

INVESTIGATION INTO PENALTY FUNCTIONS AND SELF ADAPTIVE VARIABLES

Compared to evolutionary algorithms not implementing these features.

Grant Broadwater – grbcp5@mst.edu

Computer Science 5401 FS2017 | Assignment 1c

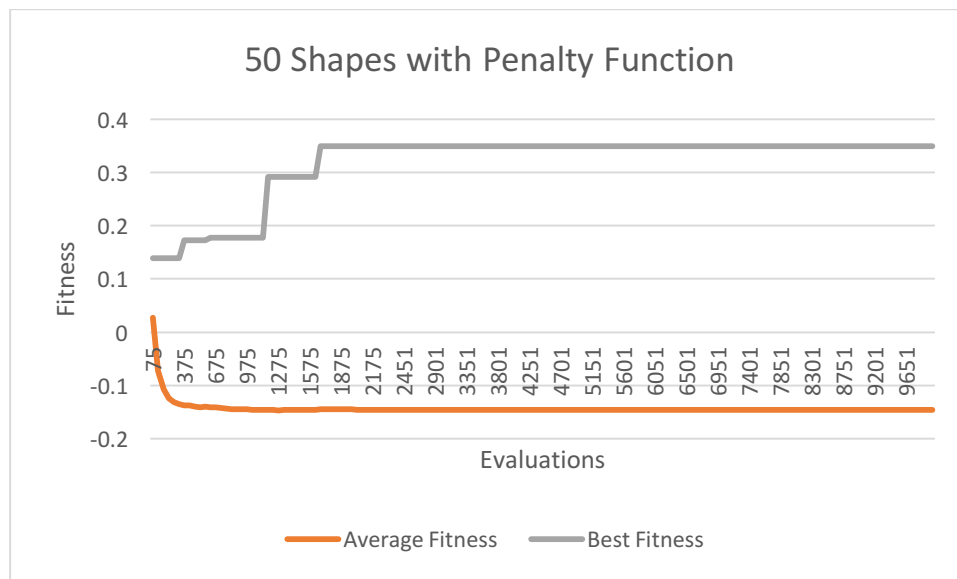
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Investigation of the Use of a Penalty Function

The primary objective of the investigation into penalty functions is to determine if there is a significant impact on the quality of solutions output by the evolutionary algorithm as compared to an evolutionary algorithm that does not implement a penalty function. The investigation should consider that different problem sets may lend themselves more or less to a penalty function than other problem sets, as well as the configuration of EA parameters such as the penalty coefficient.

50 Shapes Problem Instance



F-Test Two-Sample for Variances

	No Penalty Function	Penalty Function
Mean	0.379555423	0.280047847
Variance	0.026427848	0.004227752
Observations	30	30
df	29	29
F	6.251041107	
P(F<=f) one- tail	2.05947E-06	
F Critical one- tail	1.860811435	

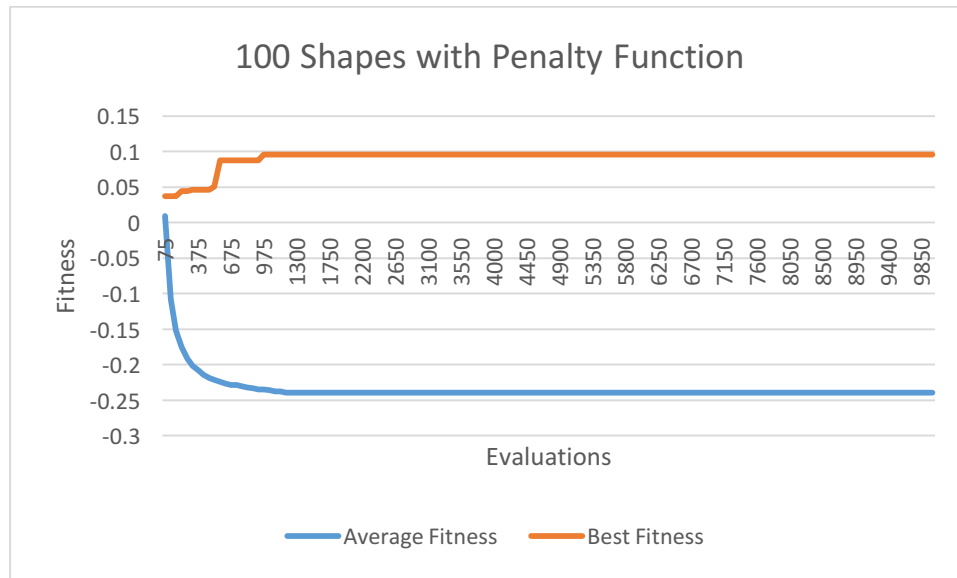
From the F-Test two sample for variance listed above, we can see that the F value (6.45) is greater than the F-Critical value (1.86) and variable 1's mean is greater than variable 2's mean. Based on these observations, we have to continue the investigation assuming unequal variances.

t-Test: Two-Sample Assuming Unequal Variances

	<i>No Penalty Function</i>	<i>Penalty Function</i>
Mean	0.379555423	0.280047847
Variance	0.026427848	0.004227752
Observations	30	30
Hypothesized Mean Difference	0	
df	38	
t Stat	3.1128763	
P(T<=t) one-tail	0.001755852	
t Critical one-tail	1.68595446	
P(T<=t) two-tail	0.003511705	
t Critical two-tail	2.024394164	

As seen in the t-test for unequal variances shown above, the t stat value is greater than the t critical two-tail value. Given this information, we should reject the null hypothesis that mean difference is zero and conclude that the variable with the better mean is a statistically better algorithm on the 50 shapes problem instance. Because the algorithm not using a penalty function has the higher mean, we can conclude that for this problem instance the algorithm without a penalty function is statistically better.

100 Shapes Problem Instance



F-Test Two-Sample for Variances

	<i>No Penalty</i>	<i>Penalty</i>
Mean	0.311331862	0.046706709
Variance	0.040077386	0.00037902
Observations	30	30
df	29	29
F	105.7396387	
P(F<=f) one-tail	1.35993E-22	
F Critical one-tail	1.860811435	

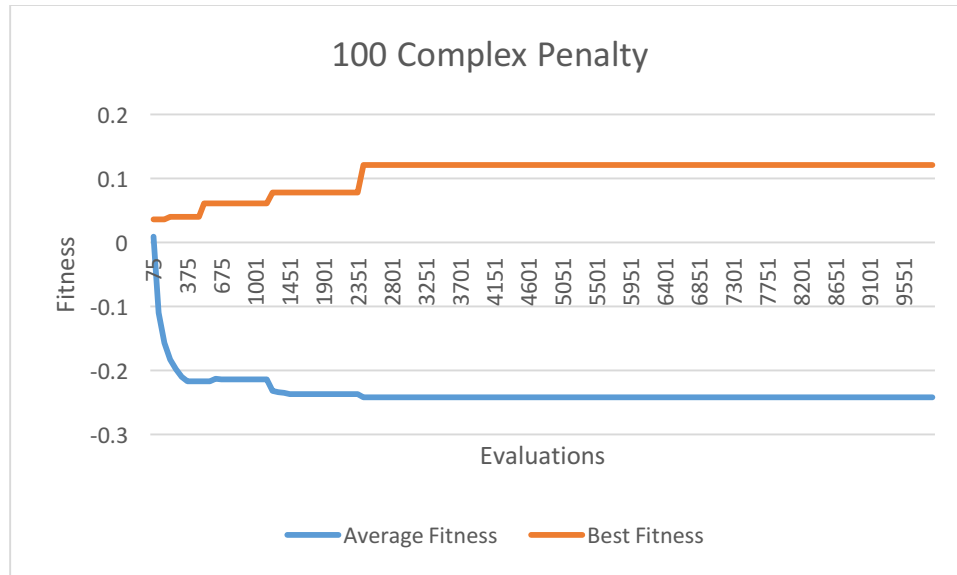
As can be seen from the F-Test above, F Critical is less than the F value, and variable 1 has a higher mean than variable 2. Due to this data, we must continue the investigation assuming that the two variables have unequal variances.

t-Test: Two-Sample Assuming Unequal Variances

	<i>No Penalty</i>	<i>Penalty</i>
Mean	0.311331862	0.046706709
Variance	0.040077386	0.00037902
Observations	30	30
Hypothesized Mean Difference	0	
df	30	
t Stat	7.206063831	
P(T<=t) one-tail	2.54447E-08	
t Critical one-tail	1.697260887	
P(T<=t) two-tail	5.08894E-08	
t Critical two-tail	2.042272456	

In the results for the t-test above, the magnitude of the T Stat is higher than the magnitude of the T Critical two tail value. Because of this we reject the null hypothesis that the mean difference is zero, and we are to conclude that the variable with the better mean is the statistically better algorithm. Since the algorithm not using the penalty function has a better mean, then we are to conclude that the algorithm not using a penalty function is the better algorithm.

100 Shapes Complex Problem Instance



As can be seen from the F-Test above, F Critical is less than the F value, and variable 1 has a higher mean than variable 2. Due to this data, we must continue the investigation assuming that the two variables have unequal variances.

t-Test: Two-Sample Assuming Unequal Variances

	No Penalty	Penalty
Mean	0.351011236	0.055187266
Variance	0.035070859	0.000567555
Observations	30	30
Hypothesized Mean Difference	0	
df	30	
t Stat	8.58291487	
P(T<=t) one-tail	7.07604E-10	
t Critical one-tail	1.697260887	
P(T<=t) two-tail	1.41521E-09	
t Critical two-tail	2.042272456	

In the results for the t-test above, the magnitude of the T Stat is higher than the magnitude of the T Critical two tail value. Because of this we reject the null hypothesis that the mean difference is zero, and we are to conclude that the variable with the better mean is the statistically better algorithm. Since the algorithm not using the penalty function has a better mean, then we are to conclude that the algorithm not using a penalty function is the better algorithm.

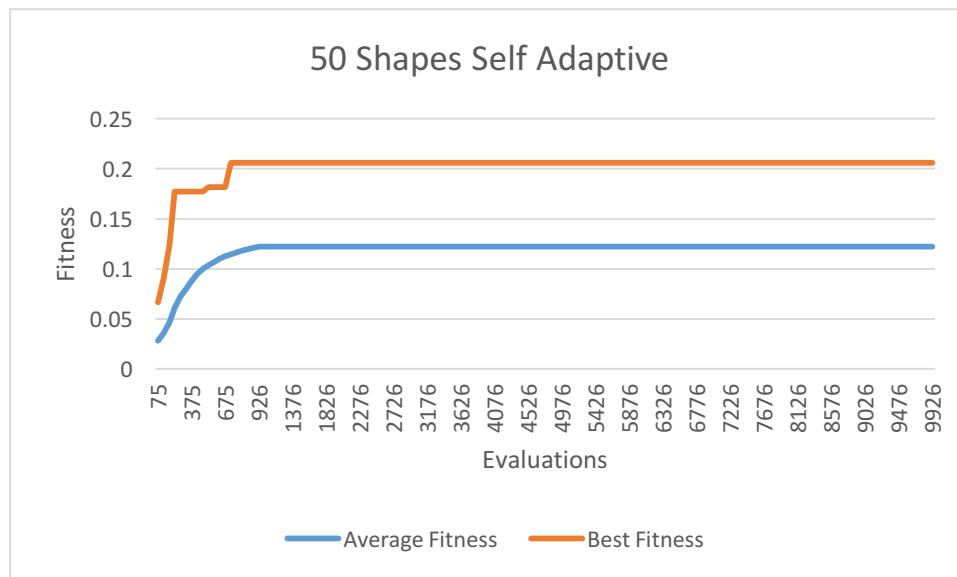
Penalty Function Investigation Conclusion

After analyzing the effects of introducing a penalty function to the evolutionary algorithm for each problem instance. It is safe to say that the penalty function hurt the performance of the algorithm. However, this being said it appears to have done better for the 50 Shapes problem instance rather than any of the other two. This does make conceptual sense, as with fewer and more simple shapes, there is a lower chance of overlap.

Investigation of Self-Adaptive Mutation Rate

For assignment 1c when investigating the effects of a self-adaptive variable I selected to self-adapt the mutation rate. To implement this, at the beginning of each generation, the algorithm gets the mean of the entire population's mutation rate gene. It then uses that mean as the mutation rate for that generation. The parents then give the child the average of their mutation rate, however there is a chance of that gene too getting mutated. The initial mutation rate for the population is normally distributed with a mean of the given mutation rate parameter and a standard deviation of 0.10.

50 Shapes Problem Instance



F-Test Two-Sample for Variances

	<i>No Self Adaptation</i>	<i>Self Adaptive</i>
Mean	0.379555423	0.15645933
Variance	0.026427848	0.000881232
Observations	30	30
df	29	29
F	29.9896539	
P(F<=f) one-tail	6.21776E-15	
F Critical one-tail	1.860811435	

As can be seen from the F-Test above, F Critical is less than the F value, and variable 1 has a higher mean than variable 2. Due to this data, we must continue the investigation assuming that the two variables have unequal variances.

t-Test: Two-Sample Assuming Unequal Variances

	<i>No Self Adaptation</i>	<i>Self Adaptive</i>
Mean	0.379555423	0.15645933
Variance	0.026427848	0.000881232
Observations	30	30
Hypothesized Mean Difference	0	
df	31	
t Stat	7.394333781	
P(T<=t) one-tail	1.2556E-08	
t Critical one-tail	1.695518783	
P(T<=t) two-tail	2.5112E-08	
t Critical two-tail	2.039513446	

In the results for the t-test above, the magnitude of the T Stat is higher than the magnitude of the T Critical two tail value. Because of this we reject the null hypothesis that the mean difference is zero, and we are to conclude that the variable with the better mean is the statistically better algorithm. Since the algorithm not using the self-adaptive mutation rate has a better mean, then we are to conclude that the algorithm not using a self-adaptive mutation rate is the better algorithm.