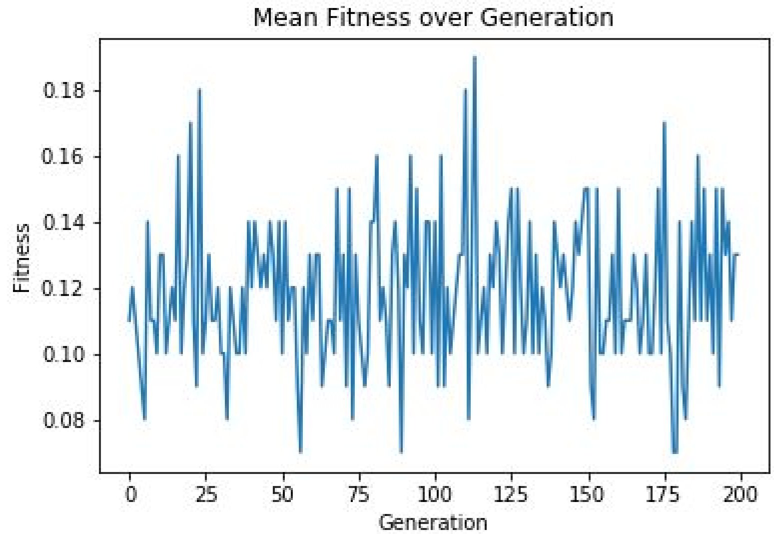
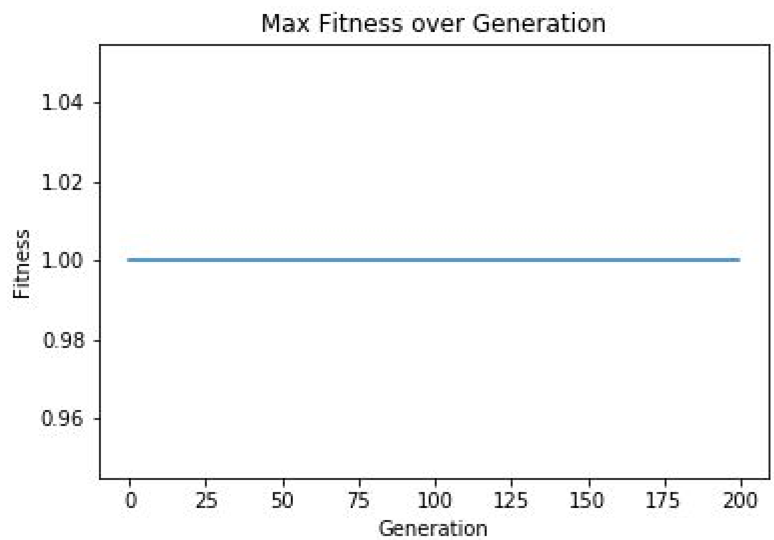
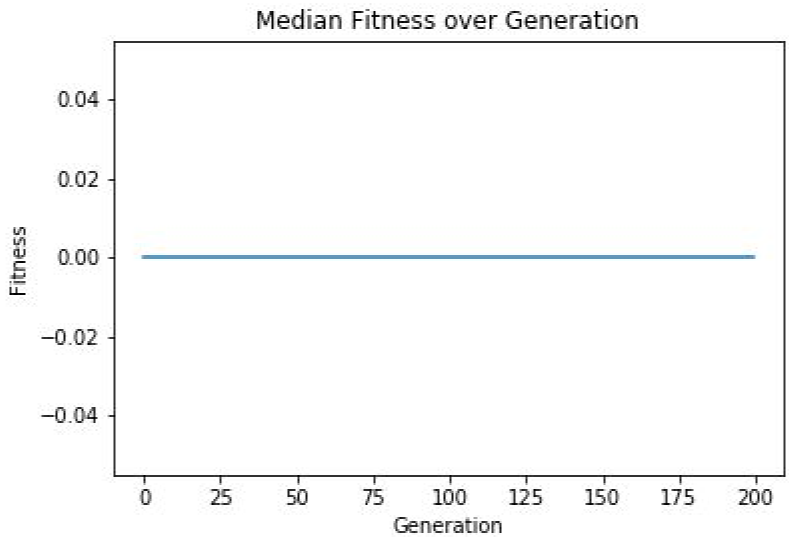
Following Genetic Algorithm PDF



In this graph it can be seen that in a normal representation of the genetic algorithm, the mean of the fitness will gradually get better over time and result in less outliers. As it approaches a significantly high enough generation level, it will plateau.

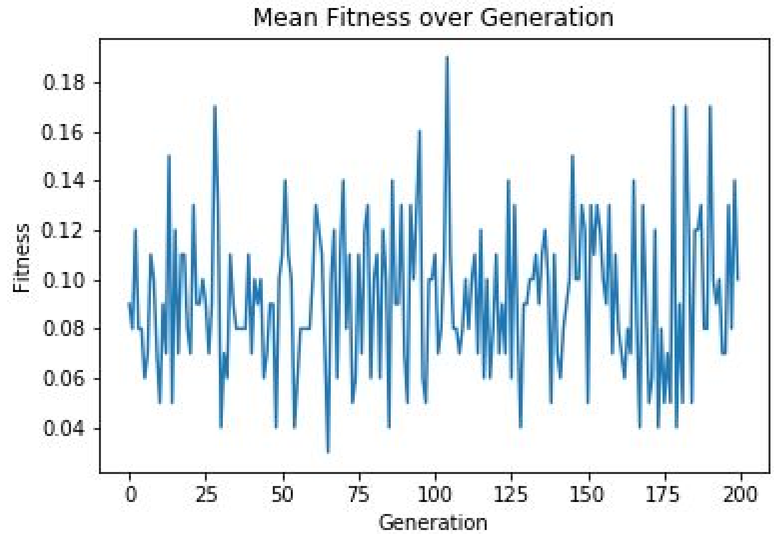


In this graph it can be seen that in a normal representation of the genetic algorithm, the max fitness didn't change since the low mutation rate of 0.001 doesn't allow for much change in the data when the number of generations isn't significantly high enough.

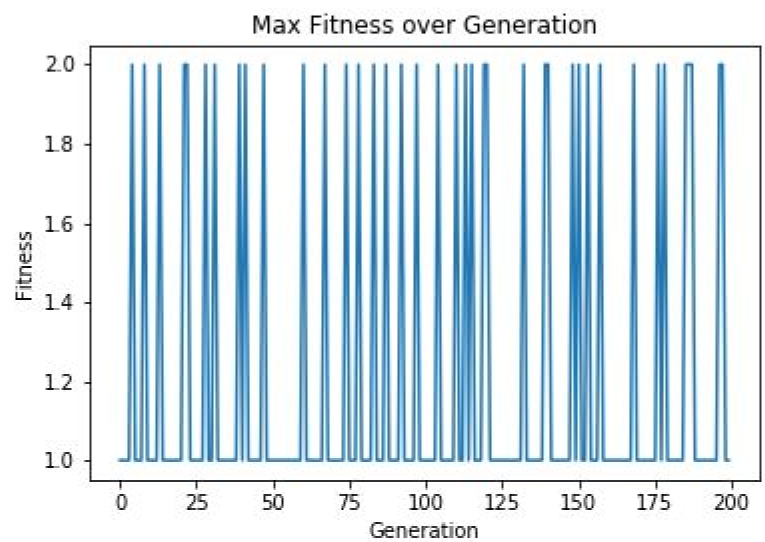


In this graph it can be seen that in a normal representation of the genetic algorithm, the median of the fitness didn't change much for the same reasons since the mutation rate and top selection percentage is low, it will take a significant number of generations before an effect will take place.

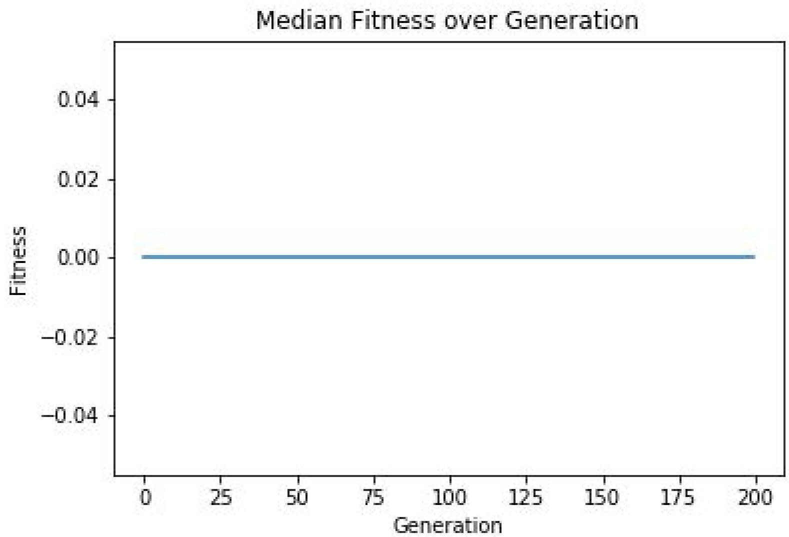
High Mutation (30%)



In this graph it can be seen that a mutation rate at high extremes leads to a graph that has a lot of outliers as the generation number increases. This is because the mutation that can take place can be both good and bad for the sequence and leads to a lot of instability.

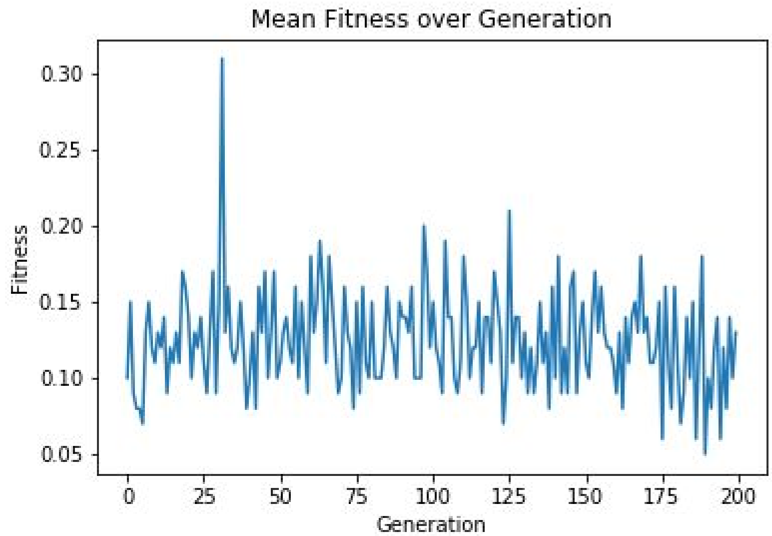


In this graph it can be seen that a high mutation rate causes the sequence to reach the relative max score in a relatively short number of generations (sequence length of ten and has only three hydrophobic amino acids). However it tends to fluctuate a lot per generation as change in the sequence is very easy.

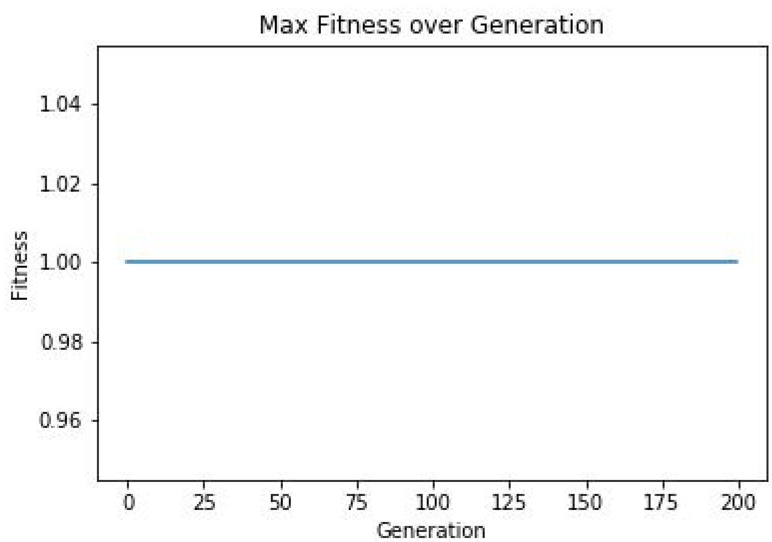


In this graph it can be seen that the high mutation rate still leads to a relatively steady median score since high mutation since the median measurement of fitness is generally more resistant to outliers on ends. The fitness is still low since most sequences will struggle to advance to a better state as it can develop a negative mutation as easily as a positive mutation.

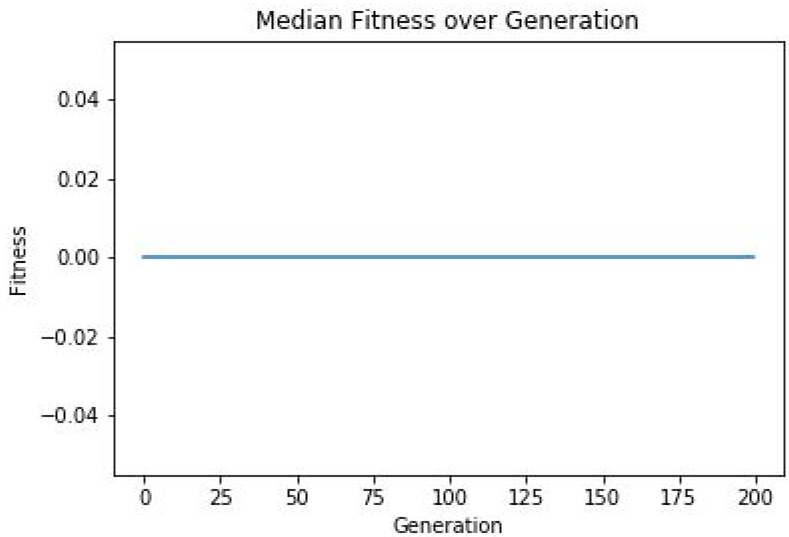
Higher Selection Rate (30%)



In this graph it can be seen that if there is a very high selection rate, the result is that the mean fitness does not fluctuate as much and does not improve as much since the pool of sequences that are being changed are becoming increasingly inbreed. The resulting effect is a higher mean fitness score than compared to the normal weights for the genetic algorithm and the extreme mutation rate, but a lesser tendency to improve or become worse.

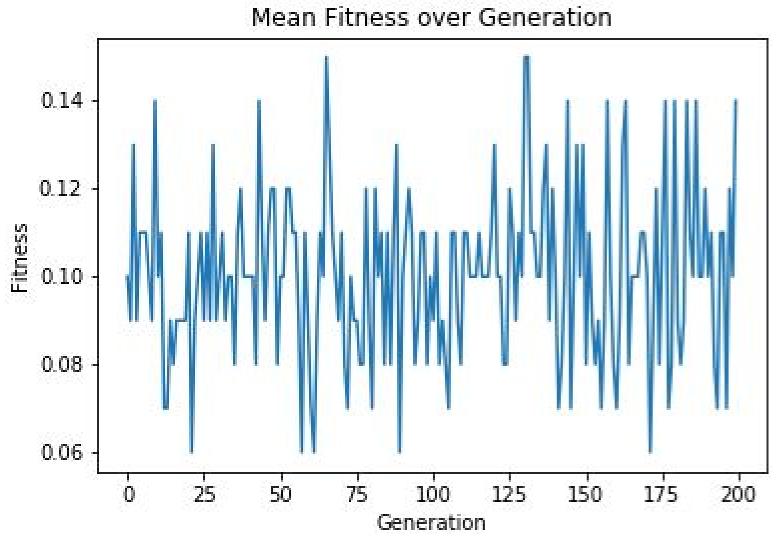


In this graph it can be seen that max is still the same in comparison to the normal genetic algorithm weights based on the pdf. Since it is very unlikely to vary as much.

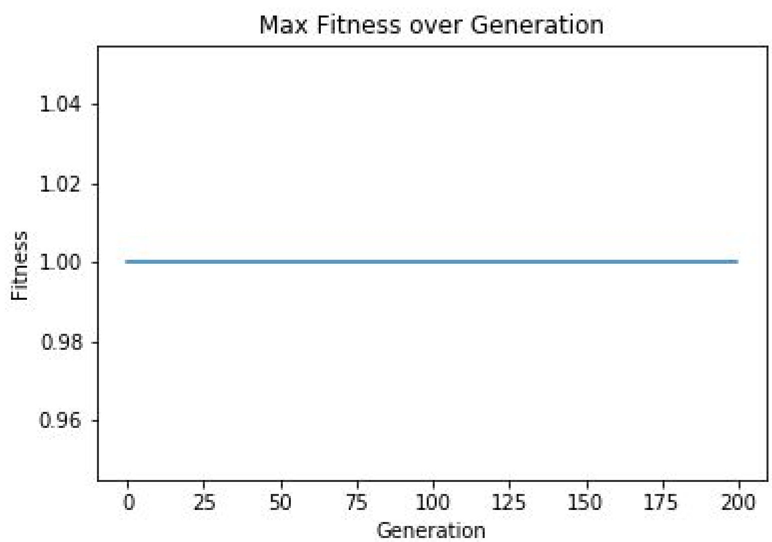


In this graph it can be seen that the median is still the same in comparison to the normal genetic algorithm and the extreme mutation rate since overall there is no change in the population's fitness since it has a low tendency to improve and may enter plateaued status much sooner due to inbreeding.

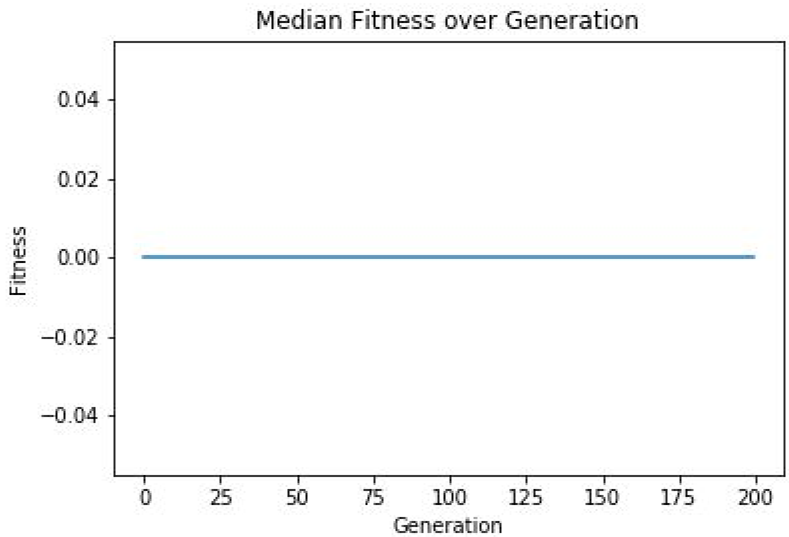
High Cross Over Cut Off (80%)



In this graph it can be seen that an extreme cross over cut off percentage would lead to behavior similar to that of the high mutation rate since effectively only the very ends of the sequence are being changed, so there is a lot of variability in the mean. However it is still more steady in comparison to the high mutation rate graph since the change is not as drastic in the sequence.



In this graph it can be seen that the max fitness is still unchanged similarly to the normal genetic algorithm and high selection rate since the change it experiences is still fairly steady and not as drastic as a high mutation rate.



In this graph it can be seen that the median fitness is also still unchanged similarly to all the other graphs since a high cross over cut off does not lead to a lot of better scores unless the randomly generated population's ends were generally better for that generation in comparison to other weighting methods.

Overall it can be noticed that for meaningful changes to be seen in the fitness score, an increase in the sequence length and generation stopping criteria would lead to a steadily increasing fitness score with the exception of the high mutation rate weight since that one is almost completely based on randomness. However, it can be noticed that by giving different weights to the different aspects of the genetic algorithm, certain aspects can be improved for steadiness or variability. In the end it is very unlikely that the genetic algorithm will reach the best possible score for each sequence since after enough generations it will begin to plateau at a score that is higher relative to where it started due to variability being decreased as the score improves positively.