CS 7641 Machine Learning
Assignment 2

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Due Sunday March 11th, 2018 11:59pm

Part 1: Neural Network Optimization

Introduction

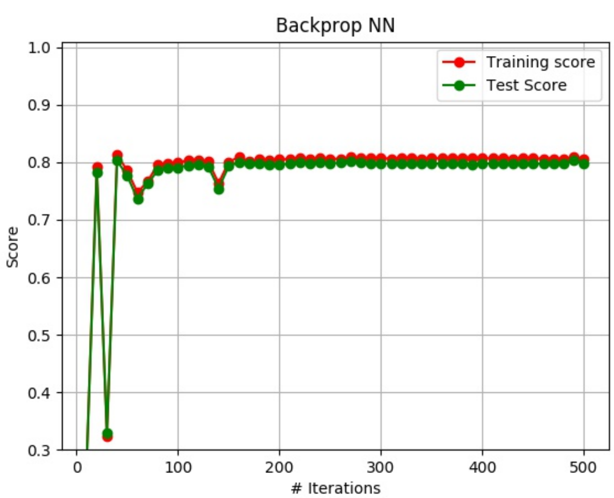
Part 1 of the assignment surrounds using randomized optimization to find the best possible weights for a specific neural network. In assignment 1, backpropogation was used to find optimal parameters for a neural network. This neural network took in various input features for US permanent visa applicants and then attempted to predict the outcome of an application. After various tests, I found the optimal parameters of: 6-node input layer, one hidden layer with 100 nodes, one output node, and about 500 iterations.

I chose this problem because, as someone who has worked with a large number of first-generation visa holders and immigrants, I am extremely interested in building tools to help others to achieve the same. At the end of the day, the goal is it to try to determine the application result before time, money, and other resources are spent.

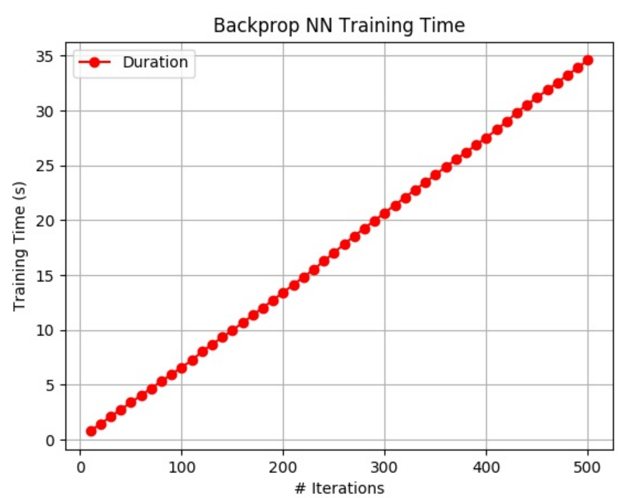
1) Backpropogation (Assignment 1)

Overview

The first weight-finding algorithm used was backpropogation. Backpropogation works by essentially calculating the error at the end of a network, and then working backwards to minimize that error over various iterations. An error (or loss) function is effectively minimized over time using this backpropogation technique. As discussed in assignment 1, the permanent visa is rather large and robust. It is quickly learnable by various different learners and in such backpropogation found significant success.



Backprop NN Success Rate vs. Iterations



Backprop NN Training Time

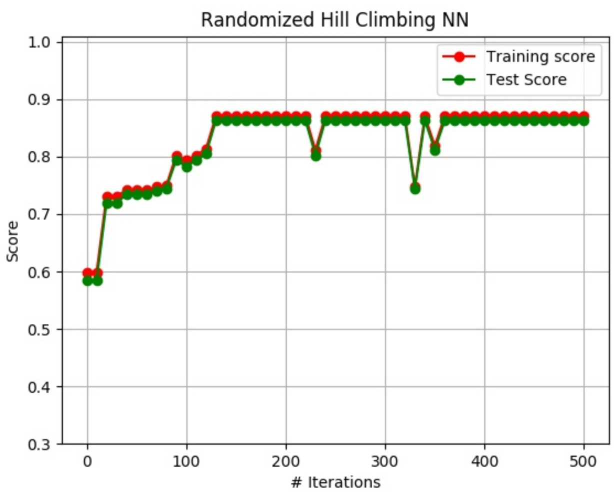
Right around 50 iterations, the network begins to converge at around an 80% successs rate. Seeing as the training and test score track either rather closely, it is apparent that the dataset is rather robust and consistent. One thing to note is that the training time scales linearly with the number of iterations–which makes sense since the same amount of calculations with similar complexity are performed on each iteration of backpropogation.

2) Randomized Hill Climbiing

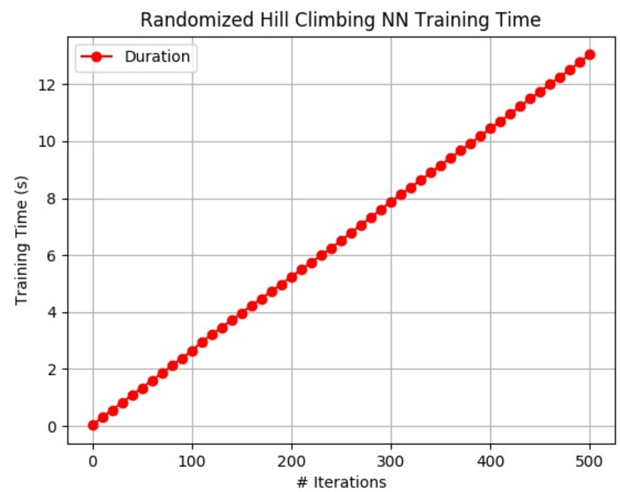
Overview

The second weight-finding algorithm used was randomized hill climbing. Randomized hill climbing works by taking a random starting point and then incrementally attempting to improve on that point. In the context of a neural network trying to find weights, randomized hill climbing selects random weights and then moves in a direction so as to try to find a better result for that weight–akin to trying to move up an optimization 'success hill'.

One thing to note is that we are using randomized hill climbing, not random restart hill climbing. In such, the algorithm is prone to getting caught in local optimizations, or local maximums.



Randomized Hill Climbing NN Success Rate vs. Iterations



Randomized Hill Climging NN Training Time

High accuracy results are achieved right around 125 iterations+. While this is subject to randomness, by looking at the results it is shown to become rather consistant. By looking at the score results, one can see various instances of the randomized hill climbing getting caught in local optimas and being unable to escape. Such is the case around 220, 320, and 350 iterations.

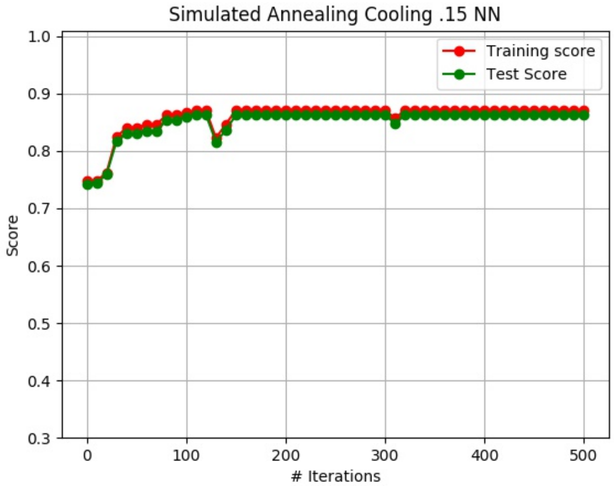
Similar to backpropogation, training time scales linearly with the number of iterations run. Training time tends to be a bit faster using randomized hill climbing because of a reducation in calculations necessary. Whereas backpropogation needed to do calcluations to minimize error moving backwards through the network, randomized hill climbing simply needs to move in one direction and determine if the new weights are better.

3) Simulated Annealing

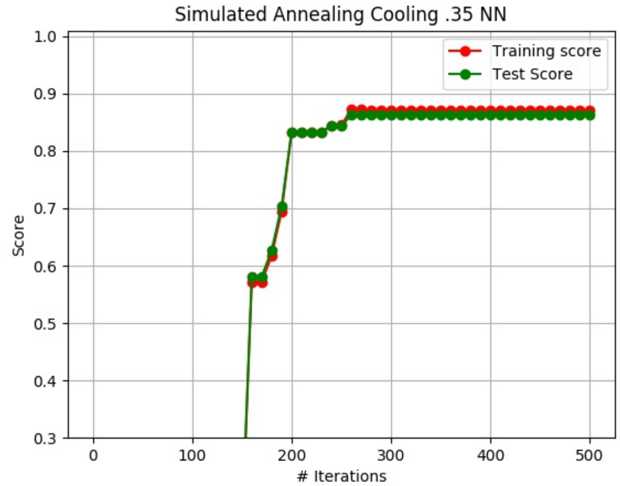
Overview

The third weight-finding algorithm used was simulated annealing. Simulated annealing works by taking a random solution and then samples nearby alternatives. By comparing the alternatives to the original solution, the optimizer decides to either stick with the original solution or move to the new one. Using a temperature and cooling parameter, the algorithm is more open to worse solutions at first but gradually moves towards only accepting better solutions.

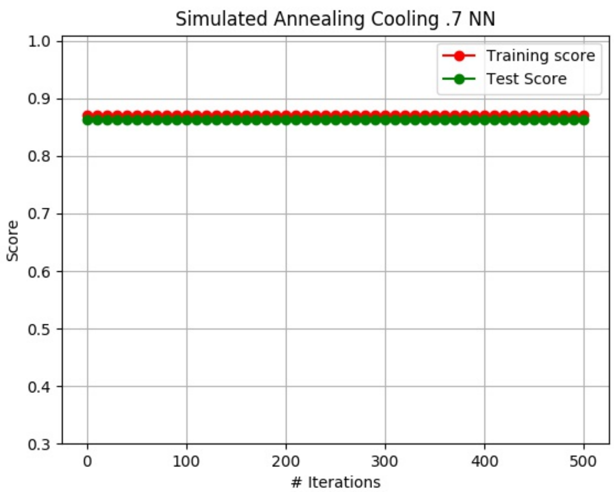
Various coolng parameters were used to try to determine the best simulate annealing approach. Below, success rates by number of iterations are showed for simulated annealing approaches with cooling parameters of .15, .35, and .7. The parameter of .15 and .35 take significantly longer to converge to the optimal solution than did a higher parameter. While part of this can be attribute to luck (the algorithm could have randomly found itself in an optimal solution earlier on)–part of this too is the way the algorithm operates by its parameters. The .7 cooling temperature here proved most effective.



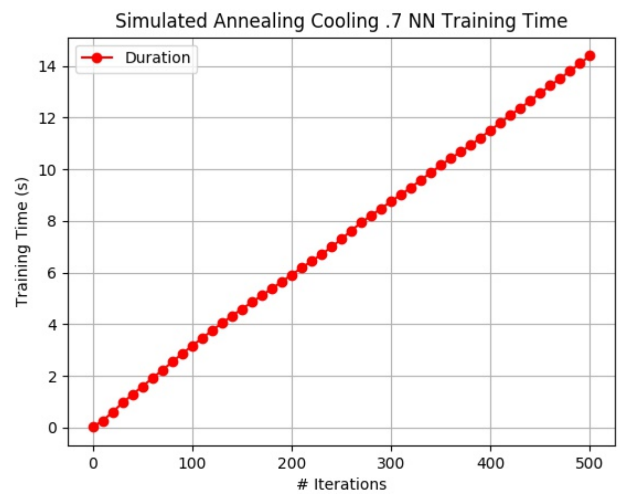
Simulated Annealing NN Success Rate vs. Iterations w/ .15 Cooling



Simulated Annealing NN Success Rate vs. Iterations w/ .35 Cooling



Simulated Annealing NN Success Rate vs. Iterations w/ .7 Cooling



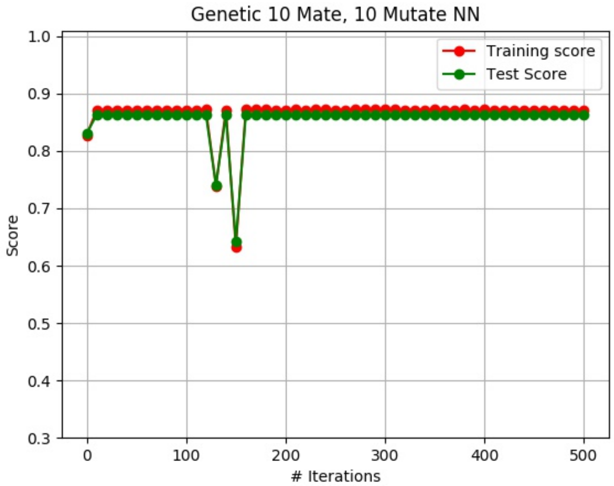
Simulated Annealing NN Training Time w/ .7 Cooling

4) Genetic Algorithms

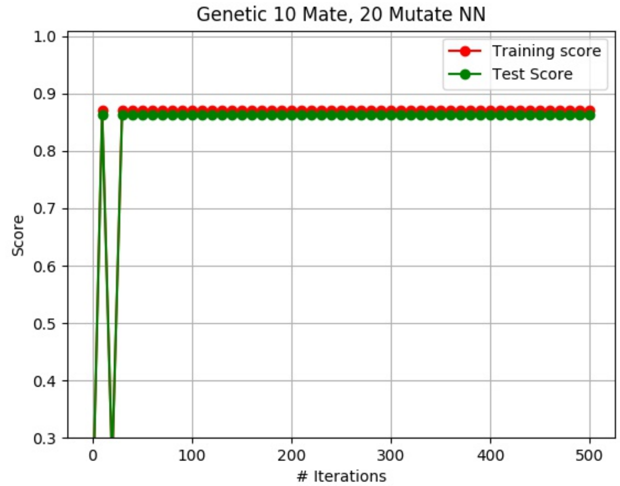
Overview

The fourth weight-finding algorithm used was a genetic algorithm. Genetic algorithms works by starting with an initial solution and then making modifications in an attempt to improve the solution. The modifications generally allowed are mutation (changing random parts of the solution), crossover (taking specific sections from various solutions and combining them), and selection (selecting certain sections from a solution to use again). In the context of a neural network, we can use genetic algorithms to make modifications to our network's weights.

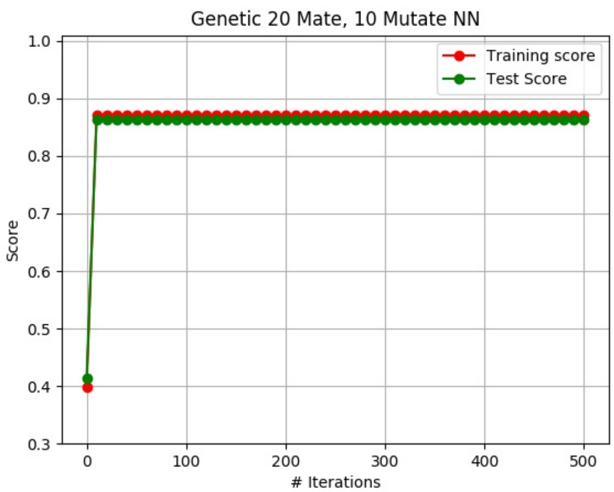
In our testing, a population size of 50 was used in order to get a diverse initial sampling of possible solutions. The number of instances to mate (aka crossover) and to mutate was varied throughout the trials.



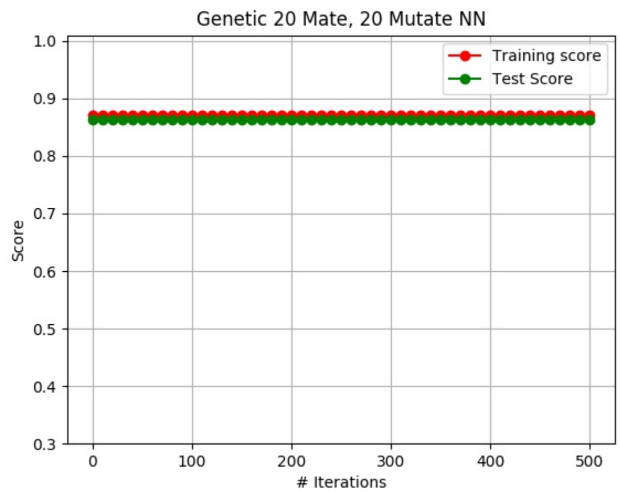
Genetic Algorithm Success Rate v. Iterations w/ 10 Mate, 10 Mutate, 50 population



Genetic Algorithm Success Rate v. Iterations w/ 10 Mate, 20 Mutate, 50 population



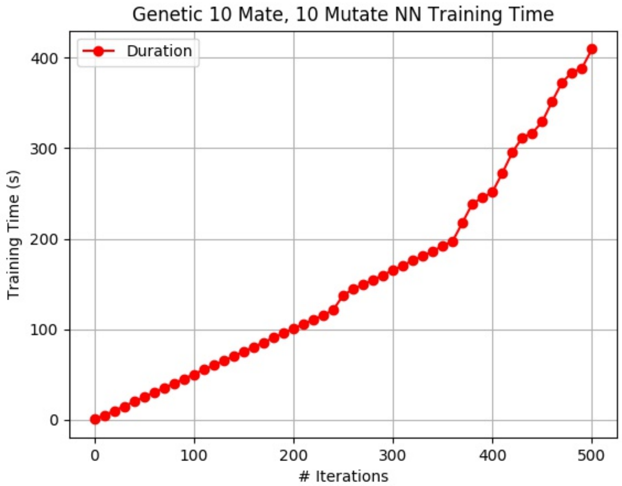
Genetic Algorithm Success Rate v. Iterations w/ 20 Mate, 10 Mutate, 50 population



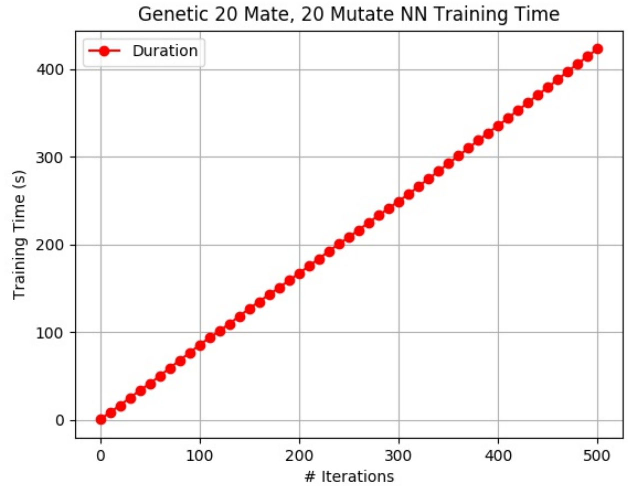
Genetic Algorithm Success Rate v. Iterations w/ 20 Mate, 20 Mutate, 50 population

Trials were run with the following mate/mutate combinations: 10/10, 10/20, /20/10, and 20/20. All trials were run with a population size of 50. As can be observed from the graphs, both mating and mutating appeared to be highly effective in finding the optimal solution. In fact, the optimal solution converged quite quickly–in under 30 iterations for each trial. This is partly due to the fact that the data is easily learnable and does not appear to maintain very many trapping local maximums.

Training times scaled roughly linearly with the number of iterations ran. This makese sense because, from a performance perspective, the number of mutation calculations from iteration to iteration is more or less the same.



Genetic Algorithm Training Time w/ 10 Mate, 10 Mutate, 50 population



Genetic Algorithm Training Time w/ 20 Mate, 20 Mutate, 50 population

Conclusion

The optimization algorithms used all inevitably produced similar results. What differed, however, was the amount of training time required, the tuning of parameters, and how many iterations were required to achieve a consisent, optimal solution. All-in-all, the genetic algorithm approach consistantly produced the best results for our network. This makes sense, as the data was rather homogenous and there appeared to be very few outliers. By learning the training data well, the learner was able to perform similarly well on the (nearly identical) test data.

Part 2: Optimization Problem Domains

Introduction

For this part of the assignment, three different optimization problems are examined: continous peaks, the traveling salesman, and flip flop. The three optimization techniques from above are used (randomized hill climbing, simulated annealing, and genetic algorithms) as well as another algorithm, MIMIC.

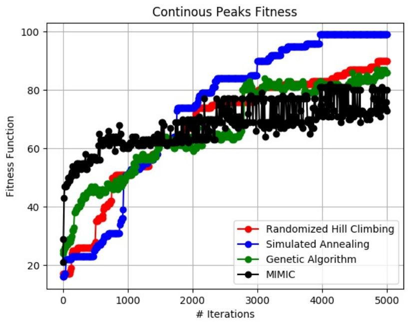
MIMIC, similar to the other algorithms, works to find the globally optimal solution. Unlike the other algorithms, however, it retains knowledge of previous iterations and uses this information to more efficiently find better solutions. MIMIC is particularly strong in regards to problems that maintain patterns between subsets of thier parameters.

Below, we apply each of the optimization algorithms to each of the three optimization problems. We then look at how each optimization problem's characteristics may favor one algorithm to another, as well as evaluate the efficiency of each.

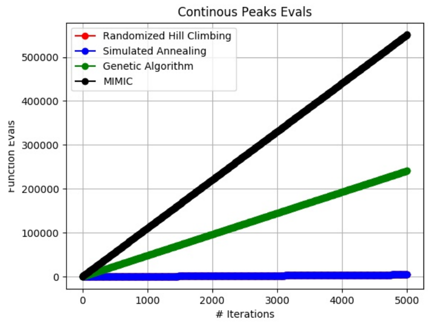
1) Continous Peaks

Overview

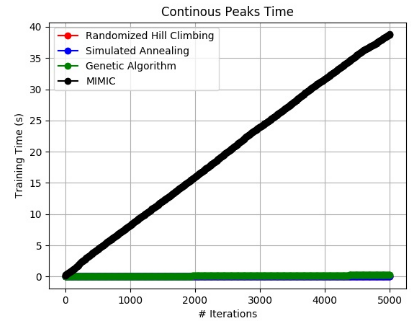
The continous peaks problem is an extension of the four peaks problem that allows for a wide variety of local maximums. This algorithm is particularly interesting due to the potentially large number of local maximums. It is especially difficult for an algorithm that cannot escape local peaks to perform well.



Fitness vs Iterations of 4 Optimization Strategies



Function Evals vs Iterations of 4 Optimization Strategies



Training Time vs Iterations of 4 Optimization Strategies

In order to ensure accuracy and a fair distribution, 5 different trials were used of 5000 iterations each. Each optimization strategy was also allowed to evaluate over a parameter range in an attempt to find the optimal parameters for that strategy.

For randomized hill climbing, there were no other parameters to tune. The algoritm was simply run for various iterations (multiples of 10) in a set of 5 trials. In terms of fitness function performance, it actually performed quite well and required no significant function evaluations. It was similarly fast to train due to the extreme simplicity of the algorithm itself.

Simulated annealing was slightly more complex, where cooling efficients of 0.15, 0.35, 0.55, 0.75, and 0.95 were used. It was found that the efficient 0.15 was the most effective here. This low cooling rate was effective because it helped to slowly overcome any local maximums but not work too aggressively to skip any optimal solution. By iteration 3k, Simulated Annealing took a clear lead over the other solutions in terms of fitness performance. Similar to randomized hill climbing, its number of function evals and training time was extremely low.

The genetic algorithm employed used a population size of 100 and various configurations of 50, 30, and 10 mutations/mate combinations. The graph above depicts the succes rates when using 30 mutation and 30 matings. As can be seen, it's performance was rather simular to randomized hill climbing–which roughly makes sense due to the random nature of both algorithms. The number of function evaluations was higher for the genetic algorithm due to the amount of attempts at mutating and mating–whereas the training time was practically irrelevant.

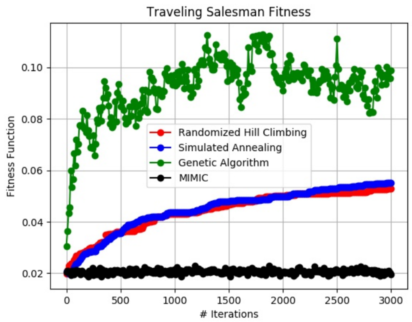
Mimic's parameters were set to 100 samples and a 'to-keep' number of 50. The threshold for the discrete dependency tree mimic used was sampled from the range 0.1, 0.3, 0.5, 0.7, and 0.9. While MIMIC started off relatively string in terms of fitness performance, it thrashed around the 60-80 range for the most part. I had suspected that MIMIC would have difficulty on the continous peaks due to the large amount of randomness in the data. The number of functional evaluations required for MIMIC was significnatly higher than the other algorithms, as was its training time. This was primarily due to the fact that MIMIC is signifciantly more complex to operate than the other algorithms.

Overall, Simulated Annealing proved to be the best strategy for the continous peaks problem, largely due to it's ability to handle large amounts of randomness well and to avoid getting caught in such local maximums. It's low training time and number of function evaluations further aided its case.

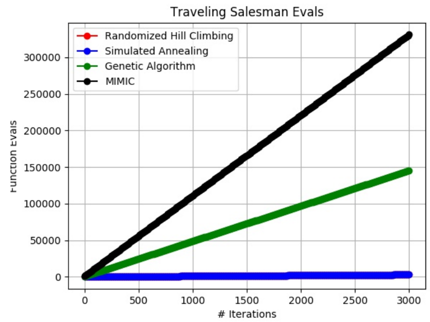
2) Traveling Salesman

Overview

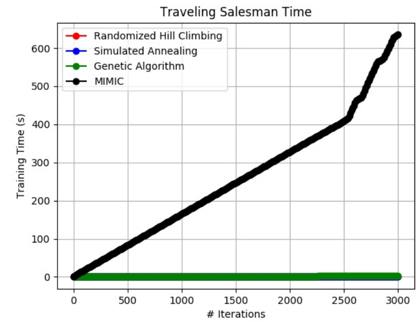
The traveling salesman problem is a frequently used, classic problem that focuses on a salesperson trying to minimize their round-trip distance between any number of cities. This problem is particularly interesting due to it's real-world implications, such as route planing for delivery trucks and everyday errands–it also has no known polynomial time solution!



Fitness vs Iterations of 4 Optimization Strategies



Function Evals vs Iterations of 4 Optimization Strategies



Training Time vs Iterations of 4 Optimization Strategies

For this optimization problem, in order to ensure accuracy and a fair distribution, 5 different trials were used of 3000 iterations each. 50 Random points were generated and used as the destinations for our faux salesman. Each optimization strategy was also allowed to evaluate over a parameter range in an attempt to find the optimal parameters for that strategy.

For randomized hill climbing, there were no other parameters to tune. The algoritm was simply run for various iterations in a set of 5 trials. In terms of fitness function performance, it performed mediocrely and required no significant function evaluations. It was similarly fast to train due to the extreme simplicity of the algorithm itself. The reason for the stragegy's mediocrity can easily be attributed to the fact that random guessing does not perform well when trying to develop the most optimal path due to the large number of possibilities and low number of optimums.

Similar to the last problem, simulated annealing was slightly more complex, where cooling efficients of 0.15, 0.35, 0.55, 0.75, and 0.95 were used. It was found that the efficient 0.55 was the most effective here. Interestingly enough, the simulated annealing approach very closely tracked the randomized hill climbing results. This was pretty cool, and clearly demonstrated the effect of the problem on the ability of a solution to perform well. As both were prone to picking random solutions and making marginal improvements on those solutions, they shared the same strenghts and weaknesses for trying to plan an optimal path. Similar to randomized hill climbing, simulated annealings' number of function evals and training time was extremely low.

The genetic algorithm employed used a population size of 100 and various configurations of 50, 30, and 10 mutations/mate combinations. The graph above depicts the succes rates when using 30 mutation and 30 matings. As can be seen, it's performance was exceeding better than the other algorithms. The mutations and matings were able to successfully identify the most optimal paths and plan extremelly well for the hypothetical salesman. This can be attributed to the fact that traveling salesman can be broken into various subjourneys that the genetic algorithm can learn and then attempt to combine for an optimal journey. The number of function evaluations was higher for the genetic algorithm due to the amount of attempts at mutating and mating–whereas the training time was practically irrelevant. The genetic algorithm was the clear winner in terms of performance for the TSP.

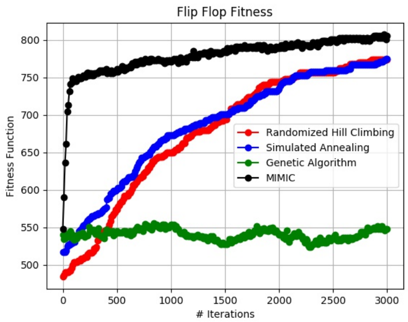
Mimic's parameters were set to 100 samples and a 'to-keep' number of 50. The threshold for the discrete dependency tree mimic used was sampled from the range 0.1, 0.3, 0.5, 0.7, and 0.9. MIMIC performed rather poorly on this problem. This was very likely due to the fact that pattern finding is of almost no use in this problem domain and that previous knowledge also is mostly unnecessary when trying to find optimal paths. The number of functional evaluations required for MIMIC was also significnatly higher than the other algorithms, as was its training time. This was primarily due to the fact that MIMIC is signifciantly more complex to operate than the other algorithms. Overall, MIMIC was a very poor candidate for the traveling salesman problem.

Overall, the genetic algorithm proved to be the best strategy for the traveling salesman problem. It's ability to combine sub-journeys and paths into an optimal route was strongly advantageous. The results showed the strong benefit of mutations on this problem. Similarly, it's speed an relative simplicity were also very beneficial.

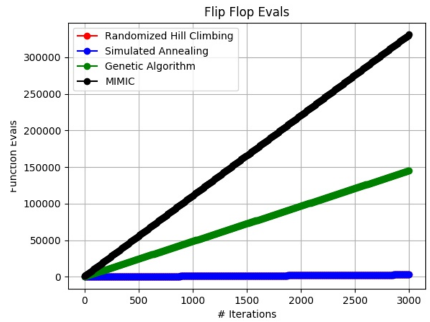
3) Flip flop

Overview

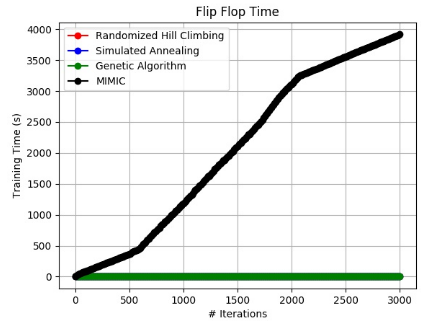
The flipflop problem is another common optimization, where one attempts to count the number of bits that alternate with its next neighbor in a bit string. This problem is particularly interesting because, since the strings are randomized, there is significant potential for a large number of local mimimum and maximums.



Fitness vs Iterations of 4 Optimization Strategies



Function Evals vs Iterations of 4 Optimization Strategies



Training Time vs Iterations of 4 Optimization Strategies

Conclusion

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