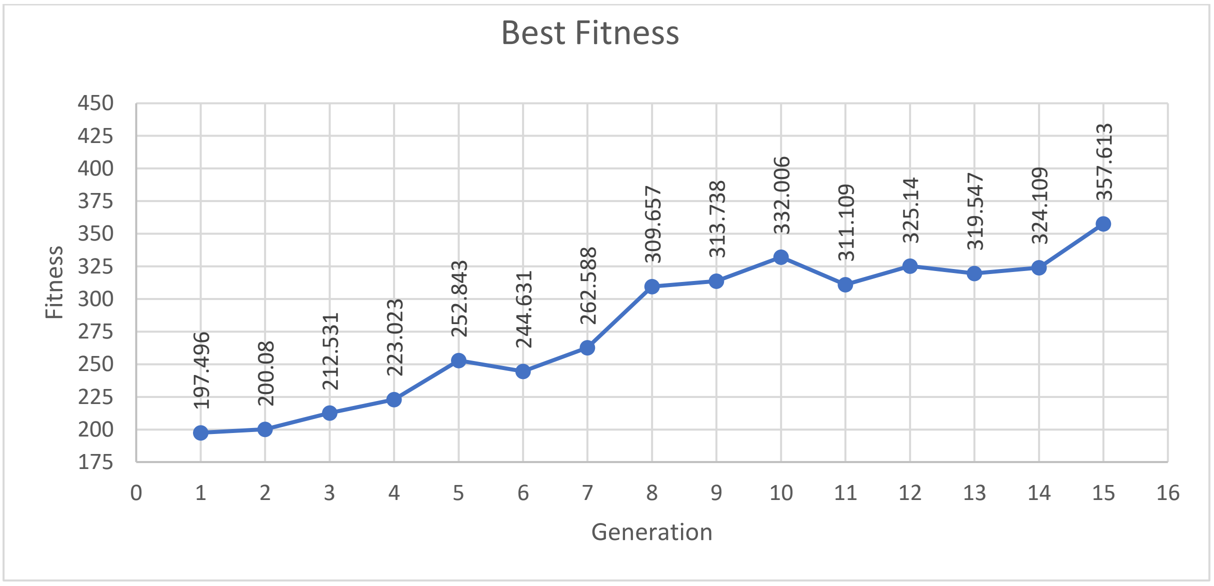


Figure 4-15 Result One Best Fitness

Evaluation

The best fitness in the population consistently increased throughout the 15 generations. The fittest organism in generation 1 had a fitness of 197.496, whereas the fittest organism in generation 15 had a fitness of 357.613. This is an increase of 81% over just 15 generations.

To show that this was not entirely luck, I measured the average fitness of each generation too, to show that the entire population was getting fitter over the 15 generations. The average fitness increased from 135.3 to 177.129. This was not as drastic an increase as the best fitness at 30.9% but still shows that the population evolved over the 15 generations. Interestingly, most of the improvement in the population happened just after generation 3, going from 130.65 average fitness to 157.733. Despite this, the population did continue to improve after this point

4.3.2 Example Two

Full output from the program can be found at the end of the document, Appendix 2.

Parameters

- Population Size: 20
- Amount of Food: 15
- Amount of Poison: 20
- Generation Time (seconds): 25
- Population Survivors: 50% (10)
- Selection: Tournament (Size: 2, Survivors: 1)
- Crossover: Uniform
- Primary Mutation: Creep
- Creep Value: 25
- Secondary Mutation: Swap
- Mutation Chance: 15%

Results

Generation	**Average Fitness**	**Best Fitness**
1	103.398	169.747
2	105.177	179.358
3	107.448	197.841
4	116.691	200.594
5	118.482	200.17
6	106.396	219.849
7	110.786	205.577
8	117.95	206.773
9	130.619	212.15
10	103.806	225.187
11	118.345	225.571
12	116.21	239.245
13	124.619	242.864
14	129.155	256.686
15	132.72	275.183

Figure 4-16 Result Two Table

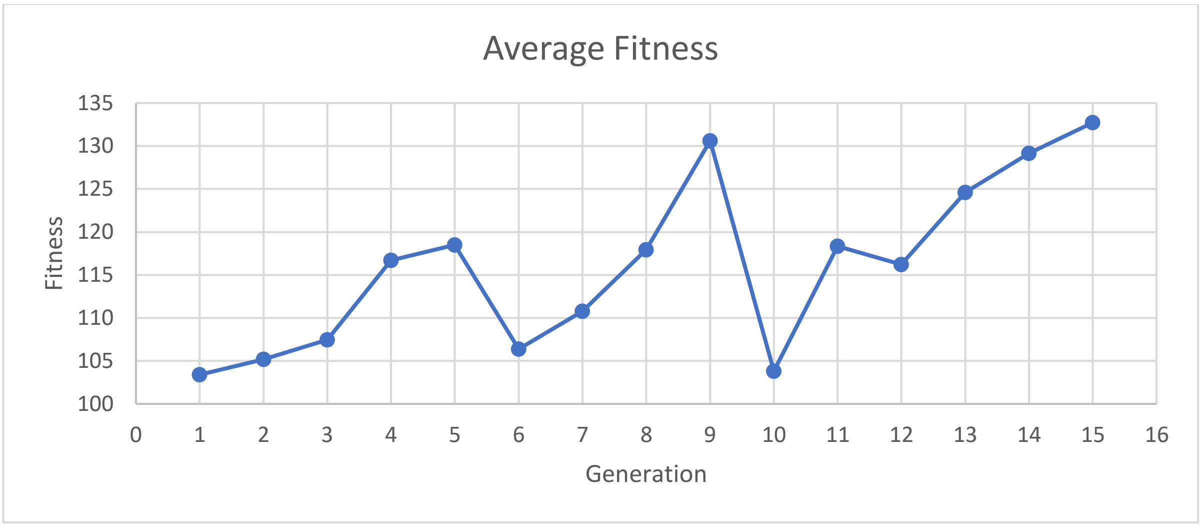


Figure 4-17 Result Two Average Fitness

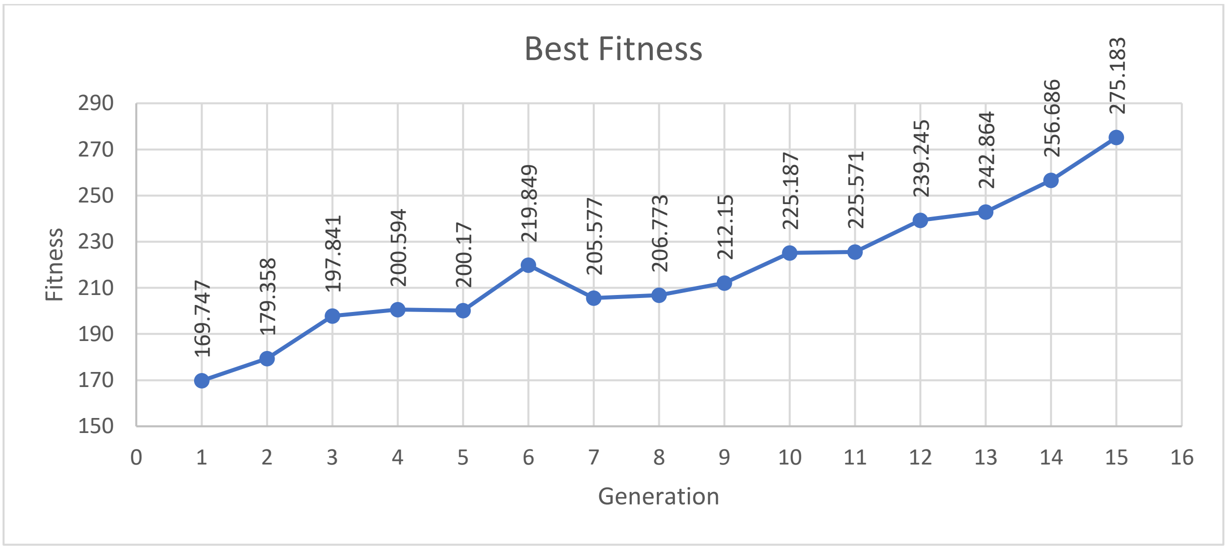


Figure 4-18 Result Two Best Fitness

Evaluation

This example once again shows that both the best fitness and average fitness improves over time. The best fitness increased by 62.11%, while the average fitness increased from 103.398 to 132.72, or an increase of 28.36%. The average fitness, although increasing over time, fluctuated wildly in this example. This could be attributed to several things. The food and poison may have spawned close together, causing the not yet intelligent organisms to completely avoid both, the selection process may have consistently picked bad organisms as competitors for the tournament, or perhaps the mutation process altered some of the fitter individuals, skewing the fitness downwards.

4.3.3 Example Three

Full output from the program can be found at the end of the document, Appendix 3.

Parameters

- Population Size: 16
- Amount of Food: 15
- Amount of Poison: 15
- Generation Time (seconds): 30
- Population Survivors: 50% (8)
- Selection: Random
- Crossover: Single-Point
- Primary Mutation: Creep
- Creep Value: 20
- Secondary Mutation: None
- Mutation Chance: 10%

Results

Generation	Average Fitness	Best Fitness
1	121.997	208.129
2	76.2252	152.227
3	90.9262	226.323
4	113.822	159.69
5	113.931	214.493
6	97.7446	203.057
7	75.1091	173.03
8	82.2169	163.003
9	81.285	127.108
10	95.028	162.917
11	97.3042	209.287
12	78.382	123.886
13	88.0719	134.109
14	106.922	218.997
15	114.133	214.193

Figure 4-19 Result Three Best Fitness

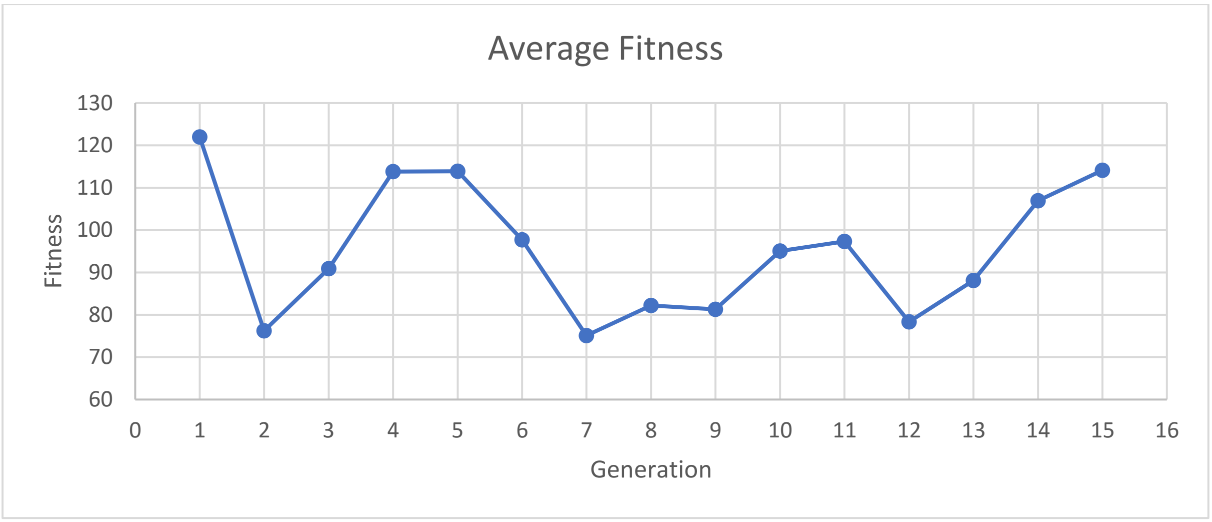


Figure 4-20 Result Three Average Fitness

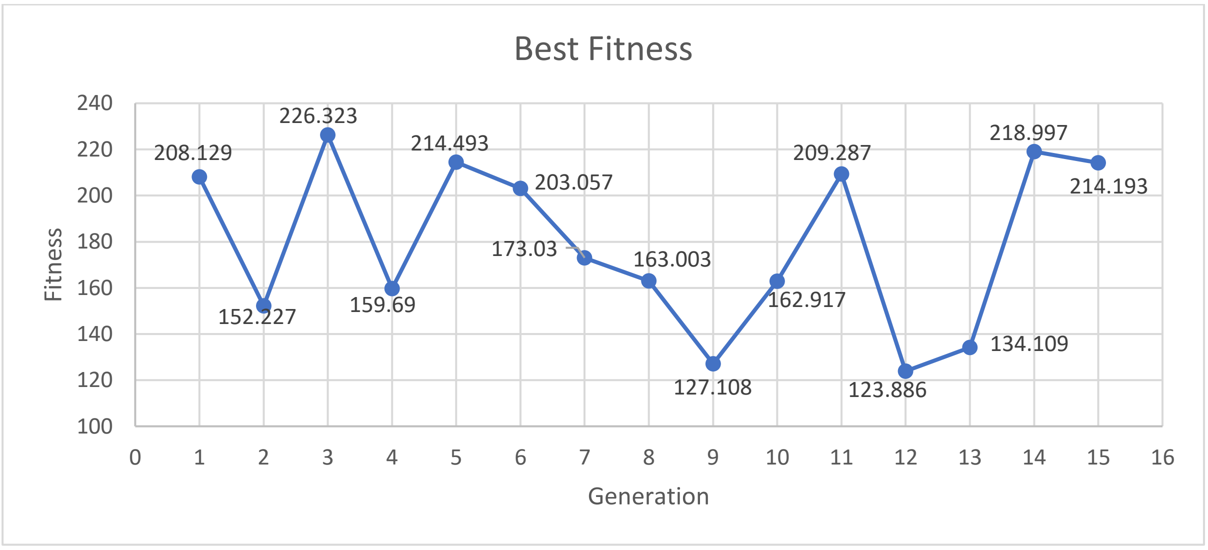


Figure 4-21 Result Three Best Fitness

Evaluation

I kept these results in to show that the population is not guaranteed to improve throughout 15 generations. This can be due to several factors, such as the parameters of the GA not being suitable for evolution to occur. In this instance, random selection is used. There is no selection pressure, meaning that the weakest organisms in the population have the same chance of producing offspring and continuing to the next generation as the fittest organisms. The smaller population size leaves less room for outstanding organisms to develop by chance and continue to improve the population. Also, the combination of single-point crossover and no secondary mutation decreases the genetic diversity of the population, meaning fewer gene combinations can be searched by the solution each generation. Another factor in poor performance is simply luck. Genetic algorithms are not guaranteed to come to a suitable solution due to the random factors involved in the selection and reproduction process.

4.4 Requirements Evaluation

4.4.1 Functional Requirement Evaluation

At program launch, the system must provide the user with a list of options regarding altering the GA and the number of elements in the environment.

I feel confident in saying that this requirement has been met as the user is prompted with a console window on the launch of the program. You can refer to Figure 4-1 to see how this prompt is displayed and the options the user is presented with. Although this requirement has been fulfilled, it deviates from the original plan of a GUI with sliders, present in the simulation window.

The system must display all organisms, food elements, poison elements and the current generation number in a window, all in the correct positions according to the physics engine.

As shown in Section 4.2.1, all elements listed above are displayed in the main simulation window. As the physics engine is the only factor manipulating the position of these elements, they must be in the positions given by the physics engine.

The console should output the current statistics of the genetic algorithm during, and after each generation.

The console outputs each organism, its chromosome, each fitness value as well as the best and average fitness for each generation. In that sense, the requirement has been met and is sufficient for the project. However, I do think more statistics could be present, such as which organisms were selected, where crossover occurred, and which organisms were mutated. It would clutter the console, but I could have found another method for presenting the information. Figure 3-16

At the end of each generation, all elements in the scene should be replaced with the new elements created by the GA.

The results posted in the previous section show that this requirement has been met. This requirement was either achieved or not achieved, leaving little room for possible improvements or alteration, making it a definite success.

The system should detect collisions between elements and pass this information to the physics engine for resolution.

Figure 4-12 shows the information that is collected by the collision detection system and passed to the physics engine. This includes the positions of both objects, their types, the penetration distance of the objects as well as the collision normal vector. For that reason, I am satisfied with the completion of this requirement.

When a collision is detected, the velocity and position of affected elements should be handled accurately by the physics engine and displayed to the user.

I was not able to effectively present the results of the collision resolution methods since presenting information from the physics engine would result in an unpresentable amount of information due to it updating thirty times a second for each element in the simulation. Visually, the resolution methods are done justice as you can see the effect of them within the simulation window. To see exactly how I implement collision resolution you can refer to Section 3.8.4.

The GA should be able to carry out multiple operations for each of the following: population selection, chromosome crossover, and gene mutation.

As shown from the testing section, there are multiple options for each of the above parameters, all working as intended. Therefore, I can safely say this requirement has been met sufficiently.

4.4.2 Non-Functional Requirement Evaluation

The system should run on Windows 10 64-bit/32-bit and Windows 7 SP1

I have tested the system, in its current state on a 64-bit version of Windows 10 Pro, running on the latest version. The program runs without needing any additional software. I have also tried a slightly older build on a 32-bit Windows 7 laptop with Service Pack 1 installed. Once again, the program ran with no issues. There is no reason the program should not also run on Windows 8 but unfortunately, I do not have the means to test this, therefore I could not add it as a requirement.

The system should support the following hardware: A video card that supports a minimum resolution of 1280x720. Ideally, a resolution of (1366x768) should be in use.

The program window itself runs at a resolution of 1280x720 so any computer running at this resolution should have no issue running the program. I found on a laptop running at 1366x768 that you could run the program while maintaining a view of the console which I believe to be the ideal way to operate the program.

The system should support the following hardware: At least 50MB free disk space.

I chose 50MB as I did not believe the program would ever require that much storage space and figured it would be a suitable target to stay under. The release build of the program currently sits at 33.8MB, which meets the requirement handily, although I did not believe it would end up this large.

The system should support the following hardware: 4GB of RAM.

I have only been able to test the system with a minimum of 6GB of RAM. Therefore, I cannot say that this requirement has been met fully. However, even with 50 organisms, 50 food objects, and 50 food objects the program never surpassed 80MB memory usage during the testing process.

5 Conclusion

5.1 Satisfaction of Aim & Objectives

This section may seem a little bit repetitive after the previous section about the requirements. However, this looks at the success of the project in its entirety, rather than just the functionality of the program.

5.1.1 Objectives

Theorize and create a genetic algorithm that increases the calculated fitness of an organism, effectively evolving it.

As mentioned above, I believe the design and execution of the genetic algorithm is a strong success for the project, capable of evolving the population, as well as providing extensive coverage of different evolutionary algorithm methods.

Implement a GUI which displays organisms, other entities, and the current statistics of the genetic algorithm.

This objective has left me feeling conflicted due to how it was worded. Taken at face value, I am satisfied that the interface displays the population, food, poison, and generation number in the main simulation window. The statistics of the algorithm are displayed within the console window. In the next section of the document, I will describe what I would do differently regarding the GUI if given the chance.

Create a movement system whereby organisms choose where to move based on their size, quality of their vision, and nearby food and poison positions.

Given the limited knowledge of how I could implement this at the start of the project, compared to how it ended up functioning, I am very satisfied with this objective. One part of the objective that is not entirely accurate is organisms moved 'based' on their size. While the organism's size does affect the speed and mass of the organism, it does not change where it decides to move. They do, however, move based on their vision of nearby poison and food elements. I do believe there is a better way I could have implemented the general movement of the population, which I will talk about in the next section.

Create a collision detection system that allows organisms to interact with food/poison entities and have their health affected accordingly. This will be visible in the program.

The collision detection and resolution system I have created is an objective I am very satisfied with. It achieves exactly what I needed it to, it checks if two objects are colliding with each other and passes the relevant information from the collision to the physics engine to resolve the collision. This can be seen in the program as the population is unable to escape the bounds of the environment and will bounce off each other in a way that both conserves momentum and accurately redirects the two organisms.

Program a death and reproduction cycle which will remove the previous organisms, reproduce them using the genetic algorithm and create a new set of organisms with new chromosome values.

This objective turned out to be a simple one to implement yet without it the project would be a failure. I cannot think of anything I could have done differently regarding this objective and think perhaps it could have been joined with the genetic algorithm objective or ignored entirely.

Introduce an interactive component to the GUI that would allow a user to modify the algorithm's specific parameters to change how fast or effective the evolution of organisms is.

This objective was a success in the sense that a user can modify the algorithm’s parameters. In addition to this, the extent to which the algorithm can be altered is much greater than I originally believed it would be, which is a plus. However, as discussed above I originally had more impressive ideas for the interactive component of the UI, which will be discussed below.

5.1.2 Aim

This project aimed to explore how a genetic algorithm can be manufactured to simulate evolution amongst artificial organisms, providing an interactive interface where parameters can be altered to adjust the effectiveness of evolution.

I feel as though the aim has been a success overall. This document covers my research into genetic algorithms and my method of implementing one, which I consider to have been an interesting learning experience. The result has produced an extensive algorithm with many parameters for a user to adjust. I have also shown that this algorithm can be used for evolution amongst the organisms I have created, however, this is not a guaranteed result, and a user would have to do research and experiment with the algorithm to see such a result. This may sound like a drawback, but I view it as a success as it captures some of the fascinating factors of evolution, random chance, and luck. In nature, evolution and survival are not guaranteed, as seen by extinctions of creatures long before humanity was a problem.

5.2 Improvements

If given the chance to go back and start from the beginning, there would be a few things I would change, some due to poor execution and some due to knowledge I only possess after creating this system.

I would change the aim of the project, focusing more on creating a system that teaches users how the algorithm functions and how each method affects the chromosome of the organism. This could be used as a tool to teach the topic to students in a way that is engaging and keeps people wanting to experiment with parameters while learning what each one does. Instead, the current project gives access to the parameters and the ability to change them but to a user who has no prior knowledge of evolutionary computing, the words will mean nothing. This leads into my second improvement of expanding the statistics given by the program. Right now, a user can see all the organisms, their chromosome, and their fitness, but not the algorithm processes that got them to that point. I would display information on which genes had been mutated, where crossover had occurred, and how each organism was selected.

If I had more time and the knowledge of C++-compatible graphical libraries, I would have created a more engaging UI that sat within the main simulation window. Although it would not have affected the functionality of the program, it would have been more satisfying to use, as you would be able to change parameters while the simulation is running with ease, as well as sliders and buttons, rather than manually typing each value. There could have been potentially graphs and charts created during the runtime of the program and displayed to the user.

Finally, I would implement neural networks for the organisms for intelligent decision making. The current population make binary decisions based on their radius to food and poison. They also move completely randomly when not in range of these elements, whereas I believe it would be more interesting if they were constantly making decisions based on numerous factors. Another possibility in the future would be to introduce predators into the environment, more barriers to impede movement and the idea of thirst and fullness. These are all things I will be considering in the future.

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7 Appendices

7.1 Appendix 1

```
Population Size: 20
Amount of Food: 20
Amount of Poison: 15
Generation Time in Seconds: 25
Population Survivors (% of population): 50
Selection Type (Roulette = 0) (Random = 1) (Tournament = 2): 0
Crossover Type (Uniform = 0) (Single-Point = 1) (Multi-Point = 2): 2
Primary Mutation Type (Creep = 0) (Random Resetting = 1): 0
Creep Value Range: 25
Secondary Mutation Type (None = 0) (Swap = 1) (Scramble = 2) (Inversion = 3): 2
Mutation Chance Percentage (0.0f - 100.0f): 15

================================================================================
Organism 1: 113.313 85.2372 119.808 118.461 92.749 97.848 Fitness: 141.291
Organism 2: 106.152 92.13 95.468 102.885 95.2008 102.327 Fitness: 150.715
Organism 3: 107.462 101.312 95.8434 99.6068 99.3216 114.48 Fitness: 172.436
Organism 4: 98.4222 118.765 96.6203 114.695 88.9969 81.2363 Fitness: 147.526
Organism 5: 118.147 88.9171 96.4577 92.4511 92.5249 86.3127 Fitness: 115.283
Organism 6: 107.643 94.6827 91.508 97.2956 107.588 116.238 Fitness: 120.128
Organism 7: 86.7976 118.731 86.9917 103.335 95.1426 89.5373 Fitness: 176.165
Organism 8: 97.7984 89.888 115.991 109.126 99.654 92.0229 Fitness: 131.957
Organism 9: 84.4283 100.238 89.1774 83.321 97.0124 95.6693 Fitness: 81.1535
Organism 10: 95.4121 113.699 105.819 114.946 115.897 105.143 Fitness: 137.778
Organism 11: 100.202 110.069 112.949 117.696 80.5813 88.2403 Fitness: 140.527
Organism 12: 95.9409 95.7797 103.164 100.014 116.926 85.7798 Fitness: 172.843
Organism 13: 111.374 90.3081 113.908 90.6791 84.117 96.3705 Fitness: 188.509
Organism 14: 82.827 86.4151 119.231 84.476 106.802 88.0455 Fitness: 132.309
Organism 15: 90.8035 102.549 80.337 81.0589 115.579 97.7948 Fitness: 103.891
Organism 16: 95.6585 93.9073 119.44 80.1541 90.6262 107.213 Fitness: 102.987
Organism 17: 115.421 118.258 97.7698 106.368 84.3325 108.213 Fitness: 64.2009
Organism 18: 111.663 92.0951 82.2935 82.7765 92.4118 86.3396 Fitness: 130.609
Organism 19: 108.37 95.9617 99.8204 100.369 110.887 95.3489 Fitness: 98.2016
Organism 20: 84.7573 80.2138 109.667 99.6639 80.673 102.446 Fitness: 197.496
Best Fitness: 197.496
Avg  Fitness: 135.3
================================================================================
Organism 1: 118.147 88.9171 96.4577 92.4511 92.5249 86.3127 Fitness: 164.837
Organism 2: 95.4121 121.596 105.819 114.946 115.897 105.143 Fitness: 162.33
Organism 3: 100.202 110.069 112.949 117.696 80.5813 88.2403 Fitness: 165.079
Organism 4: 95.4121 113.699 105.819 114.946 115.897 105.143 Fitness: 162.333
Organism 5: 100.202 110.069 112.949 117.696 78.609 88.2403 Fitness: 115.083
Organism 6: 111.663 92.0951 82.2935 82.7765 92.4118 86.3396 Fitness: 105.163
Organism 7: 113.313 85.2372 118.461 119.808 92.749 97.848 Fitness: 165.845
Organism 8: 107.643 94.6827 91.508 102.357 107.588 116.238 Fitness: 119.682
Organism 9: 98.4222 118.765 96.6203 114.695 88.9969 81.2363 Fitness: 137.08
Organism 10: 86.7976 118.731 86.9917 86.3261 95.1426 89.5373 Fitness: 100.722
Organism 11: 97.4234 101.093 105.819 114.946 92.5249 86.3127 Fitness: 122.332
Organism 12: 95.4121 113.699 96.4577 113.907 115.897 105.143 Fitness: 164.836
Organism 13: 100.202 110.069 108.283 117.696 88.2403 115.897 Fitness: 200.08
Organism 14: 95.4121 113.699 105.819 114.946 80.5813 105.143 Fitness: 137.331
Organism 15: 100.202 110.069 112.949 82.7765 86.3537 88.2403 Fitness: 115.163
Organism 16: 110.676 92.0951 82.2935 117.696 80.5813 86.3396 Fitness: 90.0832
Organism 17: 113.313 85.2372 115.791 97.2956 92.749 97.848 Fitness: 94.6826
Organism 18: 107.643 94.6827 119.808 118.461 107.588 116.238 Fitness: 165.848
Organism 19: 98.4222 118.765 108.432 103.335 88.9969 81.2363 Fitness: 100.722
Organism 20: 86.7976 118.731 96.6203 114.695 95.1426 95.5835 Fitness: 137.08
Best Fitness: 200.08
Avg  Fitness: 136.316
================================================================================
Organism 1: 85.4963 118.731 86.9917 86.3261 112.996 95.943 Fitness: 83.9149
Organism 2: 118.147 88.9171 96.4577 70.6363 92.5249 85.5428 Fitness: 50.0393
Organism 3: 98.4222 118.765 108.432 120.281 88.9969 81.2363 Fitness: 175.92
Organism 4: 100.202 110.069 108.283 115.897 88.2403 117.696 Fitness: 190.283
Organism 5: 95.4121 113.699 105.819 114.946 80.5813 105.143 Fitness: 137.532
Organism 6: 121.693 118.765 108.432 103.335 88.9969 81.2363 Fitness: 100.924
Organism 7: 100.202 110.069 108.283 133.668 88.2403 115.897 Fitness: 90.285
Organism 8: 86.7976 118.731 96.6203 114.695 95.9339 117.189 Fitness: 87.2841
Organism 9: 95.4121 121.596 105.819 114.946 115.897 105.143 Fitness: 212.531
Organism 10: 77.5396 110.069 112.949 117.696 80.5813 111.507 Fitness: 115.284
Organism 11: 86.7976 89.5373 65.7197 86.3261 110.069 117.696 Fitness: 58.9149
Organism 12: 118.147 88.9171 96.4577 92.4511 99.1877 86.3127 Fitness: 65.0399
Organism 13: 98.4222 118.765 116.91 103.335 88.2403 81.2363 Fitness: 175.92
Organism 14: 100.202 110.069 108.283 117.696 88.9969 115.897 Fitness: 165.282
Organism 15: 95.4121 89.7178 115.76 103.335 80.5813 105.143 Fitness: 125.924
Organism 16: 98.4222 98.263 105.819 114.946 88.9969 86.9917 Fitness: 162.532
Organism 17: 100.202 110.069 96.6203 114.695 86.8282 115.897 Fitness: 97.2841
Organism 18: 86.7976 138.06 108.283 117.696 88.2403 95.5835 Fitness: 115.285
Organism 19: 95.4121 110.069 112.949 117.696 115.897 105.143 Fitness: 115.284
Organism 20: 100.202 121.596 105.819 114.946 80.5813 88.2403 Fitness: 87.5349
Best Fitness: 212.531
Avg  Fitness: 130.65
================================================================================
Organism 1: 86.7976 118.731 121.414 114.695 95.9339 103.459 Fitness: 82.7746
Organism 2: 100.202 110.069 98.2808 117.696 88.9969 115.897 Fitness: 90.7757
Organism 3: 95.4121 121.596 105.819 114.946 115.897 105.143 Fitness: 138.026
Organism 4: 100.202 110.069 120.451 114.695 86.8282 115.897 Fitness: 137.772
Organism 5: 100.202 110.069 108.283 117.696 88.9969 110.429 Fitness: 90.7757
Organism 6: 96.9229 107.042 83.492 103.335 88.9969 81.2363 Fitness: 101.415
Organism 7: 100.202 110.069 108.283 115.897 88.2403 114.244 Fitness: 223.973
Organism 8: 95.4121 113.699 105.819 114.946 88.9969 80.5813 Fitness: 163.023
Organism 9: 77.5396 110.069 92.7676 128.273 102.364 111.507 Fitness: 90.7757
Organism 10: 100.202 121.596 105.819 114.946 56.6347 88.2403 Fitness: 263.022
Organism 11: 86.7976 118.731 96.6203 117.696 88.9969 117.189 Fitness: 190.772
Organism 12: 100.202 110.069 85.7649 114.695 95.9339 115.897 Fitness: 172.771
Organism 13: 95.4121 138.776 96.6203 114.695 124.573 105.143 Fitness: 147.772
Organism 14: 100.202 110.069 105.819 98.5248 86.8282 115.897 Fitness: 188.025
Organism 15: 103.335 110.069 81.2363 115.897 108.283 105.143 Fitness: 140.775
Organism 16: 121.693 118.765 102.402 103.335 88.9969 81.2363 Fitness: 126.415
Organism 17: 100.202 119.077 83.8686 114.946 80.5813 117.696 Fitness: 223.023
Organism 18: 95.4121 113.699 108.283 115.897 88.2403 105.143 Fitness: 188.976
Organism 19: 77.5396 110.069 112.949 114.946 80.5813 111.507 Fitness: 163.026
Organism 20: 100.202 116.835 82.9908 117.696 80.5813 76.2126 Fitness: 190.772
Best Fitness: 223.023
Avg  Fitness: 157.733
================================================================================
Organism 1: 86.7976 118.731 96.6203 117.696 88.9969 117.189 Fitness: 190.593
Organism 2: 86.7976 118.731 98.8883 117.696 88.9969 117.189 Fitness: 215.593
Organism 3: 100.202 85.2976 99.4764 114.695 86.8282 115.897 Fitness: 137.593
Organism 4: 95.4121 97.3853 105.819 121.547 115.897 117.293 Fitness: 252.843
Organism 5: 100.202 110.069 105.819 98.5248 102.841 115.897 Fitness: 71.4249
Organism 6: 95.4121 113.699 108.283 115.897 88.2403 105.143 Fitness: 113.797
Organism 7: 95.4121 138.776 96.6203 114.695 124.573 105.143 Fitness: 162.592
Organism 8: 77.5396 110.069 112.949 114.946 80.5813 111.507 Fitness: 187.843
Organism 9: 95.4121 121.596 105.819 114.946 115.897 105.143 Fitness: 162.844
Organism 10: 95.4121 124.23 108.283 115.897 88.2403 105.143 Fitness: 113.797
Organism 11: 86.7976 118.731 110.498 117.696 88.9969 117.189 Fitness: 165.593
Organism 12: 86.7976 118.731 80.3427 117.696 88.9969 117.189 Fitness: 115.596
Organism 13: 100.202 110.069 101.76 114.946 86.8282 115.897 Fitness: 137.846
Organism 14: 95.4121 121.596 105.819 114.695 115.897 105.143 Fitness: 162.594
Organism 15: 100.202 113.699 108.283 98.5248 86.8282 115.897 Fitness: 146.424
Organism 16: 106.269 110.069 105.819 115.897 88.2403 105.143 Fitness: 138.797
Organism 17: 95.4121 110.069 96.6203 114.695 124.573 105.143 Fitness: 212.592
Organism 18: 77.5396 138.776 112.949 114.946 80.5813 111.507 Fitness: 162.846
Organism 19: 95.4121 113.699 108.283 114.946 115.897 105.143 Fitness: 157.845
Organism 20: 103.178 121.596 105.819 115.897 88.2403 105.143 Fitness: 88.7975
Best Fitness: 252.843
Avg  Fitness: 155.392
================================================================================
Organism 1: 95.4121 114.949 105.819 121.547 115.897 117.293 Fitness: 194.63
Organism 2: 95.4121 138.776 96.6203 114.695 124.573 105.143 Fitness: 187.781
Organism 3: 77.5396 138.776 112.949 114.946 80.5813 111.507 Fitness: 213.029
Organism 4: 105.819 124.052 121.596 114.695 109.169 105.143 Fitness: 112.783
Organism 5: 107.764 97.3853 105.819 121.547 115.897 117.293 Fitness: 244.631
Organism 6: 95.4121 133.835 96.6203 114.695 124.573 105.143 Fitness: 162.78
Organism 7: 100.202 98.5248 86.8282 86.2687 115.897 113.699 Fitness: 146.609
Organism 8: 95.4121 110.069 96.6203 114.695 124.573 105.143 Fitness: 112.783
Organism 9: 106.269 110.069 105.819 115.897 105.525 105.143 Fitness: 163.981
Organism 10: 86.7976 99.9263 80.3427 117.696 88.9969 117.189 Fitness: 215.78
Organism 11: 95.4121 138.776 96.6203 114.695 115.897 117.293 Fitness: 172.78
Organism 12: 95.4121 97.3853 105.819 121.547 124.573 105.143 Fitness: 94.6341
Organism 13: 77.5396 138.776 112.949 114.695 80.5813 111.507 Fitness: 187.78
Organism 14: 95.4121 121.596 105.819 114.946 115.897 105.143 Fitness: 123.033
Organism 15: 95.4121 110.069 96.6203 121.547 115.897 117.293 Fitness: 119.634
Organism 16: 95.4121 81.8841 105.819 91.6123 124.573 105.143 Fitness: 197.779
Organism 17: 100.202 113.699 109.398 98.5248 86.8282 115.897 Fitness: 121.612
Organism 18: 113.479 110.069 108.283 114.695 124.573 105.143 Fitness: 222.779
Organism 19: 106.269 118.731 90.5336 115.897 88.2403 105.143 Fitness: 213.981
Organism 20: 86.7976 110.069 105.819 117.696 88.9969 117.189 Fitness: 90.7835
Best Fitness: 244.631
Avg  Fitness: 163.34
================================================================================
Organism 1: 106.269 110.069 105.819 115.897 122.366 105.143 Fitness: 188.79
Organism 2: 95.4121 121.596 122.414 114.946 115.897 105.143 Fitness: 172.84
Organism 3: 105.819 124.052 121.596 114.695 105.143 109.169 Fitness: 137.591
Organism 4: 107.764 97.3853 105.819 121.547 115.897 117.293 Fitness: 194.44
Organism 5: 95.4121 105.819 97.3853 97.3853 107.992 105.143 Fitness: 194.439
Organism 6: 95.4121 138.776 96.6203 114.695 124.573 105.143 Fitness: 162.588
Organism 7: 95.4121 138.776 96.6203 114.695 115.897 117.293 Fitness: 262.588
Organism 8: 107.764 97.3853 105.819 121.547 115.897 117.293 Fitness: 119.443
Organism 9: 95.4121 116.843 96.6203 114.695 115.897 117.293 Fitness: 112.591
Organism 10: 86.7976 110.069 105.819 117.696 88.9969 117.189 Fitness: 165.588
Organism 11: 106.269 121.596 101.218 114.946 105.525 105.143 Fitness: 187.838
Organism 12: 93.4545 129.052 105.819 115.897 115.897 105.143 Fitness: 163.79
Organism 13: 123.437 124.052 105.819 121.547 113.247 105.143 Fitness: 179.441
Organism 14: 107.764 97.3853 121.596 114.695 115.897 117.293 Fitness: 162.588
Organism 15: 95.4121 138.776 96.6203 114.695 117.058 105.143 Fitness: 197.588
Organism 16: 95.4121 97.3853 105.819 121.547 124.573 105.143 Fitness: 144.44
Organism 17: 108.294 97.3853 96.6203 100.217 115.897 117.293 Fitness: 72.5913
Organism 18: 107.764 138.776 105.819 121.547 115.897 117.293 Fitness: 194.44
Organism 19: 95.4121 138.776 96.6203 114.695 88.9969 122.044 Fitness: 187.589
Organism 20: 86.7976 110.069 105.819 117.696 115.897 117.189 Fitness: 165.589
Best Fitness: 262.588
Avg  Fitness: 164.979
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Organism 1: 95.4121 138.776 96.6203 117.696 107.992 88.2685 Fitness: 125.285
Organism 2: 86.7976 110.069 122.248 114.695 88.9969 117.189 Fitness: 212.28
Organism 3: 86.7976 110.069 105.819 117.696 88.9969 117.189 Fitness: 115.284
Organism 4: 86.7976 110.069 99.8288 117.696 115.897 117.189 Fitness: 115.285
Organism 5: 95.4121 138.776 96.6203 114.695 117.058 105.143 Fitness: 162.282
Organism 6: 86.7976 110.069 105.819 134.554 88.9969 135.701 Fitness: 169.657
Organism 7: 107.764 97.3853 105.819 126.563 115.897 117.293 Fitness: 99.1515
Organism 8: 107.764 98.7368 121.596 114.695 115.897 117.293 Fitness: 112.284
Organism 9: 86.7976 107.034 105.819 117.696 93.5112 117.189 Fitness: 115.284
Organism 10: 123.437 119.44 105.819 121.547 132.059 105.143 Fitness: 204.133
Organism 11: 95.4121 111.637 122.118 114.695 88.9969 88.2685 Fitness: 212.281
Organism 12: 86.7976 138.776 96.6203 132.872 117.058 112.23 Fitness: 190.281
Organism 13: 86.7976 110.069 99.8288 117.696 88.9969 117.189 Fitness: 75.2852
Organism 14: 86.7976 110.069 105.819 117.696 115.897 97.2111 Fitness: 190.284
Organism 15: 95.4121 138.776 96.6203 114.695 88.9969 105.143 Fitness: 97.2843
Organism 16: 86.7976 110.069 105.819 127.574 117.058 117.189 Fitness: 309.657
Organism 17: 107.764 97.3853 121.596 114.695 108.299 117.293 Fitness: 137.284
Organism 18: 118.699 98.7368 105.819 126.563 115.897 117.293 Fitness: 149.148
Organism 19: 86.7976 110.069 105.819 117.696 88.9969 117.189 Fitness: 190.281
Organism 20: 123.437 124.052 105.819 121.547 113.247 105.143 Fitness: 119.136
Best Fitness: 309.657
Avg  Fitness: 158.092
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Organism 1: 86.7976 110.069 105.819 134.554 88.9969 135.701 Fitness: 206.738
Organism 2: 135.097 119.44 105.819 121.547 132.059 105.143 Fitness: 178.734
Organism 3: 86.7976 125.371 105.819 127.574 117.058 106.587 Fitness: 124.76
Organism 4: 95.4121 138.776 96.6203 98.634 116.997 88.074 Fitness: 124.884
Organism 5: 95.4121 111.637 122.118 114.695 88.9969 88.2685 Fitness: 186.88
Organism 6: 62.658 119.06 105.819 117.696 93.5112 117.189 Fitness: 184.884
Organism 7: 86.7976 124.185 105.819 134.554 88.9969 133.973 Fitness: 131.74
Organism 8: 104.59 110.069 105.819 127.574 117.058 134.311 Fitness: 184.759
Organism 9: 86.7976 110.069 105.819 117.696 88.9969 117.189 Fitness: 149.884
Organism 10: 107.764 92.6095 121.125 109.212 115.897 95.4948 Fitness: 158.749
Organism 11: 86.7976 106.115 105.819 121.547 88.9969 135.701 Fitness: 93.735
Organism 12: 111.282 119.44 105.819 134.554 132.059 93.1491 Fitness: 206.738
Organism 13: 86.7976 95.5333 105.819 117.696 107.992 117.189 Fitness: 114.883
Organism 14: 95.4121 138.776 96.6203 127.574 117.058 88.2685 Fitness: 174.758
Organism 15: 95.4121 107.034 105.819 117.696 93.5112 88.2685 Fitness: 174.884
Organism 16: 86.7976 111.637 118.739 114.695 88.9969 106.553 Fitness: 71.8828
Organism 17: 86.7976 110.069 105.819 127.574 140.606 135.701 Fitness: 134.76
Organism 18: 86.7976 110.069 105.819 134.554 88.9969 110.608 Fitness: 313.738
Organism 19: 86.7976 110.069 105.819 126.563 88.9969 117.189 Fitness: 123.751
Organism 20: 107.764 97.3853 105.819 117.696 115.897 117.293 Fitness: 114.883
Best Fitness: 313.738
Avg  Fitness: 163.951
================================================================================
Organism 1: 86.7976 110.069 105.819 127.574 140.606 135.701 Fitness: 175.027
Organism 2: 111.282 119.44 105.819 134.554 153.566 93.1491 Fitness: 207.006
Organism 3: 85.126 107.034 105.819 117.696 110.068 88.2685 Fitness: 165.148
Organism 4: 130.219 119.44 105.819 134.554 132.115 93.1491 Fitness: 332.006
Organism 5: 86.7976 111.637 118.739 114.695 88.9969 101.385 Fitness: 112.151
Organism 6: 111.282 119.44 111.314 134.554 132.059 93.1491 Fitness: 207.006
Organism 7: 95.4121 122.799 96.6203 127.574 117.058 88.2685 Fitness: 110.029
Organism 8: 104.59 110.069 105.005 127.574 117.058 134.311 Fitness: 250.026
Organism 9: 86.7976 121.462 105.819 127.574 117.058 106.587 Fitness: 150.028
Organism 10: 95.4121 119.578 96.6203 113.471 128.218 88.2685 Fitness: 225.025
Organism 11: 86.7976 110.069 105.819 134.554 140.606 135.701 Fitness: 157.007
Organism 12: 111.282 119.44 105.819 127.574 132.059 93.1491 Fitness: 150.026
Organism 13: 95.4121 107.034 105.819 117.696 93.5112 88.2685 Fitness: 215.148
Organism 14: 125.218 119.44 87.1632 134.554 132.059 93.1491 Fitness: 132.008
Organism 15: 86.7976 105.964 118.739 114.695 88.9969 106.553 Fitness: 137.149
Organism 16: 111.282 111.637 105.819 134.554 132.059 93.1491 Fitness: 182.006
Organism 17: 95.4121 138.776 105.819 123.903 117.058 89.6248 Fitness: 175.026
Organism 18: 104.59 110.069 96.6203 127.574 104.546 134.311 Fitness: 150.026
Organism 19: 86.7976 138.776 96.6203 127.574 117.058 106.587 Fitness: 175.029
Organism 20: 95.4121 125.371 105.819 127.574 117.058 88.2685 Fitness: 120.025
Best Fitness: 332.006
Avg  Fitness: 164.345
================================================================================
Organism 1: 86.7976 105.964 118.739 114.695 88.9969 106.553 Fitness: 237.251
Organism 2: 133.231 111.637 105.819 134.554 132.059 93.1491 Fitness: 142.111
Organism 3: 86.7976 138.776 96.6203 127.574 117.058 106.587 Fitness: 150.131
Organism 4: 95.4121 107.034 105.819 117.696 93.5112 88.2685 Fitness: 100.252
Organism 5: 86.7976 121.462 105.819 152.262 117.058 106.587 Fitness: 135.131
Organism 6: 111.282 119.44 105.819 131.598 153.566 93.1491 Fitness: 157.113
Organism 7: 93.3342 88.2685 102.038 127.574 122.799 95.4121 Fitness: 120.132
Organism 8: 95.4121 119.578 96.6203 113.471 113.419 88.2685 Fitness: 96.0289
Organism 9: 111.282 119.44 101.141 134.554 132.059 93.1491 Fitness: 242.11
Organism 10: 104.59 110.069 120.528 127.574 104.546 134.311 Fitness: 150.129
Organism 11: 86.7976 126.475 105.819 114.695 86.0046 106.553 Fitness: 162.25
Organism 12: 111.282 105.964 118.739 134.554 132.059 93.1491 Fitness: 232.109
Organism 13: 76.2413 107.034 105.819 140.256 93.5112 106.587 Fitness: 140.255
Organism 14: 95.4121 138.776 96.6203 127.574 117.058 88.2685 Fitness: 235.129
Organism 15: 86.7976 121.462 105.819 127.574 117.058 106.587 Fitness: 150.132
Organism 16: 111.282 119.44 105.819 134.554 153.566 93.1491 Fitness: 207.109
Organism 17: 78.9977 138.548 96.6203 113.471 128.218 88.2685 Fitness: 111.03
Organism 18: 95.4121 122.799 96.6203 127.574 117.058 88.2685 Fitness: 200.129
Organism 19: 93.6308 119.44 111.314 127.574 104.546 93.1491 Fitness: 200.129
Organism 20: 104.59 110.069 108.561 134.554 132.059 134.311 Fitness: 311.109
Best Fitness: 311.109
Avg  Fitness: 173.789
================================================================================
Organism 1: 95.4121 119.578 96.6203 116.787 113.419 88.2685 Fitness: 136.041
Organism 2: 93.6308 119.44 111.314 127.574 108.415 93.1491 Fitness: 150.14
Organism 3: 76.2413 107.034 83.8201 137.406 98.4254 106.587 Fitness: 162.822
Organism 4: 95.4121 138.776 96.6203 127.574 117.058 88.2685 Fitness: 225.14
Organism 5: 104.59 110.069 120.528 127.574 104.546 134.311 Fitness: 325.14
Organism 6: 133.231 111.637 105.819 127.556 132.059 93.1491 Fitness: 227.121
Organism 7: 101.469 122.799 96.6203 127.574 117.058 88.2685 Fitness: 120.143
Organism 8: 86.7976 138.776 96.6203 127.574 117.058 106.804 Fitness: 250.142
Organism 9: 93.6308 109.125 111.314 127.574 104.546 93.1491 Fitness: 295.14
Organism 10: 95.4121 107.034 98.7484 135.441 93.5112 88.2685 Fitness: 175.264
Organism 11: 95.4121 119.578 111.314 113.471 113.419 88.2685 Fitness: 286.037
Organism 12: 106.587 127.574 117.058 104.546 105.819 93.1491 Fitness: 175.142
Organism 13: 76.2413 107.034 96.6203 140.256 93.5112 106.587 Fitness: 162.822
Organism 14: 95.4121 138.776 105.819 127.574 117.058 88.2685 Fitness: 175.14
Organism 15: 104.59 111.637 128.154 115.122 132.059 134.311 Fitness: 232.12
Organism 16: 133.231 112.283 120.528 127.574 104.546 93.1491 Fitness: 150.143
Organism 17: 95.4121 122.799 96.6203 127.574 117.058 88.2685 Fitness: 200.14
Organism 18: 86.7976 138.776 96.6203 111.637 127.574 134.311 Fitness: 200.14
Organism 19: 93.6308 119.44 111.314 117.696 104.546 93.1491 Fitness: 190.265
Organism 20: 95.4121 117.058 88.2685 105.819 95.2173 127.574 Fitness: 125.144
Best Fitness: 325.14
Avg  Fitness: 175.209
================================================================================
Organism 1: 95.4121 138.776 105.819 127.574 117.058 88.2685 Fitness: 135.551
Organism 2: 113.222 111.637 128.154 115.122 132.059 134.311 Fitness: 163.095
Organism 3: 133.231 112.283 120.528 127.574 104.546 93.1491 Fitness: 175.547
Organism 4: 97.011 107.034 96.6203 140.256 93.5112 106.587 Fitness: 163.229
Organism 5: 85.0827 138.776 105.819 119.081 117.058 88.2685 Fitness: 185.547
Organism 6: 93.6308 109.125 111.314 127.574 104.546 93.1491 Fitness: 150.548
Organism 7: 106.587 127.574 117.058 104.546 105.819 93.1491 Fitness: 172.52
Organism 8: 95.4121 138.776 105.819 127.574 117.058 90.1459 Fitness: 225.547
Organism 9: 94.8356 138.776 105.819 127.574 108.222 88.2685 Fitness: 175.548
Organism 10: 93.6308 119.44 111.314 127.574 106.035 93.1491 Fitness: 150.547
Organism 11: 91.7386 138.776 105.819 115.122 132.059 88.2685 Fitness: 163.095
Organism 12: 104.59 111.637 128.154 126.309 117.058 134.311 Fitness: 145.547
Organism 13: 133.231 112.283 120.528 140.256 93.5112 93.1491 Fitness: 163.23
Organism 14: 76.2413 107.034 96.6203 127.574 104.546 106.587 Fitness: 150.549
Organism 15: 95.4121 138.776 111.314 127.574 104.546 88.2685 Fitness: 200.547
Organism 16: 93.6308 109.125 105.819 127.574 117.058 89.683 Fitness: 175.547
Organism 17: 106.587 127.574 127.567 98.3286 117.058 93.1491 Fitness: 152.519
Organism 18: 88.6865 138.776 105.819 138.416 105.819 88.2685 Fitness: 135.548
Organism 19: 95.4121 136.739 111.314 127.574 117.058 88.2685 Fitness: 319.547
Organism 20: 104.946 138.776 105.819 127.574 108.415 93.1491 Fitness: 175.547
Best Fitness: 319.547
Avg  Fitness: 173.018
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Organism 1: 106.587 127.574 127.567 98.3286 92.1813 93.1491 Fitness: 120.792
Organism 2: 88.6865 138.776 105.819 140.799 105.819 88.2685 Fitness: 155.875
Organism 3: 91.7386 138.776 105.819 115.122 132.059 88.2685 Fitness: 107.585
Organism 4: 97.011 101.847 96.6203 140.256 111.659 106.587 Fitness: 172.716
Organism 5: 94.8356 138.776 105.819 127.574 108.222 88.2685 Fitness: 150.034
Organism 6: 133.231 112.283 120.528 127.574 93.8632 93.1491 Fitness: 225.033
Organism 7: 93.6308 109.125 108.68 127.574 117.058 70.605 Fitness: 175.035
Organism 8: 104.59 111.637 141.505 126.309 117.058 134.311 Fitness: 173.768
Organism 9: 106.587 127.574 127.567 98.3286 117.058 93.1491 Fitness: 245.789
Organism 10: 106.587 127.574 93.6308 107.034 117.058 93.1491 Fitness: 324.109
Organism 11: 123.211 138.776 105.819 138.416 105.819 93.1491 Fitness: 145.876
Organism 12: 88.6865 127.574 127.567 98.3286 117.058 88.2685 Fitness: 170.788
Organism 13: 114.893 107.034 76.7319 115.122 132.059 107.018 Fitness: 237.582
Organism 14: 97.011 138.776 105.819 140.368 93.5112 106.587 Fitness: 222.716
Organism 15: 94.8356 112.283 120.528 127.574 108.222 88.2685 Fitness: 175.035
Organism 16: 133.231 138.776 105.819 127.574 104.546 95.0179 Fitness: 150.034
Organism 17: 93.6308 109.125 122.812 126.309 117.058 89.683 Fitness: 173.769
Organism 18: 104.59 111.637 139.059 141.258 117.058 134.311 Fitness: 175.035
Organism 19: 122.012 127.574 127.567 92.6845 117.058 93.1491 Fitness: 95.7918
Organism 20: 106.587 127.574 127.567 98.3286 117.058 93.1491 Fitness: 170.789
Best Fitness: 324.109
Avg  Fitness: 171.242
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Organism 1: 122.012 127.574 127.567 92.6845 117.058 93.1491 Fitness: 166.438
Organism 2: 93.6308 109.125 108.68 127.574 117.058 70.605 Fitness: 201.326
Organism 3: 105.819 115.122 138.776 91.7386 132.059 88.2685 Fitness: 313.875
Organism 4: 106.587 127.574 127.567 98.3286 117.058 85.6845 Fitness: 122.084
Organism 5: 104.59 111.637 139.059 141.258 117.058 134.311 Fitness: 240.01
Organism 6: 97.011 138.776 105.819 140.368 93.5112 105.544 Fitness: 174.12
Organism 7: 91.7386 138.776 105.819 115.122 132.059 88.2685 Fitness: 138.878
Organism 8: 94.8356 138.776 105.819 127.574 108.222 86.9175 Fitness: 211.326
Organism 9: 114.893 85.2662 76.7319 111.424 132.059 107.018 Fitness: 138.877
Organism 10: 97.011 138.776 105.819 140.368 98.5742 106.587 Fitness: 59.1226
Organism 11: 122.012 127.574 108.68 127.574 117.058 102.309 Fitness: 136.329
Organism 12: 76.6256 109.125 111.916 92.6845 117.058 70.605 Fitness: 151.437
Organism 13: 91.7386 138.776 119.375 115.122 117.058 88.2685 Fitness: 263.874
Organism 14: 106.587 127.574 127.567 98.3286 125.749 97.8815 Fitness: 357
Organism 15: 104.59 111.637 115.873 140.368 93.5112 134.311 Fitness: 139.121
Organism 16: 97.011 138.776 153.324 141.258 117.058 106.587 Fitness: 165.01
Organism 17: 83.8892 138.776 105.819 108.222 127.574 88.2685 Fitness: 101.33
Organism 18: 94.8356 138.776 105.819 115.122 132.059 87.6964 Fitness: 138.877
Organism 19: 114.893 107.034 105.819 140.368 132.059 107.018 Fitness: 239.12
Organism 20: 97.011 138.776 76.7319 115.122 93.5112 106.587 Fitness: 163.874
Best Fitness: 357
Avg  Fitness: 177.129
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7.2 Appendix 2

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Population Size: 20
Amount of Food: 15
Amount of Poison: 20
Generation Time in Seconds: 25
Population Survivors (% of population): 50
Selection Type (Roulette = 0) (Random = 1) (Tournament = 2): 0
Crossover Type (Uniform = 0) (Single-Point = 1) (Multi-Point = 2): 0
Primary Mutation Type (Creep = 0) (Random Resetting = 1): 0
Creep Value Range: 25
Secondary Mutation Type (None = 0) (Swap = 1) (Scramble = 2) (Inversion = 3): 1
Mutation Chance Percentage (0.0f - 100.0f): 15

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Organism 1: 117.721 104.548 106.678 119.182 83.0233 104.995 Fitness: 144.746
Organism 2: 115.644 85.7378 111.803 118.239 90.4426 106.099 Fitness: 118.805
Organism 3: 117.721 104.548 130.323 119.182 83.0233 108.958 Fitness: 169.747
Organism 4: 107.865 99.8599 96.7555 88.6912 116.665 86.0808 Fitness: 64.2603
Organism 5: 117.721 104.548 113.976 119.182 88.2718 104.995 Fitness: 119.75
Organism 6: 68.9261 105.399 109.614 124.901 103.285 114.541 Fitness: 157.068
Organism 7: 87.2434 97.8027 97.0218 114.515 88.277 115.517 Fitness: 90.0841
Organism 8: 117.721 104.548 113.976 119.182 83.0233 104.995 Fitness: 94.7508
Organism 9: 91.4287 97.1735 95.3994 80.1547 115.945 97.6623 Fitness: 80.7239
Organism 10: 113.326 114.691 81.8269 93.4693 102.136 111.657 Fitness: 69.0384
Organism 11: 115.644 85.7378 113.976 119.182 90.4426 104.995 Fitness: 119.75
Organism 12: 117.721 104.548 111.803 118.239 83.0233 110.479 Fitness: 68.8083
Organism 13: 117.721 104.548 90.8834 119.182 116.665 86.0808 Fitness: 94.7508
Organism 14: 96.7555 107.865 99.8599 88.6912 83.0233 122.369 Fitness: 89.2603
Organism 15: 84.3393 105.399 103.285 106.501 104.995 109.614 Fitness: 107.07
Organism 16: 83.0233 104.548 119.182 113.976 117.721 114.541 Fitness: 119.75
Organism 17: 107.079 97.8027 94.0144 114.515 88.277 86.1145 Fitness: 65.0843
Organism 18: 87.2434 104.548 95.4995 138.319 83.0233 131.203 Fitness: 94.7508
Organism 19: 91.4287 120.303 81.8269 94.2883 115.945 111.657 Fitness: 105.724
Organism 20: 97.2962 96.6421 95.3994 75.3315 102.136 97.6623 Fitness: 94.0384
Best Fitness: 169.747
Avg  Fitness: 103.398
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Organism 1: 107.865 99.8599 96.7555 88.6912 116.665 86.0808 Fitness: 89.3629
Organism 2: 117.721 83.5046 93.2121 119.182 88.2718 104.995 Fitness: 69.8533
Organism 3: 113.249 104.548 130.323 119.182 83.0233 108.958 Fitness: 69.8533
Organism 4: 91.4287 120.303 81.8269 94.2883 115.945 111.657 Fitness: 129.958
Organism 5: 83.0233 104.548 119.182 113.976 117.721 114.541 Fitness: 64.6472
Organism 6: 115.644 85.7378 111.803 118.239 90.4426 106.099 Fitness: 118.911
Organism 7: 119.182 104.548 113.976 117.721 83.0233 104.995 Fitness: 119.853
Organism 8: 115.644 85.7378 111.803 118.239 90.4426 106.099 Fitness: 68.9109
Organism 9: 59.074 105.399 109.614 124.901 114.928 114.541 Fitness: 100.572
Organism 10: 117.721 104.548 113.976 119.182 88.2718 104.995 Fitness: 94.8533
Organism 11: 117.721 99.8599 113.976 88.6912 88.2718 86.0808 Fitness: 179.358
Organism 12: 107.865 116.68 96.7555 97.1743 128.387 104.995 Fitness: 119.85
Organism 13: 91.4287 120.303 81.8269 119.182 114.096 111.657 Fitness: 144.85
Organism 14: 117.721 104.548 130.323 94.2883 97.0158 108.958 Fitness: 94.96
Organism 15: 83.0233 85.7378 91.9845 113.976 90.4426 106.099 Fitness: 139.646
Organism 16: 115.644 104.548 119.182 118.239 129.892 114.541 Fitness: 93.9109
Organism 17: 115.644 98.6785 111.803 126.537 83.0233 106.099 Fitness: 144.848
Organism 18: 117.721 85.7378 113.976 118.239 90.4426 104.995 Fitness: 93.9109
Organism 19: 141.37 104.548 90.9385 119.182 88.2718 114.541 Fitness: 169.851
Organism 20: 68.9261 105.399 123.231 124.901 103.285 104.995 Fitness: 125.572
Best Fitness: 179.358
Avg  Fitness: 105.177
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Organism 1: 68.9261 105.399 123.231 124.901 103.285 104.995 Fitness: 120.571
Organism 2: 107.865 116.68 96.7555 97.1743 128.387 104.995 Fitness: 197.841
Organism 3: 83.0233 85.7378 91.9845 115.07 90.4426 106.099 Fitness: 89.647
Organism 4: 115.355 99.8599 113.976 88.6912 77.124 86.0808 Fitness: 89.3627
Organism 5: 91.4287 120.303 81.8269 119.182 114.096 99.4053 Fitness: 69.8531
Organism 6: 107.865 116.68 96.7555 97.1743 128.387 104.995 Fitness: 122.846
Organism 7: 117.721 85.7378 113.976 118.239 90.4426 104.995 Fitness: 93.9107
Organism 8: 127.82 98.6785 111.803 126.537 86.6072 106.099 Fitness: 77.2088
Organism 9: 119.182 104.548 113.976 117.721 67.7896 104.995 Fitness: 118.392
Organism 10: 113.249 104.548 130.323 119.182 75.1027 89.3556 Fitness: 54.8531
Organism 11: 68.9261 120.747 123.231 124.901 103.285 104.995 Fitness: 100.572
Organism 12: 107.631 105.399 96.7555 108.762 128.387 104.995 Fitness: 97.8458
Organism 13: 83.0233 85.9042 91.9845 113.976 90.4426 86.0808 Fitness: 114.645
Organism 14: 112.738 99.8599 113.976 88.6912 88.2718 96.0662 Fitness: 39.3623
Organism 15: 91.4287 116.68 81.8269 119.182 114.096 104.995 Fitness: 154.848
Organism 16: 107.865 120.303 96.7555 97.1743 128.387 111.657 Fitness: 122.846
Organism 17: 115.644 126.537 111.803 90.4426 85.7378 104.995 Fitness: 152.206
Organism 18: 117.721 111.746 119.494 118.239 83.0233 106.099 Fitness: 143.907
Organism 19: 119.182 104.548 113.976 117.721 83.0233 104.995 Fitness: 93.3929
Organism 20: 113.249 104.548 130.323 119.182 83.0233 108.958 Fitness: 94.8523
Best Fitness: 197.841
Avg  Fitness: 107.448
================================================================================
Organism 1: 107.865 101.628 77.1982 83.8101 128.387 104.995 Fitness: 147.872
Organism 2: 91.4287 116.68 82.9546 119.182 114.096 104.995 Fitness: 169.878
Organism 3: 68.9261 105.399 123.231 124.901 103.285 104.995 Fitness: 75.5988
Organism 4: 127.82 98.6785 111.803 133.563 86.6072 106.099 Fitness: 152.233
Organism 5: 107.865 104.897 104.995 86.7084 133.09 97.1743 Fitness: 97.872
Organism 6: 115.644 126.537 127.01 90.4426 85.7378 118.61 Fitness: 191.136
Organism 7: 107.631 105.399 96.7555 108.762 114.118 104.995 Fitness: 104.459
Organism 8: 69.5393 105.399 123.231 124.901 107.158 103.89 Fitness: 100.599
Organism 9: 107.865 122.49 96.7555 97.1743 128.387 116.195 Fitness: 122.872
Organism 10: 112.738 99.8599 113.976 88.6912 88.2718 96.0662 Fitness: 139.389
Organism 11: 107.865 116.68 107.593 119.182 114.096 104.995 Fitness: 194.874
Organism 12: 91.4287 116.68 79.6818 97.1743 128.387 104.995 Fitness: 122.872
Organism 13: 68.9261 105.399 111.803 106.099 111.174 149.634 Fitness: 177.234
Organism 14: 127.82 76.1824 123.231 124.901 103.285 104.995 Fitness: 200.594
Organism 15: 115.644 116.68 96.7555 97.1743 85.7378 104.995 Fitness: 47.8718
Organism 16: 107.865 126.537 111.803 88.9986 128.387 104.995 Fitness: 91.1402
Organism 17: 68.9261 105.399 147.148 124.901 115.61 104.995 Fitness: 100.599
Organism 18: 107.631 105.399 96.7555 108.762 91.5116 104.995 Fitness: 84.4594
Organism 19: 107.865 99.8599 113.976 88.6912 88.2718 104.995 Fitness: 89.3888
Organism 20: 112.738 120.602 96.7555 97.1743 128.387 96.0662 Fitness: 122.872
Best Fitness: 200.594
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Avg  Fitness: 116.691
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Organism 1: 68.9261 129.775 147.148 124.901 115.61 104.995 Fitness: 125.492
Organism 2: 127.82 98.6785 111.803 133.563 86.6072 106.099 Fitness: 109.155
Organism 3: 106.099 105.399 145.896 68.9261 111.174 111.803 Fitness: 141.691
Organism 4: 91.4287 116.68 69.1195 119.182 114.096 104.995 Fitness: 94.7725
Organism 5: 68.9261 105.399 147.148 124.901 115.61 104.995 Fitness: 175.488
Organism 6: 107.631 105.399 96.7555 108.762 114.118 104.995 Fitness: 119.354
Organism 7: 104.995 51.5026 123.231 124.901 103.285 127.82 Fitness: 100.492
Organism 8: 115.644 116.68 96.7555 97.1743 85.7378 104.995 Fitness: 72.7663
Organism 9: 107.631 103.654 96.7555 108.762 91.5116 104.995 Fitness: 84.354
Organism 10: 68.9261 105.399 147.148 124.901 115.61 104.995 Fitness: 125.493
Organism 11: 68.9261 105.399 111.803 124.901 86.6072 106.099 Fitness: 150.489
Organism 12: 115.61 98.6785 147.148 133.563 127.82 104.995 Fitness: 119.151
Organism 13: 91.4287 105.399 82.9546 106.099 111.174 149.634 Fitness: 200.17
Organism 14: 68.9261 116.68 111.803 119.182 114.096 94.5617 Fitness: 169.771
Organism 15: 107.631 96.9081 147.148 104.995 114.118 124.901 Fitness: 110.492
Organism 16: 68.9261 105.399 96.7555 108.762 115.61 104.995 Fitness: 44.3533
Organism 17: 115.644 116.68 96.7555 97.1743 85.7378 104.995 Fitness: 172.765
Organism 18: 127.82 76.1824 123.231 124.901 103.285 104.995 Fitness: 150.491
Organism 19: 68.9261 105.399 147.148 108.762 115.61 104.995 Fitness: 134.353
Organism 20: 107.631 105.399 79.9829 124.901 91.5116 104.995 Fitness: 125.492
Best Fitness: 200.17
Avg  Fitness: 118.482
================================================================================
Organism 1: 106.099 105.399 145.896 68.9261 111.174 111.803 Fitness: 9.71629
Organism 2: 68.9261 105.399 147.148 124.901 115.61 104.995 Fitness: 175.566
Organism 3: 115.644 125.329 96.7555 97.1743 85.7378 104.995 Fitness: 47.8446
Organism 4: 78.7476 115.63 147.148 124.901 115.61 104.995 Fitness: 85.5715
Organism 5: 107.631 105.399 96.7555 123.15 114.118 104.995 Fitness: 84.4323
Organism 6: 84.9611 88.2726 82.9546 106.099 111.174 149.634 Fitness: 81.7694
Organism 7: 68.9261 116.68 88.2667 119.182 114.096 94.5617 Fitness: 219.849
Organism 8: 82.9546 105.399 91.4287 106.099 111.174 149.634 Fitness: 106.769
Organism 9: 65.5847 105.399 147.148 108.762 115.61 104.995 Fitness: 109.432
Organism 10: 68.9261 105.399 92.2663 124.901 86.6072 106.099 Fitness: 75.5716
Organism 11: 68.9261 104.995 131.972 85.7378 124.901 105.399 Fitness: 100.57
Organism 12: 115.644 116.68 96.7555 97.1743 96.2927 104.995 Fitness: 172.844
Organism 13: 68.9261 105.399 147.148 108.762 115.61 104.995 Fitness: 69.4324
Organism 14: 107.631 105.399 96.7555 124.901 114.118 104.995 Fitness: 125.571
Organism 15: 91.4287 116.68 82.9546 119.182 114.096 94.5617 Fitness: 219.849
Organism 16: 68.9261 105.399 111.803 106.099 111.174 149.634 Fitness: 181.765
Organism 17: 91.4287 88.0003 145.896 106.099 111.174 149.634 Fitness: 81.7694
Organism 18: 106.099 105.399 82.9546 68.9261 111.174 111.803 Fitness: 44.5961
Organism 19: 68.9261 105.399 147.148 124.901 123.034 104.995 Fitness: 75.5716
Organism 20: 68.9261 105.399 111.803 108.762 86.6072 106.099 Fitness: 84.4324
Best Fitness: 219.849
Avg  Fitness: 106.396
================================================================================
Organism 1: 105.399 82.9546 149.634 106.099 111.174 91.4287 Fitness: 81.7794
Organism 2: 78.7476 115.63 147.148 124.901 137.139 104.995 Fitness: 75.5816
Organism 3: 96.2927 97.1743 96.7555 116.68 115.644 104.995 Fitness: 122.855
Organism 4: 91.4287 116.68 82.9546 119.182 114.096 106.895 Fitness: 119.859
Organism 5: 91.4287 116.68 82.9546 119.182 107.585 94.5617 Fitness: 79.8613
Organism 6: 91.4287 116.68 90.3636 119.182 114.096 94.5617 Fitness: 104.862
Organism 7: 115.644 116.68 96.7555 97.1743 96.2927 104.995 Fitness: 97.8547
Organism 8: 68.9261 105.399 111.803 125.654 111.174 149.634 Fitness: 106.778
Organism 9: 115.644 125.329 96.7555 97.1743 85.7378 104.995 Fitness: 72.8547
Organism 10: 78.7476 104.525 147.148 124.901 115.61 104.995 Fitness: 205.577
Organism 11: 78.7476 105.399 147.148 124.901 111.174 169.913 Fitness: 125.58
Organism 12: 82.9546 91.5757 91.4287 106.099 115.61 104.995 Fitness: 106.778
Organism 13: 132.268 115.644 82.9546 116.68 96.2927 94.5617 Fitness: 144.858
Organism 14: 91.4287 116.68 96.7555 107.914 114.096 108.364 Fitness: 82.8547
Organism 15: 91.4287 116.68 82.9546 119.182 127.118 94.5617 Fitness: 144.858
Organism 16: 91.4287 116.68 82.9546 119.182 114.096 94.5617 Fitness: 119.862
Organism 17: 68.9261 126.342 111.803 97.1743 111.174 149.634 Fitness: 122.855
Organism 18: 115.644 105.399 96.7555 106.099 96.2927 104.995 Fitness: 106.779
Organism 19: 112.491 115.63 147.148 118.621 85.7378 104.995 Fitness: 47.8545
Organism 20: 78.7476 125.329 84.9161 118.573 115.61 104.995 Fitness: 125.58
Best Fitness: 205.577
Avg  Fitness: 110.786
================================================================================
Organism 1: 91.4287 116.68 82.9546 119.182 107.585 94.5617 Fitness: 69.8572
Organism 2: 91.4287 116.68 82.9546 119.182 94.611 94.5617 Fitness: 94.8561
Organism 3: 91.4287 116.68 96.7555 107.914 114.096 108.364 Fitness: 133.59
Organism 4: 78.7476 104.525 147.148 124.901 117.241 104.995 Fitness: 75.5768
Organism 5: 78.7476 104.525 147.148 124.901 115.61 104.995 Fitness: 100.577
Organism 6: 115.644 116.68 96.7555 97.1743 87.6332 104.995 Fitness: 122.85
Organism 7: 115.644 105.399 96.7555 90.616 96.2927 104.995 Fitness: 156.774
Organism 8: 82.9546 91.5757 91.4287 106.099 113.634 104.995 Fitness: 81.7746
Organism 9: 78.7476 105.399 147.148 135.934 111.174 169.913 Fitness: 125.577
Organism 10: 78.7476 104.525 147.148 124.901 115.61 98.6151 Fitness: 200.572
Organism 11: 91.4287 140.329 82.9546 119.182 107.585 94.5617 Fitness: 79.857
Organism 12: 91.4287 116.68 82.9546 119.182 107.585 94.5617 Fitness: 119.856
Organism 13: 78.7476 100.688 147.148 124.901 115.61 104.995 Fitness: 150.575
Organism 14: 85.7125 130.239 90.6403 107.914 114.096 108.364 Fitness: 58.5896
Organism 15: 78.7476 116.68 147.148 124.901 115.61 104.995 Fitness: 125.577
Organism 16: 115.644 91.1748 104.525 104.995 96.2927 97.1743 Fitness: 97.8499
Organism 17: 130.199 105.399 96.7555 106.099 115.61 104.995 Fitness: 206.773
Organism 18: 82.9546 91.5757 91.4287 108.278 96.2927 104.995 Fitness: 81.7745
Organism 19: 89.9866 104.525 124.901 169.913 111.174 147.148 Fitness: 125.576
Organism 20: 78.7476 105.399 146.3 124.901 115.61 104.995 Fitness: 150.576
Best Fitness: 206.773
Avg  Fitness: 117.95
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Organism 1: 82.9546 104.995 91.5757 106.099 113.634 91.4287 Fitness: 131.675
Organism 2: 78.281 91.5757 91.4287 106.099 113.634 104.995 Fitness: 131.674
Organism 3: 78.7476 100.688 147.148 124.901 115.61 104.995 Fitness: 85.4752
Organism 4: 101.417 116.68 104.995 97.1743 87.6332 96.7555 Fitness: 72.75
Organism 5: 78.7476 105.399 146.3 124.901 115.61 104.995 Fitness: 175.472
Organism 6: 91.4287 116.68 82.9546 119.182 107.585 94.5617 Fitness: 144.756
Organism 7: 78.7476 100.094 116.68 147.148 115.61 104.995 Fitness: 160.472
Organism 8: 78.7476 104.995 162.947 135.521 115.61 100.688 Fitness: 85.4768
Organism 9: 78.7476 100.688 147.148 124.901 115.61 104.995 Fitness: 100.476
Organism 10: 85.5683 78.6347 147.148 124.901 115.61 104.995 Fitness: 125.475
Organism 11: 82.9546 91.5757 91.4287 106.099 113.634 123.658 Fitness: 212.15
Organism 12: 82.9546 91.5757 91.4287 106.099 113.634 104.995 Fitness: 56.6746
Organism 13: 115.644 100.688 160.598 97.1743 115.61 112.398 Fitness: 122.747
Organism 14: 96.7555 114.014 78.7476 85.9454 124.901 104.995 Fitness: 100.477
Organism 15: 92.2269 116.68 146.3 124.901 115.61 104.995 Fitness: 175.471
Organism 16: 91.4287 105.399 82.9546 119.182 107.585 94.5617 Fitness: 154.755
Organism 17: 147.148 100.688 124.901 78.7476 115.61 104.995 Fitness: 125.477
Organism 18: 78.7476 116.68 147.148 124.901 115.61 104.995 Fitness: 150.476
Organism 19: 78.7476 100.688 147.148 124.901 126.672 104.995 Fitness: 125.475
Organism 20: 78.7476 100.688 147.148 124.901 115.61 104.995 Fitness: 85.4749
Best Fitness: 212.15
Avg  Fitness: 130.619
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Organism 1: 82.9546 91.5757 91.4287 106.099 113.634 140.768 Fitness: 22.0146
Organism 2: 78.281 91.5757 91.4287 106.099 113.634 104.995 Fitness: 81.1974
Organism 3: 71.9846 78.6347 147.148 124.901 115.61 104.995 Fitness: 124.999
Organism 4: 113.634 129.24 91.5757 104.995 82.9546 91.4287 Fitness: 131.196
Organism 5: 78.7476 104.995 147.148 100.688 115.61 136.121 Fitness: 149.999
Organism 6: 78.7476 100.688 104.995 124.901 126.672 147.148 Fitness: 99.9981
Organism 7: 101.417 116.68 126.853 97.1743 87.6332 96.7555 Fitness: 72.2726
Organism 8: 78.7476 116.68 147.148 107.97 115.61 104.995 Fitness: 99.9996
Organism 9: 115.644 100.688 160.598 97.9604 115.61 112.398 Fitness: 122.272
Organism 10: 78.281 91.5757 77.8385 106.099 113.634 104.995 Fitness: 81.1974
Organism 11: 89.2728 91.5757 91.4287 106.099 113.634 123.658 Fitness: 81.1974
Organism 12: 82.9546 73.9282 91.4287 106.099 113.634 104.995 Fitness: 56.1974
Organism 13: 104.995 78.6347 113.634 105.801 91.5757 85.5683 Fitness: 225.187
Organism 14: 82.9546 104.995 147.148 124.901 115.61 91.4287 Fitness: 99.9988
Organism 15: 102.701 75.9892 147.148 124.901 125.971 104.995 Fitness: 194.996
Organism 16: 126.672 78.7476 147.148 124.901 100.688 104.995 Fitness: 124.996
Organism 17: 96.1649 104.14 104.995 111.012 115.61 104.995 Fitness: 57.2727
Organism 18: 78.7476 116.68 147.148 124.901 87.6332 96.7555 Fitness: 149.995
Organism 19: 137.785 100.688 91.4287 97.1743 113.634 107.683 Fitness: 122.272
Organism 20: 78.281 91.5757 160.598 114.75 115.61 112.398 Fitness: 106.197
Best Fitness: 225.187
Avg  Fitness: 103.806
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Organism 1: 78.7476 116.68 147.148 107.97 115.61 104.995 Fitness: 118.645
Organism 2: 100.545 129.24 91.5757 104.995 94.7146 91.4287 Fitness: 115.67
Organism 3: 102.701 75.9892 147.148 124.901 125.971 104.995 Fitness: 125.573
Organism 4: 96.4426 73.9282 91.4287 106.099 113.634 104.995 Fitness: 56.7738
Organism 5: 78.7476 116.68 147.148 107.97 115.61 104.995 Fitness: 68.6453
Organism 6: 78.7476 104.995 147.148 100.688 115.61 136.121 Fitness: 76.3628
Organism 7: 126.672 78.7476 147.148 104.67 100.688 104.995 Fitness: 75.576
Organism 8: 78.281 70.5318 91.4287 88.7861 113.634 104.995 Fitness: 106.773
Organism 9: 78.7476 82.6167 147.148 100.688 115.61 136.121 Fitness: 176.362
Organism 10: 78.7476 100.688 104.995 124.901 126.672 147.148 Fitness: 100.575
Organism 11: 78.7476 106.344 147.148 107.97 82.9546 91.4287 Fitness: 158.642
Organism 12: 113.634 116.68 91.6456 104.995 115.61 104.995 Fitness: 155.669
Organism 13: 102.701 73.9282 75.5749 124.901 113.634 104.995 Fitness: 225.571
Organism 14: 82.9546 75.9892 147.148 106.099 125.971 104.995 Fitness: 26.7733
Organism 15: 91.0348 104.995 147.148 100.688 115.61 104.995 Fitness: 151.358
Organism 16: 78.7476 116.68 147.148 107.97 115.61 135.105 Fitness: 133.643
Organism 17: 78.281 91.5757 91.4287 106.099 100.688 104.995 Fitness: 81.7738
Organism 18: 128.408 78.7476 147.148 124.901 113.634 104.995 Fitness: 150.575
Organism 19: 78.7476 91.1021 104.995 78.868 115.61 147.148 Fitness: 176.359
Organism 20: 78.7476 104.995 122.152 124.901 126.672 139.179 Fitness: 85.5746
Best Fitness: 225.571
Avg  Fitness: 118.345
=================================================================================
Organism 1: 104.995 58.2942 99.9256 113.634 116.087 102.701 Fitness: 75.1918
Organism 2: 78.7476 82.6167 147.148 100.38 115.61 136.121 Fitness: 75.9786
Organism 3: 126.672 78.7476 147.148 104.67 100.688 104.995 Fitness: 54.9608
Organism 4: 78.7476 116.68 147.148 107.97 115.61 104.995 Fitness: 133.257
Organism 5: 78.7476 116.68 147.148 107.97 118.365 135.105 Fitness: 83.2611
Organism 6: 78.7476 116.68 147.148 107.97 115.61 135.105 Fitness: 58.2611
Organism 7: 102.701 96.6255 75.5749 124.901 113.634 91.485 Fitness: 110.189
Organism 8: 102.701 75.9892 147.148 124.901 125.971 104.995 Fitness: 125.188
Organism 9: 103.036 100.688 104.995 124.901 126.672 144.851 Fitness: 75.1918
Organism 10: 104.995 70.5318 91.4287 88.7861 78.281 113.634 Fitness: 114.077
Organism 11: 81.6167 73.9282 147.148 124.901 113.634 136.121 Fitness: 100.192
Organism 12: 78.7476 82.6167 91.0864 85.0475 127.995 104.995 Fitness: 150.977
Organism 13: 126.672 116.68 166.696 107.97 132.143 104.995 Fitness: 108.26
Organism 14: 78.7476 63.8134 147.148 104.67 100.688 104.995 Fitness: 54.9608
Organism 15: 78.7476 126.044 147.148 107.97 115.61 146.114 Fitness: 83.2611
Organism 16: 78.7476 94.8118 142.27 107.97 104.91 135.105 Fitness: 58.2611
Organism 17: 134.139 73.9282 147.148 102.701 113.634 104.995 Fitness: 100.192
Organism 18: 102.701 75.9892 75.5749 124.901 125.971 104.995 Fitness: 239.245
Organism 19: 78.281 124.901 113.798 100.688 113.634 104.995 Fitness: 150.187
Organism 20: 78.7476 70.5318 91.4287 88.7861 126.672 147.148 Fitness: 39.0764
Best Fitness: 239.245
Avg  Fitness: 116.21
================================================================================
Organism 1: 102.701 96.6255 75.5749 124.901 113.634 91.485 Fitness: 125.174
Organism 2: 78.7476 82.6167 147.148 100.38 115.61 136.121 Fitness: 175.65
Organism 3: 78.7476 94.8118 142.27 107.97 104.91 135.105 Fitness: 108.244
Organism 4: 78.7476 94.8118 142.27 107.97 104.91 135.105 Fitness: 108.244
Organism 5: 78.7476 82.6167 75.5126 98.0221 127.995 104.995 Fitness: 45.3207
Organism 6: 104.995 64.6199 91.4287 88.7861 78.281 113.634 Fitness: 139.059
Organism 7: 126.672 116.68 166.696 107.97 132.143 104.995 Fitness: 108.244
Organism 8: 102.701 75.9892 147.148 124.901 125.971 86.0224 Fitness: 242.864
Organism 9: 104.995 70.5318 91.4287 88.7861 78.281 113.634 Fitness: 114.06
Organism 10: 78.7476 82.6167 147.148 100.38 115.61 136.121 Fitness: 100.654
Organism 11: 113.634 96.6255 147.148 115.709 78.7476 124.901 Fitness: 175.17
Organism 12: 102.701 72.6416 75.5749 100.38 115.61 91.485 Fitness: 135.653
Organism 13: 78.7476 71.0472 142.27 107.97 104.91 135.105 Fitness: 183.24
Organism 14: 78.7476 135.105 94.8118 107.97 104.91 142.27 Fitness: 83.2444
Organism 15: 104.995 70.5318 101.975 88.7861 127.995 104.995 Fitness: 114.06
Organism 16: 78.7476 99.991 91.4287 85.0475 78.281 113.634 Fitness: 60.3214
Organism 17: 126.672 116.68 147.148 124.901 151.823 104.995 Fitness: 95.1748
Organism 18: 75.9892 102.701 115.422 107.97 125.971 166.696 Fitness: 158.242
Organism 19: 111.312 99.5844 147.148 88.7861 78.281 113.634 Fitness: 89.06
Organism 20: 78.7476 70.5318 91.4287 100.38 115.61 136.121 Fitness: 50.6541
Best Fitness: 242.864
Avg  Fitness: 124.619
================================================================================
Organism 1: 104.995 70.5318 91.4287 88.7861 78.281 113.634 Fitness: 138.971
Organism 2: 78.7476 70.5318 91.4287 100.38 115.61 136.121 Fitness: 125.565
Organism 3: 104.995 64.6199 91.4287 88.7861 78.281 113.634 Fitness: 113.971
Organism 4: 85.3049 75.9892 147.148 124.901 125.971 86.0224 Fitness: 135.083
Organism 5: 124.901 96.6255 75.5749 102.701 116.602 91.485 Fitness: 100.085
Organism 6: 115.61 82.6167 147.148 100.38 78.7476 152.463 Fitness: 75.565
Organism 7: 78.7476 94.8118 142.27 107.97 104.91 135.105 Fitness: 83.1552
Organism 8: 78.7476 63.2029 147.148 100.38 115.61 136.121 Fitness: 100.565
Organism 9: 78.7476 94.8118 142.27 107.97 104.91 135.105 Fitness: 118.155
Organism 10: 102.701 96.6255 75.5749 124.901 113.634 91.485 Fitness: 150.082
Organism 11: 104.995 58.9513 91.4287 100.38 115.61 113.634 Fitness: 75.565
Organism 12: 78.7476 70.5318 91.4287 70.1858 78.281 136.121 Fitness: 138.971
Organism 13: 102.701 91.4287 64.7143 123.802 125.971 113.634 Fitness: 125.086
Organism 14: 104.995 64.6199 147.148 88.7861 78.281 86.0224 Fitness: 113.971
Organism 15: 98.3665 120.213 75.5749 100.38 68.6764 113.634 Fitness: 150.562
Organism 16: 102.701 82.6167 147.148 124.901 115.61 136.121 Fitness: 150.084
Organism 17: 78.7476 82.6167 142.27 100.38 115.61 136.121 Fitness: 175.561
Organism 18: 56.7188 94.8118 147.148 97.4184 104.91 135.105 Fitness: 256.686
Organism 19: 102.701 94.8118 75.5749 107.97 113.634 91.485 Fitness: 183.154
Organism 20: 142.27 117.634 80.95 124.901 91.6639 96.6255 Fitness: 150.086
Best Fitness: 256.686
Avg  Fitness: 129.155
================================================================================
Organism 1: 78.7476 70.5318 91.4287 70.1858 78.281 136.121 Fitness: 18.4314
Organism 2: 104.995 82.098 91.4287 100.38 115.61 135.072 Fitness: 145.6658
Organism 3: 102.701 96.6255 75.5749 124.901 93.5728 91.485 Fitness: 275.183
Organism 4: 78.7476 70.5318 91.4287 70.1858 77.8654 136.121 Fitness: 45.4706
Organism 5: 104.995 58.9513 91.4287 100.38 115.61 113.634 Fitness: 100.666
Organism 6: 104.995 58.9513 99.6506 100.38 115.61 113.634 Fitness: 50.6657
Organism 7: 56.7188 117.953 147.148 97.4184 104.91 135.105 Fitness: 47.7037
Organism 8: 124.901 96.6255 102.701 75.5749 113.634 91.485 Fitness: 125.184
Organism 9: 142.27 136.121 78.7476 100.38 115.61 82.6167 Fitness: 50.6657
Organism 10: 56.7188 94.8118 147.148 86.3775 104.91 135.105 Fitness: 47.7037
Organism 11: 64.6199 97.0238 91.4287 104.995 63.519 113.634 Fitness: 99.0711
Organism 12: 102.701 58.9513 75.5749 124.901 113.634 91.485 Fitness: 100.187
Organism 13: 104.995 90.7478 91.4287 100.38 115.61 113.634 Fitness: 85.6653
Organism 14: 104.995 76.948 66.8686 100.38 115.61 113.634 Fitness: 75.6658
Organism 15: 56.7188 58.9513 147.148 100.38 134.021 113.634 Fitness: 150.661
Organism 16: 104.995 94.8118 91.4287 97.4184 104.91 135.105 Fitness: 47.7037
Organism 17: 78.7476 82.6167 142.27 124.901 113.634 136.121 Fitness: 175.181
Organism 18: 102.701 75.5749 91.485 83.4891 115.61 96.6255 Fitness: 125.666
Organism 19: 104.995 72.5455 147.148 97.4184 78.281 135.105 Fitness: 72.7039
Organism 20: 56.7188 113.634 91.4287 78.8001 104.91 64.6199 Fitness: 69.0713
Best Fitness: 275.183
Avg  Fitness: 137.72
```

7.3 Appendix 3

```
Population Size: 16
Amount of Food: 15
Amount of Poison: 15
Generation Time in Seconds: 30
Population Survivors (% of population): 50
Selection Type (Roulette = 0) (Random = 1) (Tournament = 2): 1
Crossover Type (Uniform = 0) (Single-Point = 1) (Multi-Point = 2): 1
Primary Mutation Type (Creep = 0) (Random Resetting = 1): 0
Creep Value Range: 20
Secondary Mutation Type (None = 0) (Swap = 1) (Scramble = 2) (Inversion = 3): 0
Mutation Chance Percentage (0.0f - 100.0f): 10



Organism 1: 118.755 100.052 116.332 111.498 85.7218 94.5316 Fitness: 76.7281
Organism 2: 111.662 115.109 111.835 91.9597 117.922 101.144 Fitness: 182.187
Organism 3: 119.606 88.2356 118.732 118.851 101.697 86.0328 Fitness: 109.081
Organism 4: 91.2118 93.665 98.0752 98.712 111.683 112.3 Fitness: 163.94
Organism 5: 87.857 88.6036 84.1864 108.049 89.9685 83.931 Fitness: 148.278
Organism 6: 88.8062 80.0751 94.9389 88.0938 93.9657 118.046 Fitness: 103.322
Organism 7: 102.59 116.296 83.3136 90.509 95.7231 102.289 Fitness: 55.7385
Organism 8: 93.6558 108.543 114.564 117.905 109.827 93.6154 Fitness: 208.129
Organism 9: 92.0055 113.863 112.433 92.9871 101.445 99.8905 Fitness: 133.217
Organism 10: 110.909 115.209 106.018 107.89 107.379 89.6726 Fitness: 173.116
Organism 11: 112.961 103.227 102.159 82.4149 106.575 108.976 Fitness: 82.6445
Organism 12: 97.9942 97.2912 108.153 85.7762 116.258 116.78 Fitness: 101.006
Organism 13: 111.042 89.6432 96.8167 107.122 112.099 83.2429 Fitness: 97.3512
Organism 14: 81.5334 97.6248 96.2762 118.915 93.9311 114.085 Fitness: 134.142
Organism 15: 114.029 89.4261 98.7649 111.534 84.5259 98.8115 Fitness: 101.763
Organism 16: 96.0443 87.7239 88.148 106.074 84.158 84.0092 Fitness: 81.304
Best Fitness: 208.129
Avg  Fitness: 121.997
================================================================================
Organism 1: 112.961 103.227 102.159 82.4149 93.9311 114.085 Fitness: 27.6804
Organism 2: 91.2118 83.805 98.0752 98.712 85.7218 94.5316 Fitness: 28.1144
Organism 3: 88.8062 80.0751 94.9389 88.0938 93.9657 118.046 Fitness: 29.5607
Organism 4: 87.857 88.6036 84.1864 108.049 108.533 83.931 Fitness: 98.746
Organism 5: 92.0055 113.863 112.433 92.9871 101.445 99.8905 Fitness: 133.685
Organism 6: 118.755 100.052 116.332 101.786 85.7218 94.5316 Fitness: 77.1959
Organism 7: 91.2118 93.665 98.0752 107.454 111.683 112.3 Fitness: 64.4095
Organism 8: 114.029 89.4261 98.7649 111.534 84.5259 98.8115 Fitness: 77.231
Organism 9: 81.5334 97.6248 96.2762 118.915 97.2972 114.085 Fitness: 84.6112
Organism 10: 112.961 103.227 102.159 82.4149 117.467 108.976 Fitness: 73.1123
Organism 11: 87.857 88.6036 84.1864 108.049 101.445 99.8905 Fitness: 98.7457
Organism 12: 92.0055 113.863 112.433 92.9871 107.791 83.931 Fitness: 58.6845
Organism 13: 118.755 100.052 116.332 93.3178 111.683 107.392 Fitness: 77.1959
Organism 14: 88.8062 80.0751 94.9389 88.0938 84.5259 98.8115 Fitness: 78.7913
Organism 15: 114.029 89.4261 112.439 111.534 93.9657 118.046 Fitness: 152.227
Organism 16: 81.5334 97.6248 96.2762 118.915 106.575 108.976 Fitness: 59.6121
Best Fitness: 152.227
Avg  Fitness: 76.2252
================================================================================
Organism 1: 92.0055 113.863 112.433 92.9871 107.791 83.931 Fitness: 36.2642
Organism 2: 81.5334 97.6248 96.2762 118.915 106.575 108.976 Fitness: 112.192
Organism 3: 114.029 89.4261 98.7649 116.569 84.5259 98.8115 Fitness: 54.811
Organism 4: 87.857 88.6036 84.1864 108.049 108.533 83.931 Fitness: 101.326
Organism 5: 81.5334 97.6248 90.6992 118.915 98.2756 114.085 Fitness: 137.192
Organism 6: 114.029 89.4261 112.439 111.534 93.9657 118.046 Fitness: 54.811
Organism 7: 91.2118 83.805 98.0752 98.712 85.7218 94.5316 Fitness: 91.989
Organism 8: 87.857 88.6036 84.1864 108.049 101.445 99.8905 Fitness: 51.3259
Organism 9: 79.4616 126.74 112.433 92.9871 126.748 108.976 Fitness: 61.2644
Organism 10: 81.5334 97.6248 96.2762 118.915 106.575 83.931 Fitness: 87.1916
Organism 11: 114.029 89.4261 98.7649 111.534 84.5259 83.931 Fitness: 104.81
Organism 12: 87.857 88.6036 84.1864 108.049 108.533 98.8115 Fitness: 126.326
Organism 13: 81.5334 111.324 96.2762 118.915 97.2972 118.046 Fitness: 62.1922
Organism 14: 114.029 89.4261 112.439 111.534 93.9657 115.286 Fitness: 79.811
Organism 15: 91.2118 83.805 110.669 98.712 85.7218 99.8905 Fitness: 66.9896
Organism 16: 87.857 88.6036 84.1864 108.049 101.445 94.5316 Fitness: 226.323
Best Fitness: 226.323
Avg  Fitness: 90.9262
================================================================================
Organism 1: 87.857 88.6036 84.1864 112.278 101.445 99.8905 Fitness: 148.826
Organism 2: 114.029 89.4261 98.7649 121.791 84.5259 83.931 Fitness: 77.3118
Organism 3: 81.5334 97.6248 96.2762 118.915 121.174 70.9489 Fitness: 159.69
Organism 4: 114.029 89.4261 112.439 111.534 93.9657 104.968 Fitness: 102.31
Organism 5: 91.2118 83.805 95.7145 98.712 85.7218 99.8905 Fitness: 139.486
Organism 6: 79.4616 126.74 112.433 92.9871 126.748 108.976 Fitness: 83.7654
Organism 7: 91.2118 83.805 98.0752 98.712 85.7218 94.5316 Fitness: 139.49
Organism 8: 81.5334 111.324 96.2762 118.915 97.2972 118.046 Fitness: 134.693
Organism 9: 87.3696 88.6036 84.1864 111.534 84.5259 83.931 Fitness: 102.312
Organism 10: 114.029 89.4261 98.7649 108.049 101.445 99.8905 Fitness: 148.827
Organism 11: 95.1999 97.6248 96.2762 111.534 93.9657 118.046 Fitness: 102.312
Organism 12: 114.029 89.4261 112.439 120.248 106.575 83.931 Fitness: 109.692
Organism 13: 91.2118 83.805 110.669 92.9871 126.748 108.976 Fitness: 133.765
Organism 14: 79.4616 126.74 112.433 98.712 85.7218 99.8905 Fitness: 64.4903
Organism 15: 91.2118 83.805 98.0752 118.915 97.2972 118.046 Fitness: 109.693
Organism 16: 81.5334 111.324 96.2762 98.712 85.7218 77.2542 Fitness: 64.4903
Best Fitness: 159.69
Avg  Fitness: 113.822
================================================================================
Organism 1: 114.029 104.158 98.7649 121.791 84.5259 83.931 Fitness: 162.57
Organism 2: 79.4616 126.74 112.433 92.9871 126.748 108.976 Fitness: 158.768
Organism 3: 95.1999 97.6248 96.2762 111.534 93.9657 118.046 Fitness: 52.319
Organism 4: 91.2118 83.805 98.0752 98.712 85.7218 94.5316 Fitness: 164.496
Organism 5: 114.029 89.4261 112.439 120.248 106.575 83.931 Fitness: 96.0332
Organism 6: 87.857 88.6036 84.1864 112.278 101.445 99.8905 Fitness: 78.0632
Organism 7: 81.5334 111.324 96.2762 98.712 84.5872 77.2542 Fitness: 214.493
Organism 8: 81.5334 111.324 96.2762 118.915 97.2972 118.046 Fitness: 84.7003
Organism 9: 114.029 89.4261 98.7649 121.791 84.5259 108.976 Fitness: 87.5751
Organism 10: 79.4616 126.74 112.433 98.5381 126.748 83.931 Fitness: 68.7727
Organism 11: 95.1999 97.6248 96.2762 122.338 93.9657 94.5316 Fitness: 77.3191
Organism 12: 91.2118 83.805 98.0752 98.712 85.7218 118.046 Fitness: 114.498
Organism 13: 114.029 89.4261 112.439 120.248 106.575 99.8905 Fitness: 161.028
Organism 14: 87.857 88.6036 79.1661 112.278 83.8909 83.931 Fitness: 103.062
Organism 15: 81.5334 111.324 96.2762 98.712 85.7218 118.046 Fitness: 89.4976
Organism 16: 81.5334 111.324 96.2762 118.915 97.2972 95.9576 Fitness: 109.699
Best Fitness: 214.493
Avg  Fitness: 113.931
================================================================================
Organism 1: 95.1999 97.6248 96.2762 111.534 99.5665 118.046 Fitness: 77.3173
Organism 2: 122.136 89.4261 98.7649 121.791 84.5259 108.976 Fitness: 112.573
Organism 3: 109.488 84.1977 96.2762 122.338 93.9657 94.5316 Fitness: 173.119
Organism 4: 91.2118 83.805 98.0752 98.712 85.7218 94.5316 Fitness: 89.4958
Organism 5: 81.5334 111.324 96.2762 118.915 97.2972 95.9576 Fitness: 109.698
Organism 6: 91.2118 83.805 98.0752 98.712 85.7218 118.046 Fitness: 64.4958
Organism 7: 81.5334 111.324 96.2762 118.915 97.2972 118.046 Fitness: 119.697
Organism 8: 87.857 88.6036 84.1864 112.278 101.445 99.8905 Fitness: 203.057
Organism 9: 94.8528 97.6248 96.2762 111.534 87.9053 108.976 Fitness: 127.317
Organism 10: 114.029 89.4261 100.127 121.791 84.5259 118.046 Fitness: 112.573
Organism 11: 95.1999 97.6248 96.2762 122.338 93.9657 94.5316 Fitness: 98.1213
Organism 12: 103.096 83.805 98.0752 98.712 85.7218 94.5316 Fitness: 39.4954
Organism 13: 81.5334 111.324 96.2762 118.915 97.2972 118.046 Fitness: 59.6984
Organism 14: 91.2118 83.805 98.0752 98.712 85.7218 95.9576 Fitness: 64.4956
Organism 15: 81.5334 111.324 96.2762 118.915 97.2972 99.8905 Fitness: 59.6984
Organism 16: 87.857 88.6036 84.1864 112.278 101.445 118.046 Fitness: 53.0615
Best Fitness: 203.057
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Avg  Fitness: 97.7446
================================================================================
Organism 1: 81.5334 111.324 96.2762 118.915 97.2972 95.9576 Fitness: 59.6125
Organism 2: 95.1999 97.6248 96.2762 111.534 99.5665 118.046 Fitness: 127.231
Organism 3: 94.8528 97.6248 96.2762 93.2983 87.9053 108.976 Fitness: 52.2313
Organism 4: 109.488 84.1977 96.2762 122.338 93.9657 94.5316 Fitness: 63.0354
Organism 5: 103.096 83.805 98.0752 98.712 85.7218 94.5316 Fitness: 39.4095
Organism 6: 91.2118 83.805 98.0752 98.712 85.7218 118.046 Fitness: 64.4099
Organism 7: 91.2118 83.805 98.0752 98.712 85.7218 94.5316 Fitness: 64.4097
Organism 8: 95.1999 97.6248 96.2762 122.338 93.9657 94.5316 Fitness: 63.0354
Organism 9: 91.8629 111.324 96.2762 118.915 97.2972 118.046 Fitness: 59.6125
Organism 10: 95.1999 97.6248 96.2762 111.534 99.5665 95.9576 Fitness: 52.2313
Organism 11: 94.8528 97.6248 96.2762 111.534 87.9053 94.5316 Fitness: 77.2314
Organism 12: 109.488 78.7018 96.2762 122.338 93.9657 108.976 Fitness: 63.0354
Organism 13: 103.096 83.805 98.0752 98.712 85.7218 118.046 Fitness: 64.4099
Organism 14: 91.2118 83.805 98.0752 98.712 85.7218 80.9364 Fitness: 64.4099
Organism 15: 91.2118 83.805 98.0752 98.712 85.7218 94.5316 Fitness: 114.41
Organism 16: 95.1999 97.6248 86.4699 122.338 93.9657 94.5316 Fitness: 173.03
Best Fitness: 173.03
Avg  Fitness: 75.1091
================================================================================
Organism 1: 91.2118 83.805 98.0752 98.712 85.7218 80.9364 Fitness: 64.3818
Organism 2: 95.1999 97.6248 96.2762 111.534 99.5665 95.9576 Fitness: 102.204
Organism 3: 94.8528 97.6248 96.2762 111.534 101.125 94.5316 Fitness: 77.2037
Organism 4: 81.5334 111.324 96.2762 118.915 97.2972 95.9576 Fitness: 109.584
Organism 5: 95.1999 97.6248 86.4699 122.338 93.9657 94.5316 Fitness: 163.003
Organism 6: 91.2118 83.805 98.0752 98.712 85.7218 94.5316 Fitness: 39.3818
Organism 7: 94.8528 97.6248 114.15 93.2983 87.9053 108.976 Fitness: 83.9685
Organism 8: 109.488 78.7018 96.2762 122.338 93.9657 108.976 Fitness: 63.0077
Organism 9: 91.2118 83.805 98.0752 98.712 99.5665 95.9576 Fitness: 39.3818
Organism 10: 95.1999 97.6248 96.2762 111.534 85.7218 80.9364 Fitness: 52.2036
Organism 11: 94.8528 97.6248 96.2762 111.534 97.2972 95.9576 Fitness: 137.202
Organism 12: 81.5334 111.324 96.2762 118.915 87.9053 94.5316 Fitness: 84.5848
Organism 13: 95.1999 97.6248 86.4699 122.338 85.7218 94.5316 Fitness: 113.007
Organism 14: 75.1194 83.805 98.0752 98.712 93.9657 94.5316 Fitness: 39.3818
Organism 15: 94.8528 97.6248 96.2762 93.2983 93.9657 108.976 Fitness: 58.968
Organism 16: 109.488 78.7018 96.2762 122.338 87.9053 108.976 Fitness: 88.0077
Best Fitness: 163.003
Avg  Fitness: 82.2169
================================================================================
Organism 1: 109.488 78.7018 96.2762 122.338 93.9657 108.976 Fitness: 62.9123
Organism 2: 75.1194 83.805 98.0752 98.712 93.9657 94.5316 Fitness: 64.2868
Organism 3: 81.9416 97.6248 96.2762 111.534 85.7218 80.9364 Fitness: 77.1083
Organism 4: 94.8528 97.6248 96.2762 93.2983 93.9657 108.976 Fitness: 33.8726
Organism 5: 109.488 78.7018 96.2762 117.243 103.888 108.976 Fitness: 112.912
Organism 6: 91.2118 95.0714 98.0752 81.4833 85.7218 88.7234 Fitness: 89.2868
Organism 7: 95.1999 97.6248 86.4699 122.338 93.9657 94.5316 Fitness: 62.9123
Organism 8: 81.5334 111.324 96.2762 118.915 97.2972 106.528 Fitness: 59.4894
Organism 9: 109.488 78.7018 98.0752 98.712 93.9657 94.5316 Fitness: 89.2868
Organism 10: 75.1194 83.805 96.2762 122.338 93.9657 122.296 Fitness: 87.9123
Organism 11: 95.1999 89.201 96.2762 93.2983 93.9657 108.976 Fitness: 83.873
Organism 12: 94.8528 97.6248 96.2762 112.192 85.7218 80.9364 Fitness: 127.108
Organism 13: 109.488 78.7018 98.0752 98.712 85.7218 74.3669 Fitness: 64.2866
Organism 14: 91.2118 83.805 96.2762 122.338 87.9053 120.721 Fitness: 112.911
Organism 15: 104.346 97.6248 96.2762 118.915 97.2972 84.3072 Fitness: 109.489
Organism 16: 81.5334 111.324 86.4699 122.338 93.9657 94.5316 Fitness: 62.9123
Best Fitness: 127.108
Avg  Fitness: 81.285
================================================================================
Organism 1: 91.2118 95.0714 98.0752 81.4833 85.7218 88.7234 Fitness: 27.2998
Organism 2: 89.7581 78.7018 98.0752 98.712 85.7218 74.3669 Fitness: 64.296
Organism 3: 109.488 78.7018 96.2762 122.338 93.9657 108.976 Fitness: 87.9204
Organism 4: 75.1194 83.805 98.0752 98.712 93.9657 94.5316 Fitness: 64.296
Organism 5: 104.346 97.6248 96.2762 118.915 97.2972 84.3072 Fitness: 59.4986
Organism 6: 81.9416 97.6248 96.2762 111.534 85.7218 80.9364 Fitness: 77.1176
Organism 7: 81.5334 111.324 86.4699 122.338 113.1 85.6013 Fitness: 87.9216
Organism 8: 81.5334 111.324 96.2762 118.915 97.2972 106.528 Fitness: 84.4987
Organism 9: 91.2118 91.2966 116.23 98.712 70.7139 74.3669 Fitness: 74.296
Organism 10: 109.488 78.7018 97.0314 81.4833 85.7218 88.7234 Fitness: 122.067
Organism 11: 109.488 78.7018 98.0752 98.712 80.3803 94.5316 Fitness: 89.296
Organism 12: 75.1194 66.9369 96.2762 134.432 93.9657 108.976 Fitness: 162.917
Organism 13: 104.346 97.6248 96.2762 111.534 85.7218 80.9364 Fitness: 112.116
Organism 14: 81.9416 97.6248 96.2762 118.915 97.2972 84.3072 Fitness: 134.495
Organism 15: 81.5334 111.324 96.2762 118.915 97.2972 106.528 Fitness: 134.496
Organism 16: 81.5334 111.324 86.4699 122.338 93.9657 94.5316 Fitness: 137.916
Best Fitness: 162.917
Avg  Fitness: 95.028
================================================================================
Organism 1: 91.2118 95.0714 98.0752 81.4833 85.7218 95.8632 Fitness: 27.2308
Organism 2: 104.346 97.6248 110.014 81.4833 85.7218 88.7234 Fitness: 27.2308
Organism 3: 81.5334 92.3116 71.9146 98.712 85.7218 74.3669 Fitness: 27.9985
Organism 4: 81.5334 111.324 89.3086 108.502 97.2972 106.528 Fitness: 59.2932
Organism 5: 81.5334 111.324 96.2762 118.915 97.2972 106.528 Fitness: 59.2932
Organism 6: 121.606 78.7018 97.0314 81.4833 85.7218 90.9289 Fitness: 46.8616
Organism 7: 109.488 78.7018 96.2762 122.338 93.9657 108.976 Fitness: 112.715
Organism 8: 81.5334 111.324 86.4699 122.338 113.1 85.6013 Fitness: 112.713
Organism 9: 89.7581 78.7018 105.922 91.4181 85.7218 74.3669 Fitness: 64.0903
Organism 10: 95.0104 97.6248 96.2762 118.915 97.2972 84.3072 Fitness: 109.292
Organism 11: 81.5334 111.324 96.2762 118.915 97.2972 106.528 Fitness: 159.288
Organism 12: 81.5334 111.324 96.2762 118.915 97.2972 106.528 Fitness: 209.287
Organism 13: 109.488 78.7018 97.0314 122.338 93.9657 106.872 Fitness: 112.713
Organism 14: 109.488 78.7018 96.2762 81.4833 104.883 88.7234 Fitness: 121.862
Organism 15: 89.7581 78.7018 98.0752 122.338 113.1 85.6013 Fitness: 147.711
Organism 16: 91.2118 95.0714 98.0752 118.915 97.2972 84.3072 Fitness: 159.287
Best Fitness: 209.287
Avg  Fitness: 97.3042
================================================================================
Organism 1: 109.488 78.7018 96.2762 81.4833 104.883 88.7234 Fitness: 27.2428
Organism 2: 81.5334 111.324 110.014 81.4833 85.7218 88.7234 Fitness: 27.2428
Organism 3: 81.5334 111.324 96.2762 118.915 97.2972 106.528 Fitness: 109.298
Organism 4: 104.346 97.6248 93.6613 81.4833 85.7218 88.7234 Fitness: 71.867
Organism 5: 89.7581 78.7018 105.922 91.4181 85.7218 74.3669 Fitness: 31.8013
Organism 6: 81.5334 111.324 89.3086 108.502 97.2972 117.364 Fitness: 73.8858
Organism 7: 95.0104 97.6248 96.2762 118.915 97.2972 84.3072 Fitness: 69.2983
Organism 8: 81.5334 111.324 96.2762 118.915 97.2972 106.528 Fitness: 94.2964
Organism 9: 121.606 78.7018 78.3394 81.4833 85.7218 90.9289 Fitness: 71.867
Organism 10: 104.346 97.6248 95.15 118.915 97.2972 106.528 Fitness: 59.2983
Organism 11: 89.7581 78.7018 89.3086 101.635 97.2972 106.528 Fitness: 123.886
Organism 12: 81.5334 111.324 105.922 91.4181 85.7218 74.3669 Fitness: 81.8018
Organism 13: 109.488 78.7018 96.2762 118.915 97.2972 84.3072 Fitness: 84.2984
Organism 14: 95.0104 97.6248 96.2762 81.4833 104.883 88.7234 Fitness: 121.865
Organism 15: 81.5334 111.324 97.0314 81.4833 85.7218 90.9289 Fitness: 96.867
Organism 16: 130.687 78.7018 96.2762 118.915 97.2972 106.528 Fitness: 109.297
Best Fitness: 123.886
Avg  Fitness: 78.382
================================================================================
Organism 1: 81.5334 111.324 105.922 91.4181 85.7218 74.3669 Fitness: 25.5188
Organism 2: 81.5334 111.324 110.014 81.4833 85.7218 88.7234 Fitness: 96.6808
Organism 3: 109.488 78.7018 96.2762 86.1228 104.883 88.7234 Fitness: 46.6805
Organism 4: 89.7581 78.7018 105.922 91.4181 85.7218 73.599 Fitness: 56.6155
Organism 5: 81.5334 111.324 105.922 91.4181 85.7218 74.3669 Fitness: 56.6155
Organism 6: 81.5334 111.324 96.2762 118.915 97.2972 106.528 Fitness: 109.11
Organism 7: 103.448 78.7018 106.331 118.915 97.2972 84.3072 Fitness: 134.109
Organism 8: 81.5334 111.324 89.3086 99.867 87.0421 117.364 Fitness: 98.6995
Organism 9: 130.687 78.7018 96.2762 133.364 79.1241 106.528 Fitness: 109.112
Organism 10: 81.5334 111.324 124.834 81.4833 85.7218 103.08 Fitness: 96.6808
Organism 11: 127.027 66.0281 96.2762 79.325 104.883 88.7234 Fitness: 96.6807
Organism 12: 89.7581 78.7018 105.922 91.4181 85.7218 74.3669 Fitness: 106.616
Organism 13: 81.5334 111.324 96.2762 118.915 97.2972 84.3072 Fitness: 84.1114
Organism 14: 109.488 78.7018 96.2762 118.915 97.2972 106.528 Fitness: 59.1121
Organism 15: 81.5334 111.324 89.3086 92.413 97.2972 106.528 Fitness: 98.6991
Organism 16: 130.687 78.7018 96.2762 118.915 97.2972 117.364 Fitness: 134.109
Best Fitness: 134.109
Avg  Fitness: 88.0719
================================================================================
Organism 1: 127.027 66.0281 94.4778 79.325 104.883 88.7234 Fitness: 44.4134
Organism 2: 87.1919 111.324 96.2762 118.915 97.2972 84.3072 Fitness: 84.0035
Organism 3: 109.488 78.7018 96.2762 110.469 97.2972 106.528 Fitness: 109.004
Organism 4: 103.448 78.7018 106.331 118.915 97.2972 88.2039 Fitness: 84.0025
Organism 5: 130.687 78.7018 96.2762 133.364 79.1241 106.528 Fitness: 148.449
Organism 6: 72.5911 111.324 89.3086 92.413 97.2972 106.528 Fitness: 107.502
Organism 7: 130.687 78.7018 96.2762 118.915 117.176 117.364 Fitness: 84.0035
Organism 8: 81.5334 111.324 96.2762 118.915 117.206 106.528 Fitness: 218.997
Organism 9: 138.627 66.0281 96.2762 118.915 97.2972 84.3072 Fitness: 109.003
Organism 10: 81.5334 111.324 96.2762 79.325 104.883 88.7234 Fitness: 69.4134
Organism 11: 117.168 78.7018 96.2762 118.915 97.2972 84.3072 Fitness: 84.0034
Organism 12: 103.448 89.9526 106.331 118.915 97.2972 106.528 Fitness: 109.004
Organism 13: 130.687 78.7018 96.2762 92.413 97.2972 106.528 Fitness: 182.501
Organism 14: 81.5334 111.324 89.3086 133.364 79.1241 106.528 Fitness: 123.452
Organism 15: 130.687 84.9404 96.2762 118.915 97.2972 106.528 Fitness: 84.0025
Organism 16: 81.5334 111.324 96.2762 118.915 97.2972 117.364 Fitness: 69.0033
Best Fitness: 218.997
Avg  Fitness: 106.922
================================================================================
Organism 1: 109.488 78.7018 96.2762 110.469 97.2972 106.528 Fitness: 125.751
Organism 2: 103.448 89.9526 112.973 118.915 97.2972 106.528 Fitness: 159.194
Organism 3: 81.5334 126.5 89.3086 133.364 79.1241 106.528 Fitness: 98.6457
Organism 4: 87.1919 111.324 96.2762 118.915 83.5787 84.3072 Fitness: 134.193
Organism 5: 64.117 111.324 96.2762 118.915 117.206 106.528 Fitness: 109.197
Organism 6: 130.687 84.9404 96.2762 118.915 97.2972 106.528 Fitness: 119.195
Organism 7: 130.687 78.7018 96.2762 118.915 117.176 117.364 Fitness: 59.1968
Organism 8: 130.687 78.7018 96.2762 92.413 97.2972 106.528 Fitness: 57.6951
Organism 9: 109.488 78.7018 96.2762 118.915 97.2972 106.528 Fitness: 184.192
Organism 10: 103.448 89.9526 106.331 110.469 97.2972 99.9745 Fitness: 100.75
Organism 11: 81.5334 111.324 89.3086 118.915 97.2972 84.3072 Fitness: 84.1963
Organism 12: 87.1919 111.324 96.2762 133.364 79.1241 106.528 Fitness: 73.6457
Organism 13: 81.5334 111.324 96.2762 118.915 97.2972 106.528 Fitness: 109.194
Organism 14: 130.687 84.9404 96.2762 118.915 117.206 106.528 Fitness: 214.193
Organism 15: 130.687 65.8804 96.2762 92.413 97.2972 106.528 Fitness: 82.6948
Organism 16: 130.687 78.7018 96.2762 118.915 117.176 117.364 Fitness: 94.1969
Best Fitness: 214.193
Avg  Fitness: 114.133
```

7.4 Appendix 4

```
// Top Left of Shape 1
float topLeftX = position_.x() - width_ / 2;
float topLeftY = position_.y() - height_ / 2;

// Top Left of Shape 2
float topLeftX2 = col->getPosition().x() - col->getWidth() / 2;
float topLeftY2 = col->getPosition().y() - col->getHeight() / 2;


// If Collided
if (topLeftX + width_ > topLeftX2 && topLeftX < topLeftX2 + col->getWidth() &&
    topLeftY + height_ > topLeftY2 && topLeftY < topLeftY2 + col->getHeight()) {
        // /*
        float xPenetration = 0;
        float yPenetration = 0;
        Vector2f normal_;
        float penetration;

        //Calculate Penetration Distance and Collison Normal

        if (position_.x() < col->getPosition().x()) {
                xPenetration = -1 * ((position_.x() + width_ / 2) -
                (col-> getPosition().x() - col->getWidth() / 2));
        }

        else if (position_.x() > col->getPosition().x()) {
                xPenetration = ((col->getPosition().x() + col->getWidth() / 2) -
                (position_.x() - width_ / 2));
        }

        if (position_.y() < col->getPosition().y()) {
                yPenetration = -1 * ((position_.y() + height_ / 2) -
                (col->getPosition().y() - col->getHeight() / 2));
        }
        else if (position_.y() > col->getPosition().y()) {
                yPenetration = ((col->getPosition().y() + col->getHeight() / 2) -
                (position_.y() - height_ / 2));
        }
        if (abs(xPenetration) < abs(yPenetration)) {
                normal_ = Vector2f(0, 1);
                penetration = xPenetration;
        }
        else {
                normal_ = Vector2f(1, 0);
                penetration = yPenetration;
        }

        return std::make_tuple(true, penetration, normal_);
                                //*/
}
else {
        // No Collision
        return std::make_tuple(false, 0.0f, Vector2f(0, 0));
}
```