COMP 6660 Fall 2022
Assignment 1b

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Background

This assignment series focuses on generating structurally sound bridges to support a roadbed. In this assignment, the goal was to find the strongest bridge using an evolutionary algorithm (EA) approach. A program was given to simulate the bridges. A fitness function was also given which tests the strength of the bridge and returns the weight at which it broke, the fitness in this case. The evolutionary algorithm creates population of bridges a list of x and y coordinate pairs to be tested. The number of pairs and the bounds of both x and y are user defined. It creates a user defined amount of these bridges, the population, and tests them. After testing the initial population's data, it creates children from two parent bridges and tests them as well. Finally, the population is culled and the best fitness is recorded, along with the run's data.

Experimentation

A default configuration was given in green1b.txt as a starting point to experimentation. Beginning with different combinations of parent selection and survival selection, it became clear that some selection processes took less time and gave better results. It was important to keep in mind the amount of time for each run as it would affect how much experimentation could be done with other elements. There needed to be enough selective pressure to properly create better results, but not so much it got stuck in a local optimum. The survival selection should also not kill the best bridge in the population. The survival selection that gave the best results was truncation. A lot of selective pressure is put on the EA as it culls the weakest individuals. The parent selection that gave the best results based on the experiments run was fitness proportionate selection. This also puts in selective pressure but has a stochastic nature to it. The pressure in this configuration is high, so the maximum fitness found could be stuck at a local optimum.

The next configuration to note is the number of children and the number in a population. Based on the experiments run, the lower the initial population, the better results by the 5000th evaluation. To compliment this, creating more children also produced better results. The best results found had a population of 50 and created 10 children per generation. The mutation rate was not changed from the default due to time constraints. A higher mutation rate might have helped combat the high selective pressure being put on the EA.

Results

Configurations

Configurations for the first experiment of the evolutionary algorithm (green) is saved in the configs file as green1b.txt. Some important parameters changed from the default given. Notably, the parent selection was set to fitness proportionate selection, the survival selection was set to truncation, the number of children was set to 10, and the population size was set to 50.

Best Fitness

The best fitness found within all 30 runs for the configurations under green1b_configs.txt was 72000000 and this individual's corresponding bridge is plotted in Figure 1.

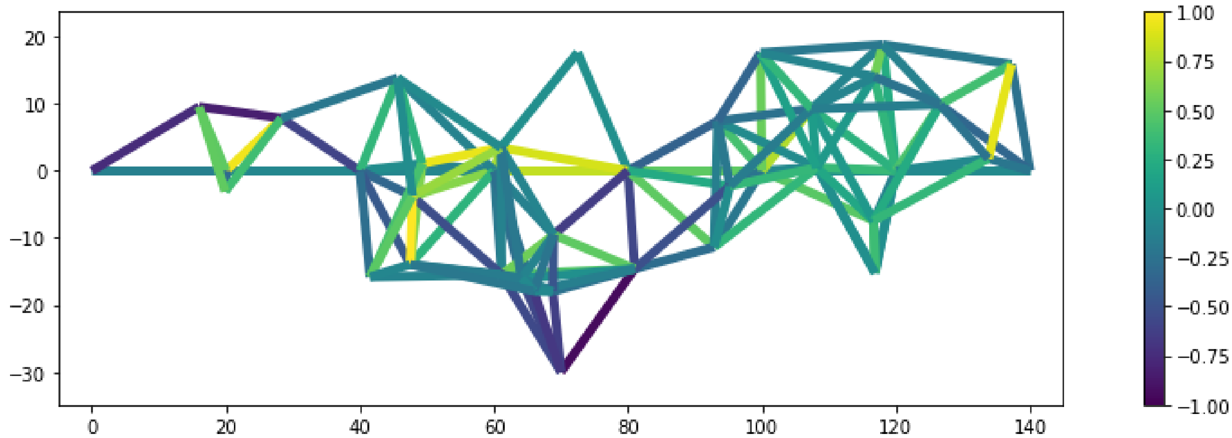

Figure 1: Best Bridge found from Experiment 1 (green)

The data from this experiment was saved under run_data.csv in the data folder, which is organized as one run's data per line. This data included the number of evaluations, highest fitness, and average fitness for each generation as well as the best fitness of the run and its corresponding bridge. The best and average fitness for each generation was averaged over the thirty runs and plotted to their corresponding evaluations in Figure 2.

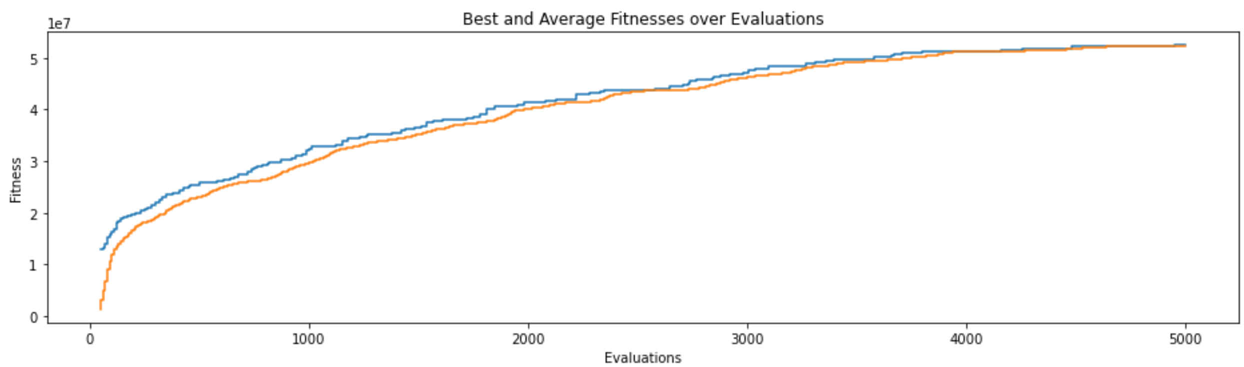

Figure 2: Best and Average Fitness from Experiment 1 (green)

Stochastic Universal Sampling

A second experiment was run with the same configurations as above, but the survival selection changed to stochastic universal sampling. Unfortunately, the experiment did not give results in time. The selection is implemented, but no results were generated for this report.

Statistical analysis

A set of data was given to compare to Experiment 1, uniformRandomResults.txt. This is set in the following tables as Variable 1. The results of the best fitness from each run found from Experiment 1 is saved under best_of_runs.csv and is labeled as Variable 2 in the following tables. The first test run on this data was an F-Test for equality of variances. The α was set to 0.025. Since F > 1 and F < F Critical one-tail, there was no significant difference in the two variances.

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	33950000	52483333
Variance	2.8506E+13	1.19E+14
Observations	30	30
df	29	29
F	0.23904489	
P(F<=f) one-tail	0.000118908	
F Critical one-tail	0.475964774	

Table 1: F-Test for Experiment 1

Based on the F-test, the proper t-Test is two-sample assuming equal variances. For this test, the α was set to 0.05. Since the t Stat < 0 and t Stat < - t Critical two-tail, the two experiments produced significantly different mean fitness. Based on the results, Experiment 1 (Variable 2) has a significantly higher mean fitness.

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	33950000	52483333
Variance	2.8506E+13	1.19E+14
Observations	30	30

Pooled Variance	7.38779E+13
Hypothesized Mean Difference	0
df	58
t Stat	-8.3510671
P(T<=t) one-tail	7.92164E-12
t Critical one-tail	1.671552762
P(T<=t) two-tail	1.58433E-11
t Critical two-tail	2.001717484

Table 2: t-Test assuming equal variances for Experiment 1