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Winter 2020CS 441/541 Artificial Intelligence
Programming Assignment #2

Write-UP

Install

```
virtualenv -p python3 env
source env/bin/activate
python -m pip install matplotlib
```

To Run Code

```
python3 app.py <PopulationSize> <NumIterations> <MutationPct>
```

example:

```
python3 app.py 100 1000 10
```

Or to use default values of: PopulationSize =100, NumIterations=1000, and MutationPct = 10. Simply enter:

```
python3 app.py
```

Determining Fitness

Fitness is calculated by counting up number of pairs of mutually non-attacking queens and subtracting it from 28. A configuration with no pairs of attacking queens will have the highest score of 28.

String Configuration

Each individual in the population has a eight character long string to represent its board configuration. Each character is a number 0-7 to represent which row a queen is placed in for that column.

Mutations

`mutationPct` is the percent probability that a mutation will occur at random location in the string configuration of each child. A random number is produced between 0 and 100 for each child. If that number is lower than the `mutationPct` then a mutation occurs and replaces a random character in the configuration string with a random number from 0 to 7.

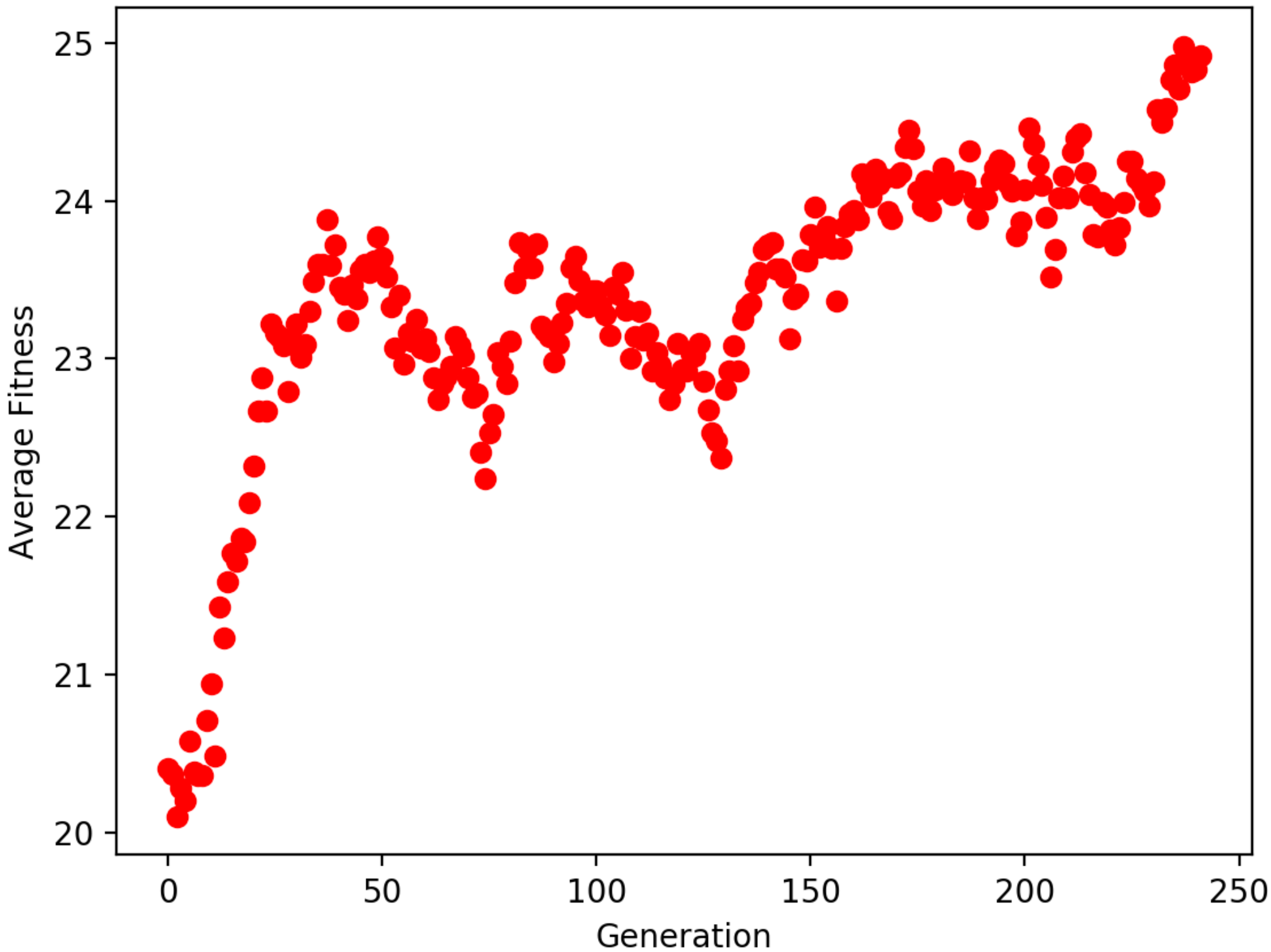
Determining Breeding Pairs

Each generation, k new configurations are produced where k is equal to `PopulationSize`. To produce each new configuration two parent configurations are selected from the list of configurations from the previous generation. Parents are chosen from the previous generation with a probability that is proportional to their fitness score. This is implemented in the `get_reproducer` function. The list of board configurations is sorted according to fitness score. In the `get_reproducer` function, a random fitness score is produced between 0 and the sum of the population's fitness score. A local fitness variable is initialized to zero, and the first individual in the list with the lowest fitness score is initially assigned to reproduce. The function then loops through the sorted list. During each iteration, the fitness score of the next individual is added to the local fitness variable and the next next individual is assigned to reproduce. When the local fitness score variable is equal to or greater than the random fitness score, the loop terminates leaving to individual from the last iteration being assigned to breed. In this way, an individual's likely hood of breeding is proportional to their fitness score. At the end of each iteration in the GA, the curren population is replaced by the next generation of children.

The Effect of Mutations on Completeness

When the GA algorithm was complete I initially ran it a number of times before implementing the effect of mutations because the textbook had mentioned that it had been shown that mutations are not necessary to achieve solutions if the initial population was sufficiently large and diverse due to random starting configurations. I experimented with various population sizes. Significantly increasing the population size resulted in much longer run times because this increased the number of iterations of the inner loop where k number of children were produce where k is equal to to `PopulationSize`. However, the program was never able to find the optimal solution even with very large `NumIterations`. Once I implemented the mutations with probability equal to `MutationPct`, the GA was able to find the optimal solution relatively quickly every time the GA was run. The `MutationPct` was initially set to ten. The thinking was that in biological populations, mutations are rare and usually deleterious. Although mutations are necessary to introduce new genetic variations, the mutation probability should not be too high because most mutations are not beneficial. Using a `MutationPct` of 10 with `PopulationSize` of 100 was sufficient to find the optimal solution within several hundred generations (iterations). Once the solution is found, the GA halts and returns the solution, as it is not necessary for all individuals in population to reach the optimal solution.

Plot of Average Fitness over Generations



The above figure shows the change in average fitness over generations. Average Fitness was calculated by dividing the sum of the each individual configurations fitness score by `PopulationSize`. Each generation represents one iteration of the outermost loop in the GA.

Random Individuals Sampled From Each Generation

Generation:0, Score:22, Configuration:60362746
Generation:10, Score:22, Configuration:75157446
Generation:20, Score:20, Configuration:00611416
Generation:30, Score:25, Configuration:50667147
Generation:40, Score:24, Configuration:50663140
Generation:50, Score:24, Configuration:50614642
Generation:60, Score:26, Configuration:70257144
Generation:70, Score:21, Configuration:52664612
Generation:80, Score:19, Configuration:54355141
Generation:90, Score:19, Configuration:73236224
Generation:100, Score:24, Configuration:52657314
Generation:110, Score:22, Configuration:52653664
Generation:120, Score:24, Configuration:53657414
Generation:130, Score:20, Configuration:22654144
Generation:140, Score:26, Configuration:02657114
Generation:150, Score:25, Configuration:53647404
Generation:160, Score:27, Configuration:52637414
Generation:170, Score:26, Configuration:53637414

Generation:180, Score:23, Configuration:53337461
Generation:190, Score:23, Configuration:13627416

Solution

Configuration:13627504, Score:28
0 0 0 0 0 0 X 0

X 0 0 0 0 0 0 0

0 0 0 X 0 0 0 0

0 X 0 0 0 0 0 0

0 0 0 0 0 0 0 X

0 0 0 0 0 X 0 0

0 0 X 0 0 0 0 0

0 0 0 0 X 0 0 0