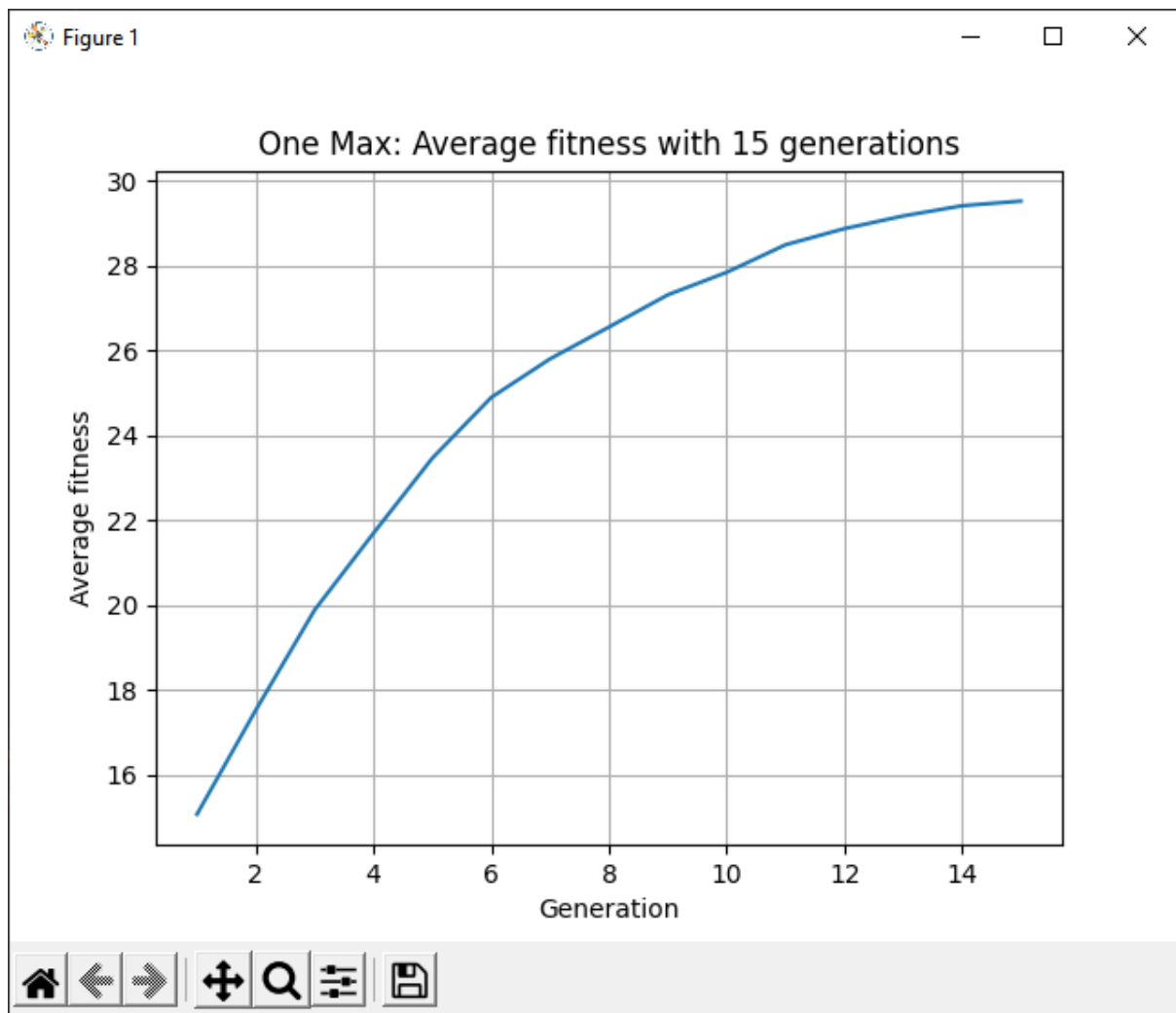


# CT421 Assignment 1

## Part A

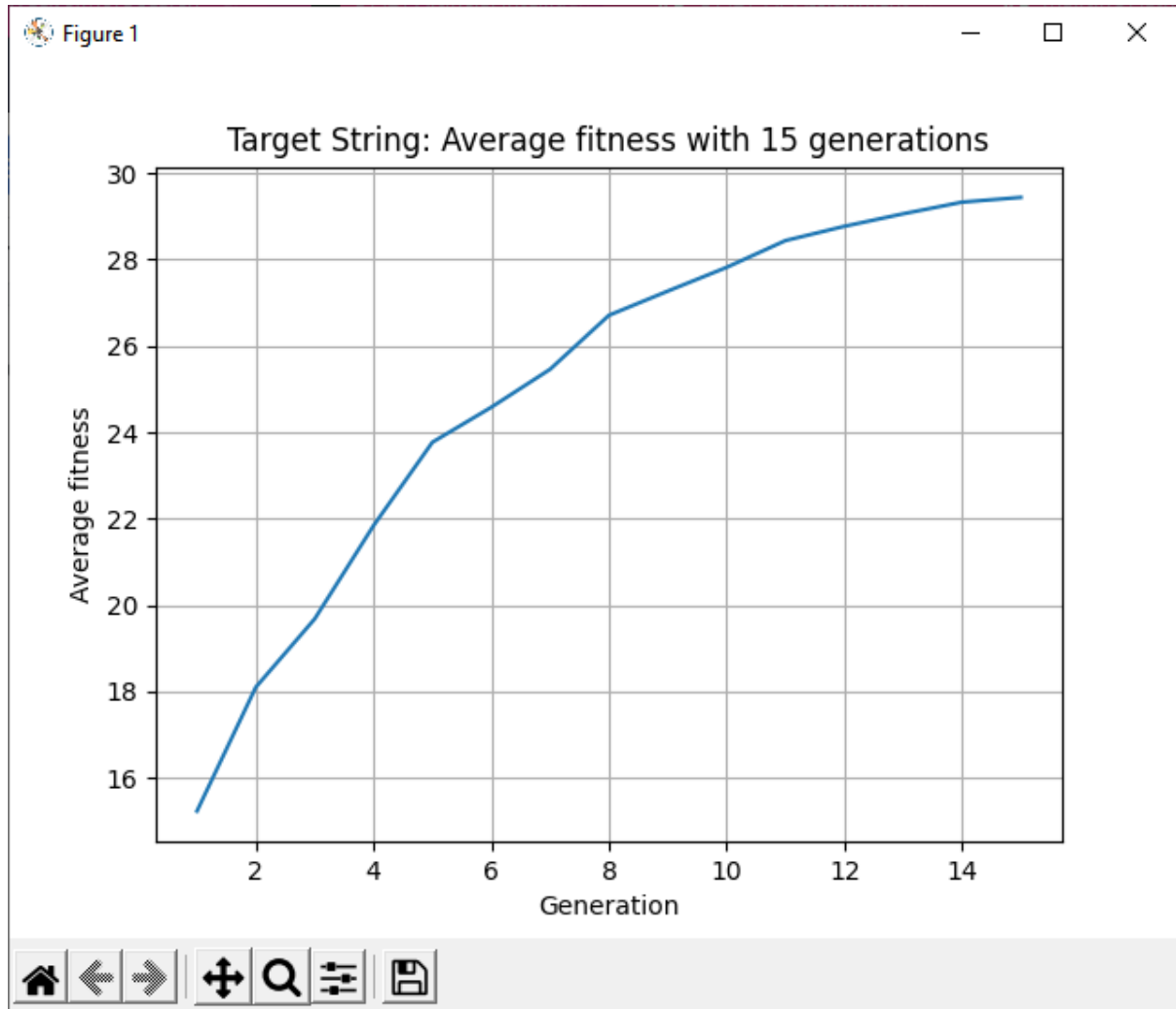
### One-max Problem

The one-max problem implementation reached the target of '1111111111111111111111111111' by generation 8 when the average fitness was 26.38. By generation 15 the average fitness was 29.52.



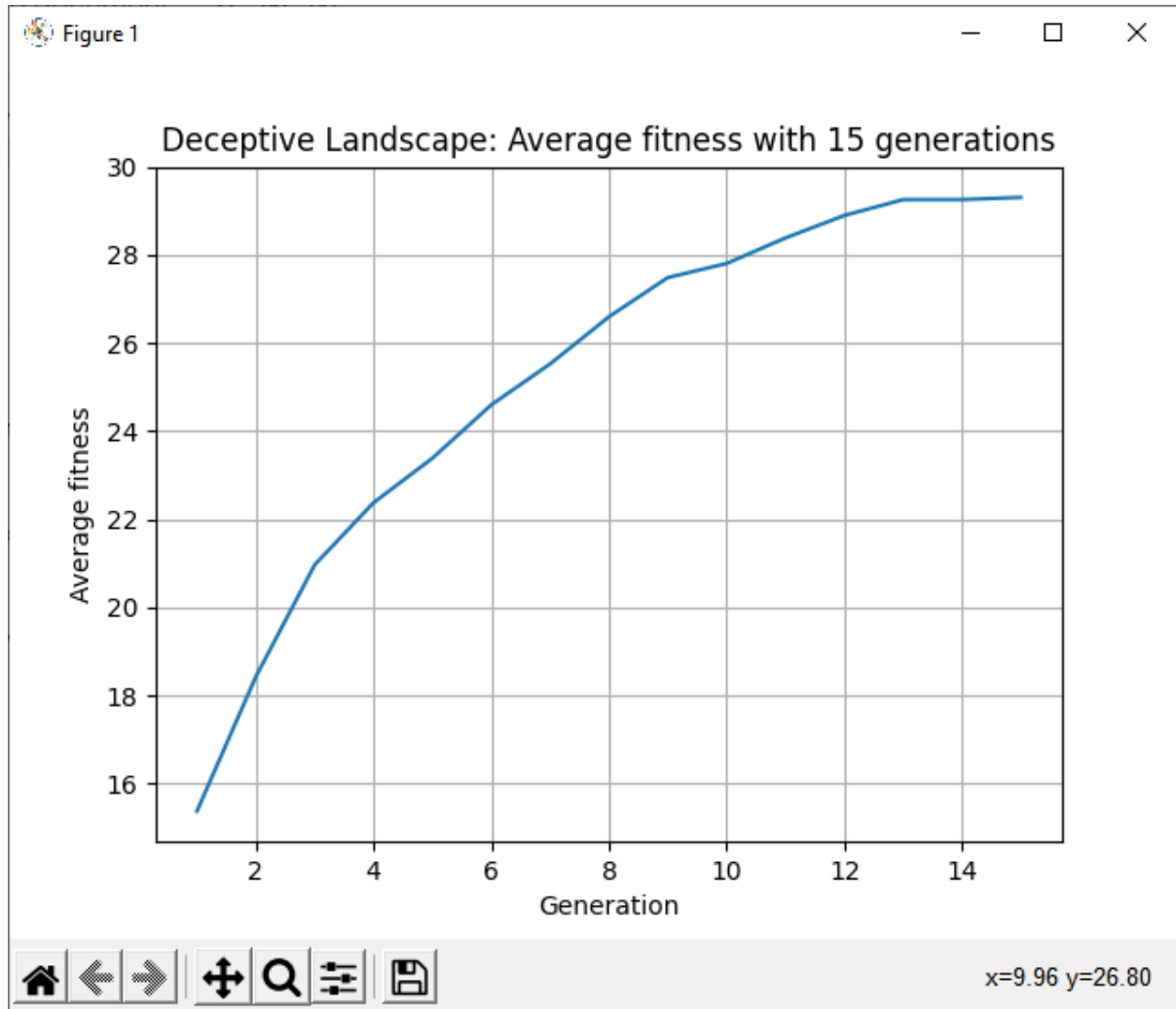
## Evolving to a target string

The target string problem implementation reached the target of '110001011100010110011110101110' (randomly generated every time) by generation 8 when the average fitness was 26.25. By generation 15 the average fitness was 29.53.



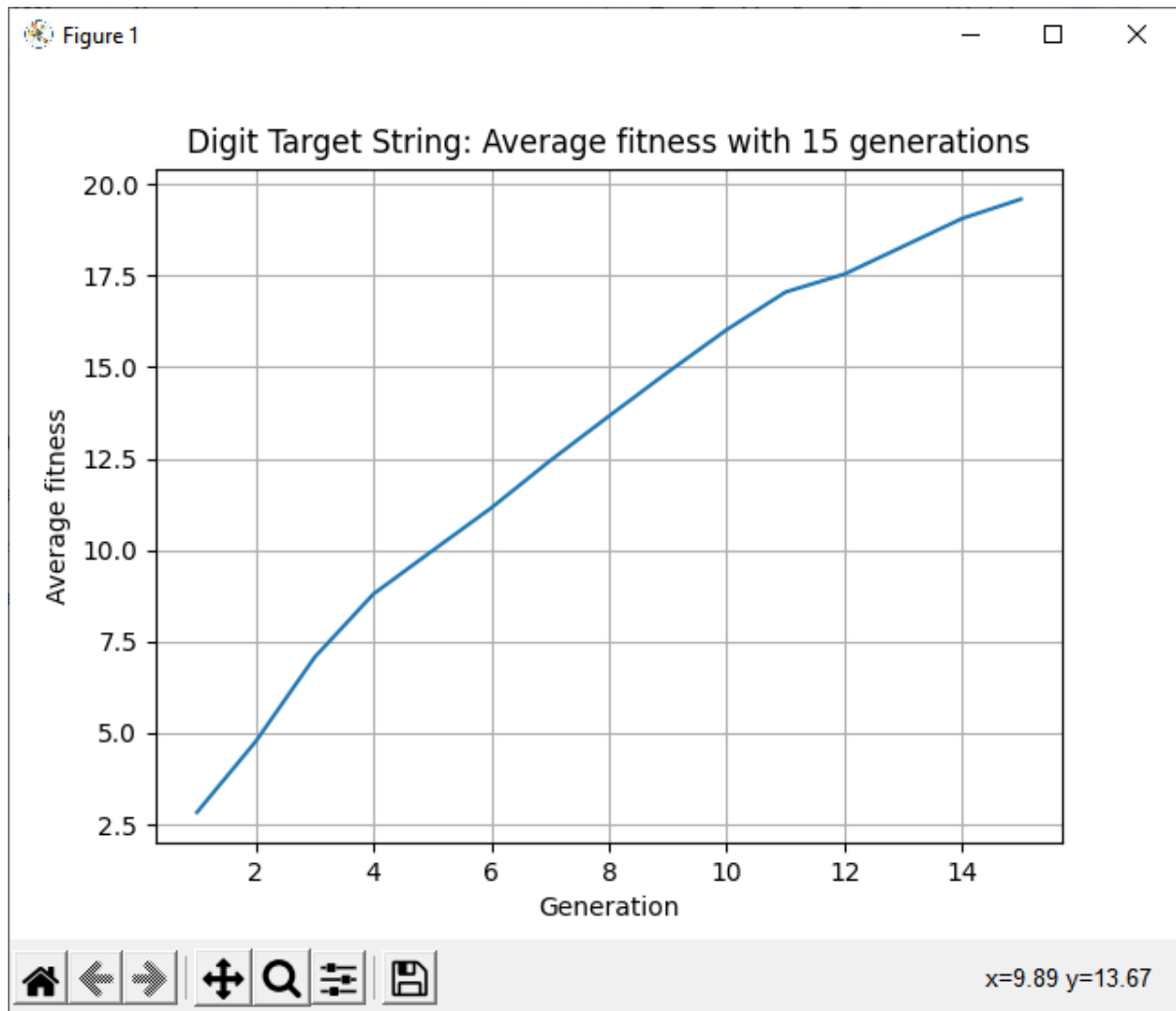
## Deceptive Landscape

The deceptive landscape problem implementation reached the target of '1111111111111111111111111111' by generation 9 when the average fitness was 27.17. By generation 15 the average fitness was 29.42.



## Evolving to a target string with a larger alphabet

The target string with digits problem implementation never reached its target string. By generation 15, its fitness was only 21 with an average fitness of 19.8.



## Part B

### Fitness Function

The fitness function I used I kept track of the total value and weight of the string, and I iterated over every index in the binary number and checked whether it was a 1 or 0. If it was a 1, I added the value at index  $i$  in the values array we were given to the sum total, the same was done for weights. Once I had iterated over all of the binary string, I checked if the weight of the string was higher than the knapsack capacity, if it was, I returned the fitness as zero.

### Mutation Function

The same mutation function was used for the one max, deceptive landscape, target string, and knapsack problem. It did a mutation 'rate\_of\_mutation' of the time. When it did, it simply flipped one of the bits in the binary string.

### Crossover Function

The same crossover function was used for the one max, deceptive landscape, target string, and knapsack problem. It did a crossover 'rate\_of\_crossover' of the time. When it did, it made a copy of the parents and put them into two children objects that would replace the parents eventually, for each child it took a section from each parent ( $n$  bits from the front of one and  $\text{length} - n$  bits from the other).

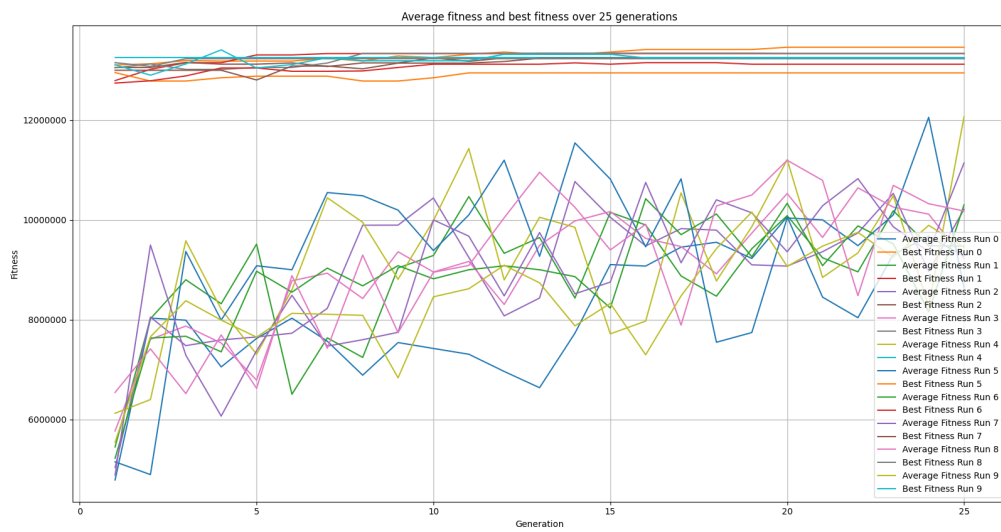
### Selection Function

The same selection function was used for all problems. I based it off of tournament selection. Tournament selection is a method of selecting an individual from a population of individuals. Tournament selection involves running several tournaments among a few individuals chosen at random from the population. The winner of each tournament (the one with the best fitness) is selected for crossover.

### Representation

I tried to add all graphs to one plot but it didn't give a good representation.

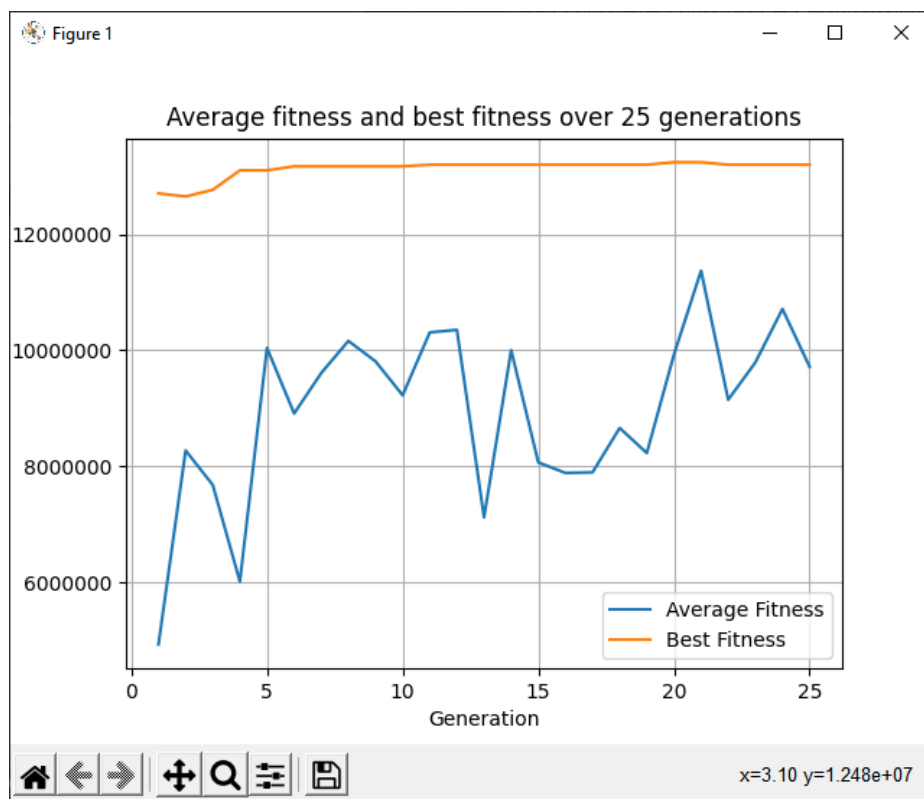
Figure 1



x=5.64 y=1.083e+07

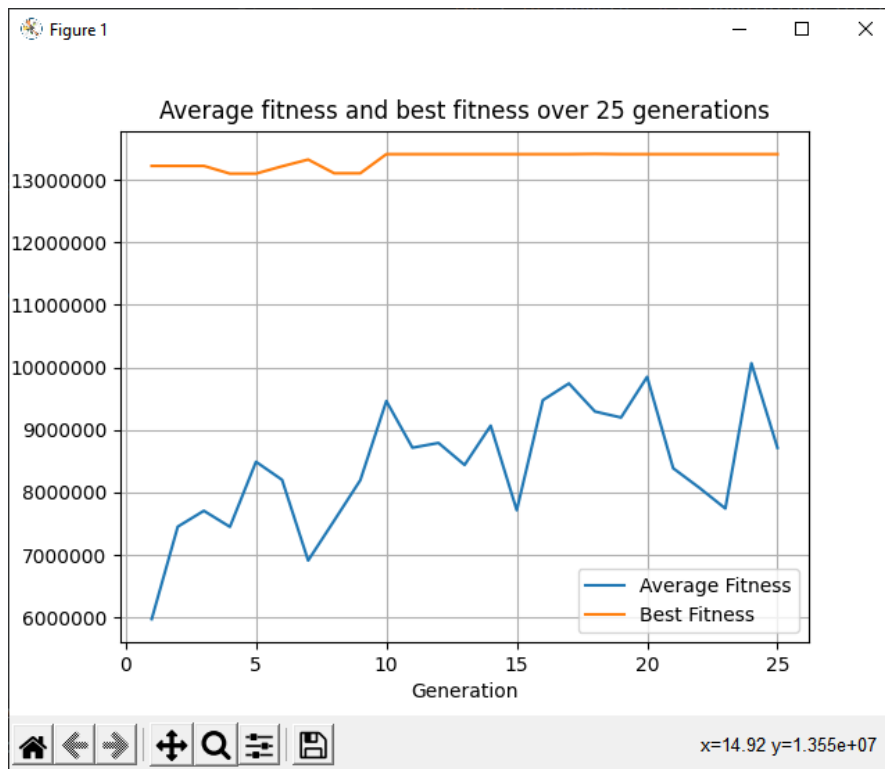
Instead I ran each one manually with a random population between 20 and 180. I'll record the results and graphs below.

## Run 1



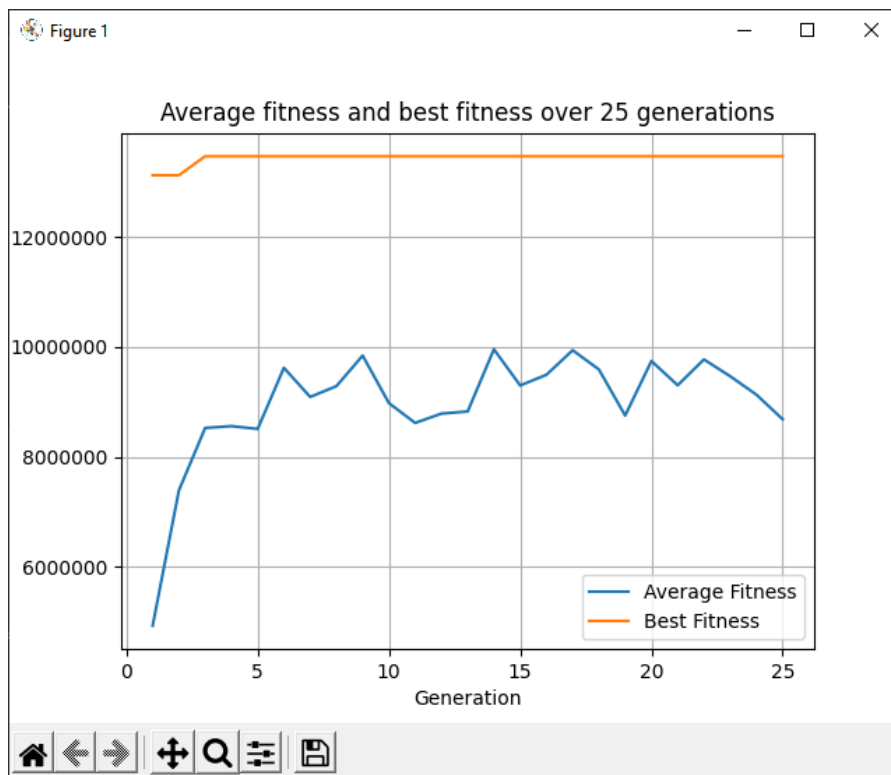
Population size: 32

## Run 2



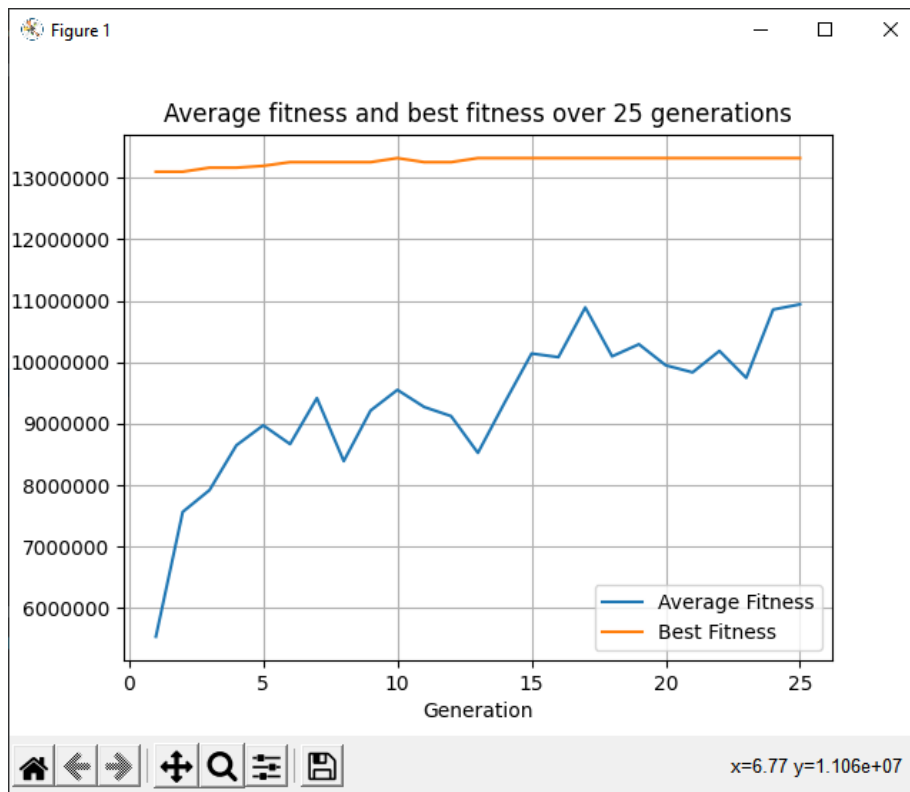
Population size: 122

## Run 3

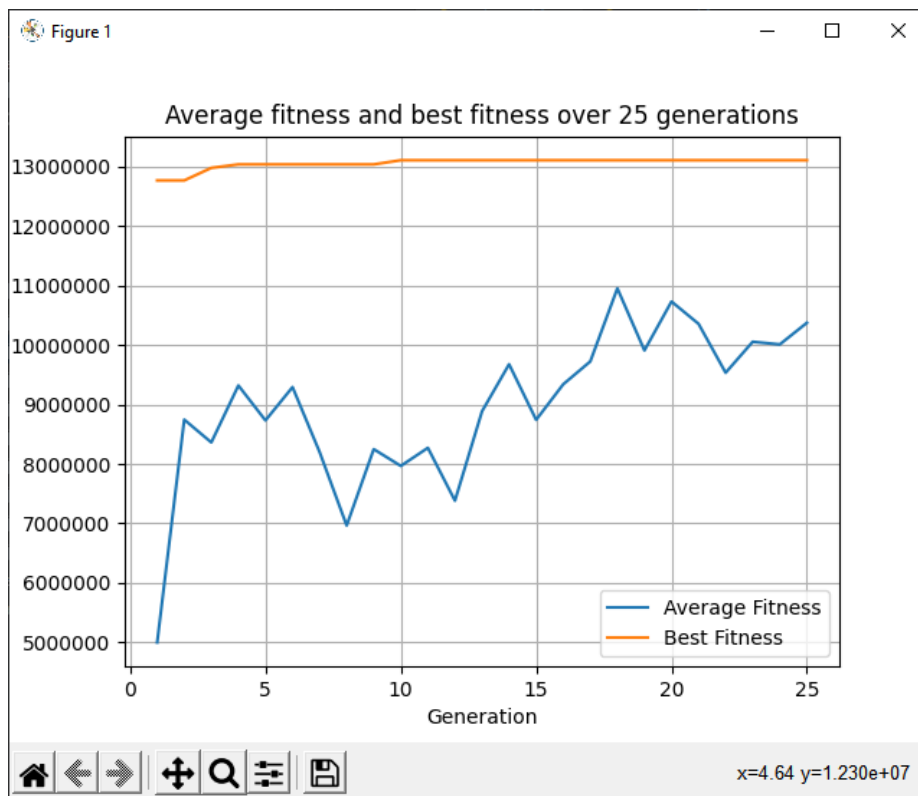


Population size: 74

## Run 4

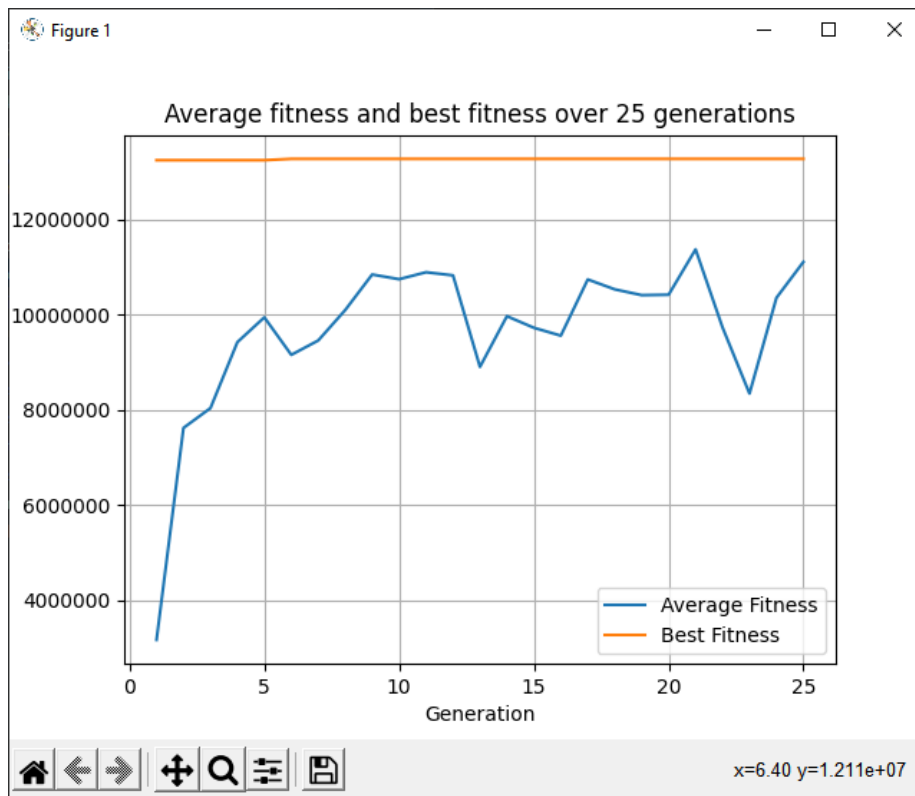


## Run 5



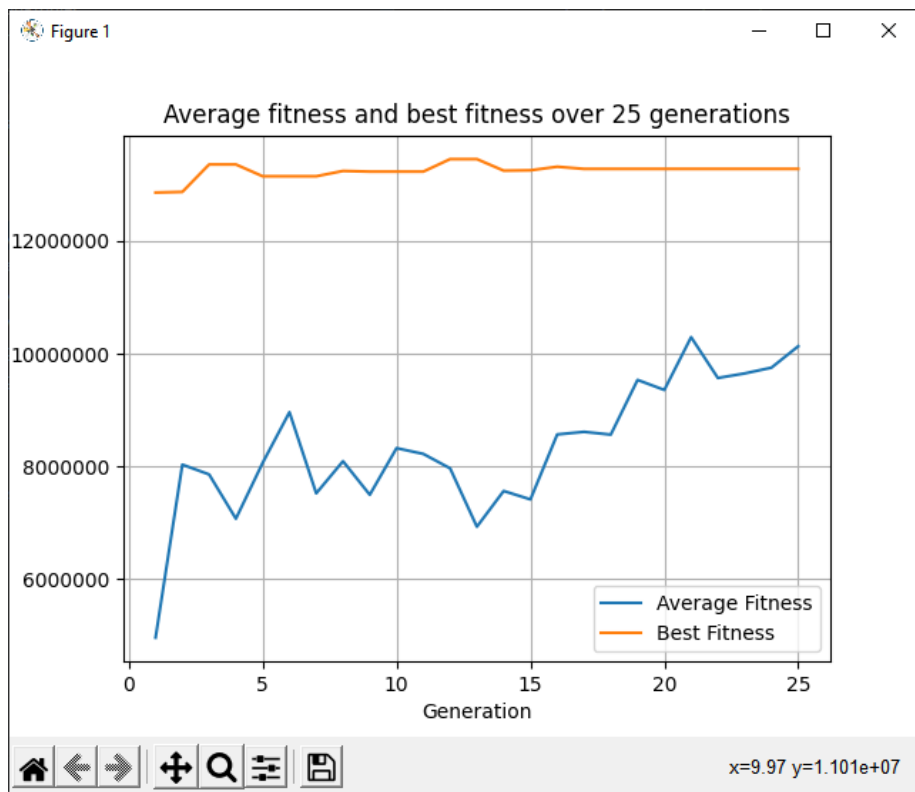


## Run 6



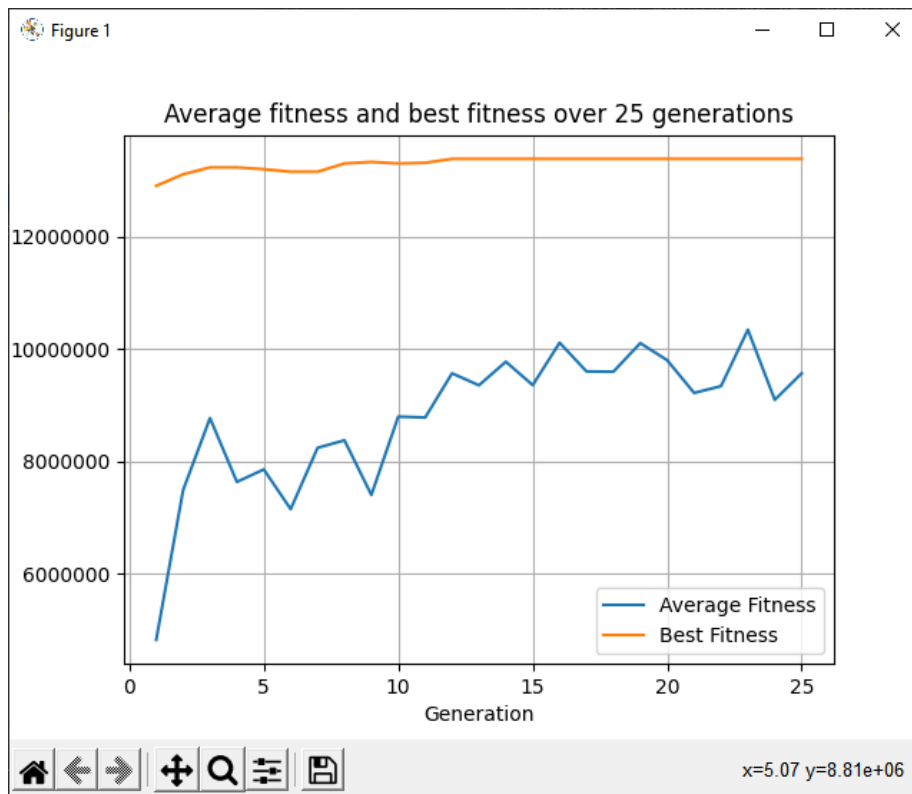
Population size: 50

## Run 7



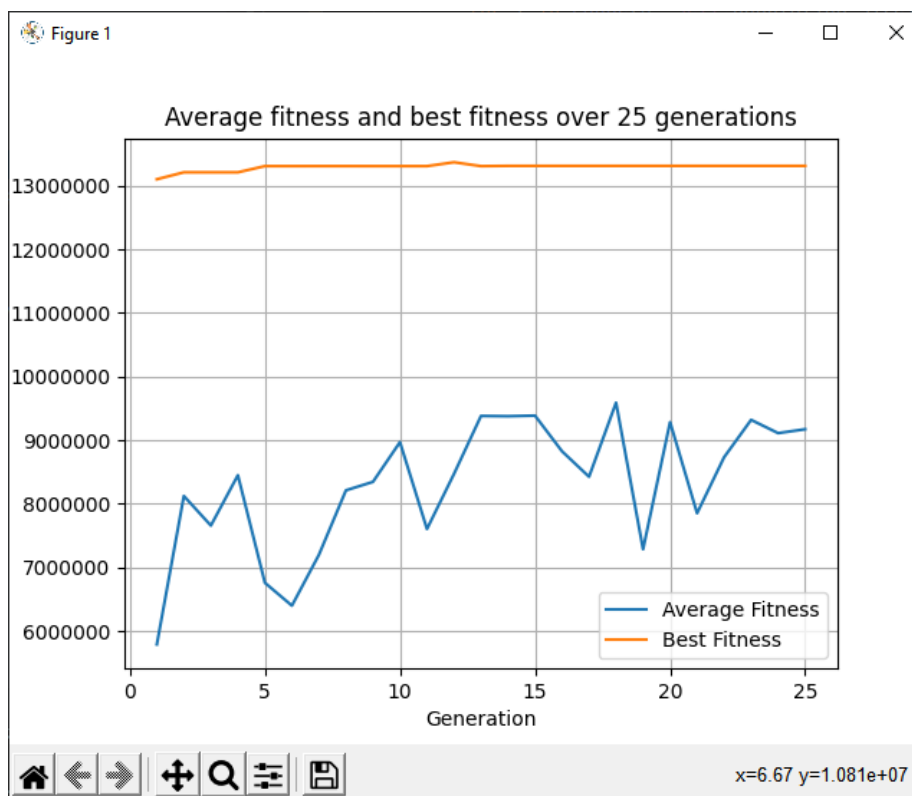
Population size: 146

## Run 8



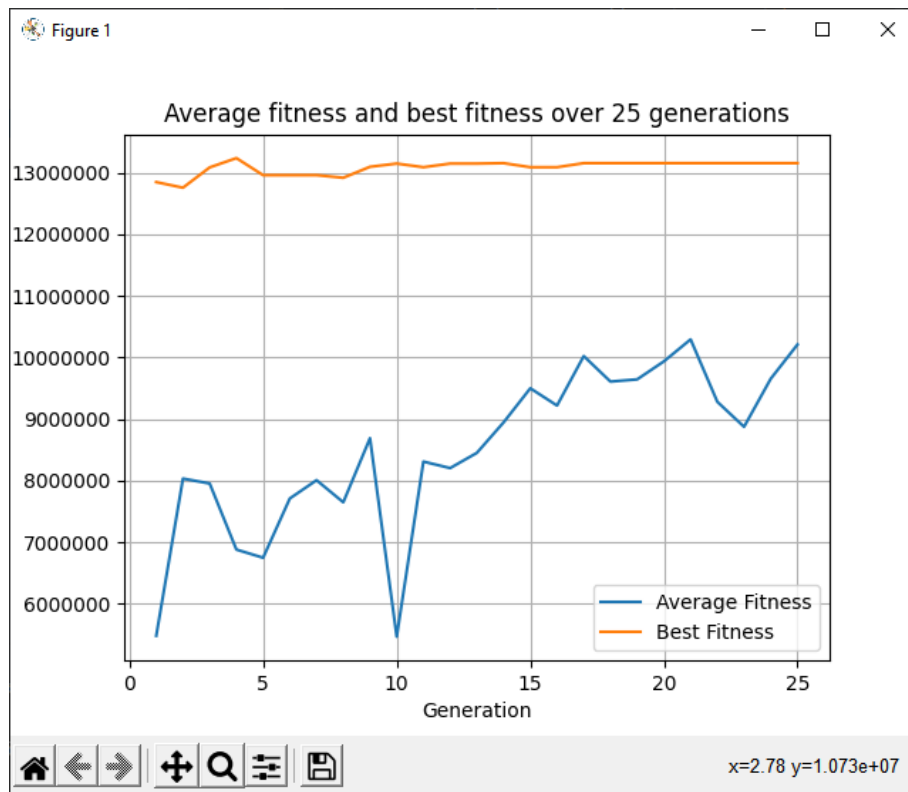
Population size: 152

## Run 9



Population size: 112

## Run 10



Population size: 62