Randomized Optimization (Assignment 2)

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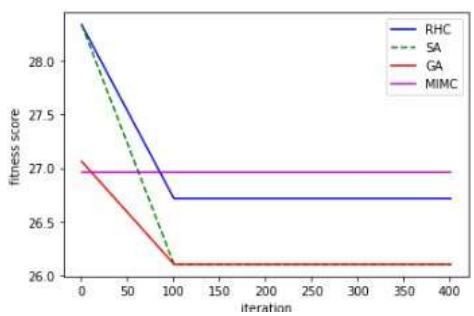
Abstract
This is an analysis regarding randomized optimization and four search techniques, which are randomized hill climbing, simulated annealing, genetic algorithm and MIMC. The Section A is about using these four techniques to solve three optimization problem, Section B is about using the first three techniques to optimize weights in neural network.

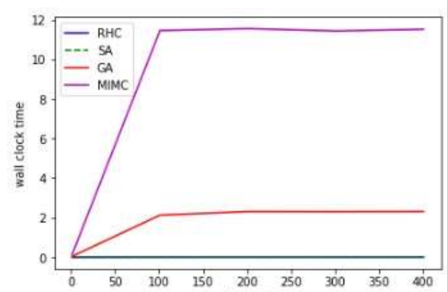
Section A – Apply four search techniques to three optimization problem

In this section, three optimization problems were chosen to highlight simulated annealing, genetic algorithm and MIMC.

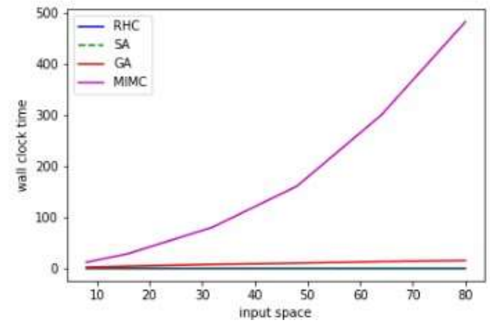
Problem 1 - Travelling Salesperson Problem

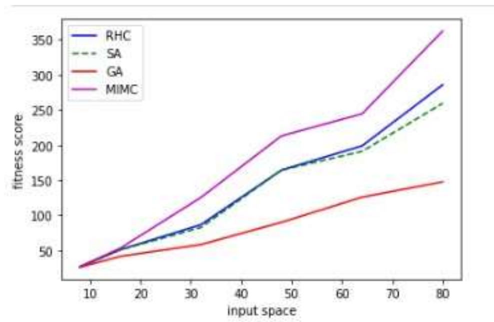
The goal is to find the route while minimizing the length of the route. It would highlight stimulated annealing technique as the natural process of annealing and getting smaller free energy mimic the process of finding the route with smaller distance. In this problem, the fitness problem is the distance of the route, thus we want to minimize it.

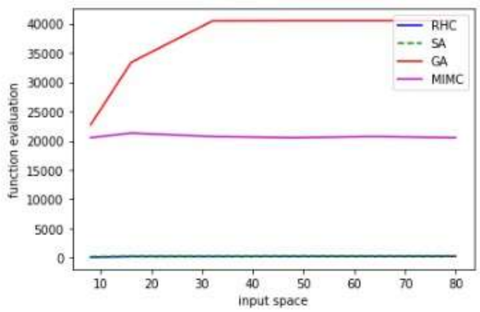




The plot on the left (fitness score under different iterations) showed that both of SA and GA improved quickly as iteration went up. The plot on the right (wall clock time under different iterations) showed that the time complexity of SA and RHC behaved stable compared to MIMC and GA. SA could reach a relatively good fitness score in small iteration number while taking limited time.





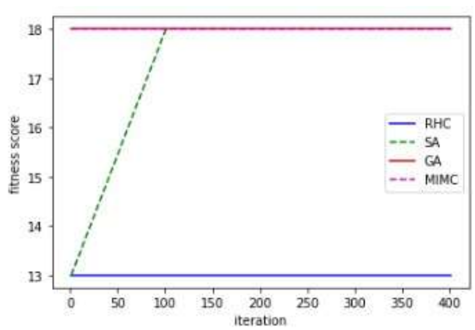


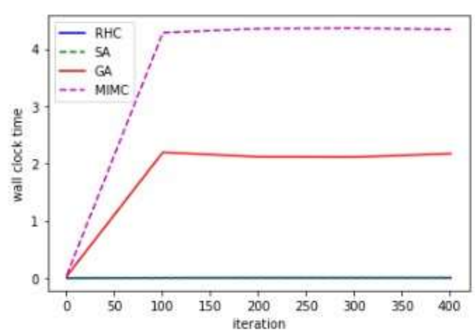
The plot on top left (wall clock time under input space) and the last one (function evaluation under input space) showed the time complexity and number of times to evaluate fitness function of SA and RHC behaved stable compared to MIMC and GA. The plot on top right (fitness score under input space) showed that GA was more likely to find the optimal solution among the four and SA came next.

Overall, we can see that SA performed the best because in problems where finding an approximate global optimum is more important than finding a precise local optimum in a fixed amount of time. SA also had the best time complexity.

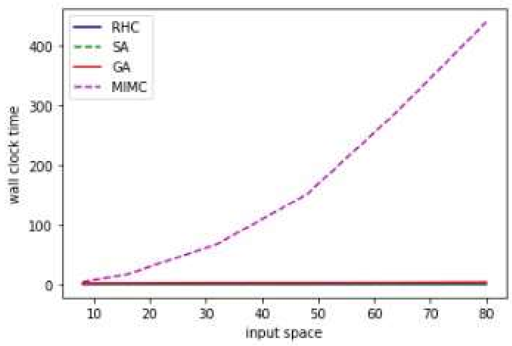
Problem 2 - Knapsack

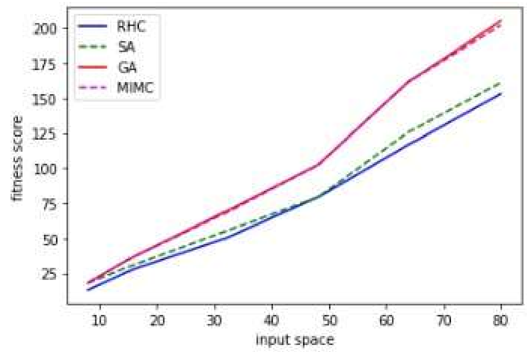
The goal is to maximize the value from the available items under weight limits. It would highlight MIMC. In this problem, the fitness represent the total value of chosen items, thus we want to maximize it.

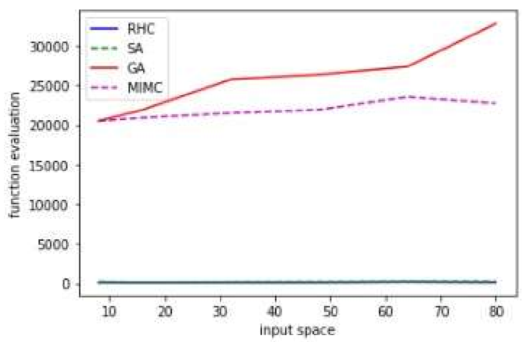




The plot on the left (fitness score under different iterations) showed that both of GA and MIMC found the optimal solution from the start. The plot on the right (wall clock time under different iterations) showed that the time complexity of SA and RHC behaved stable compared to MIMC and GA. However, since GA and MIMC found a state with the best fitness score at small iteration number. It can be concluded that GA and MIMC performed the best.







The plot on top left (wall clock time under input space) and the last one (function evaluation under input space) showed the time complexity and number of times to evaluate fitness function of SA and RHC behaved stable compared to MIMC and GA. The plot on top right (fitness score under input space) showed that GA and MIMC were trustworthy to find the optimal solution regardless the problem size.

Overall, we can see that MIMC was the best because it can found the state with optimal fitness score when input space change with less function evaluation compare to GA. The last plot showed that function evaluation for MIMC was stable but an increase trend for GA, which might leads to worse time complexity.

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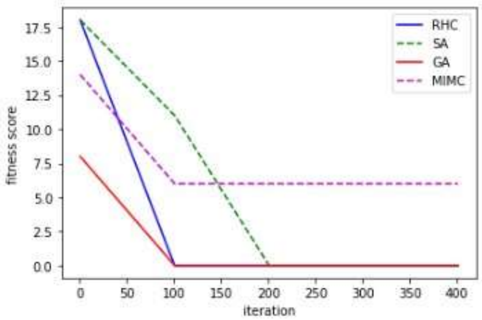
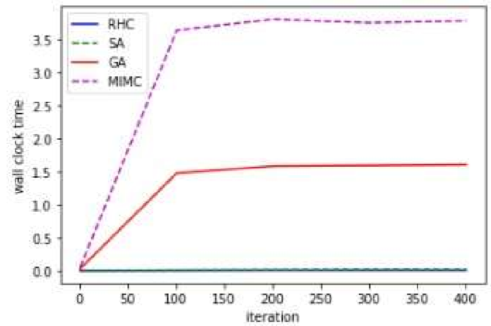
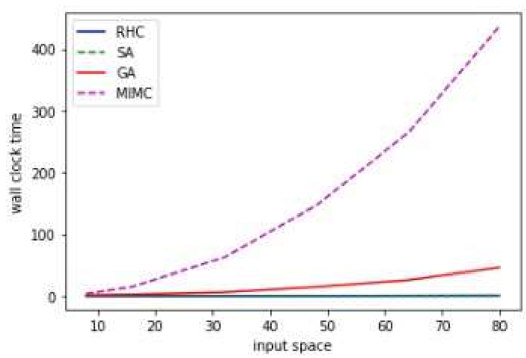
Problem 3 – N Queen

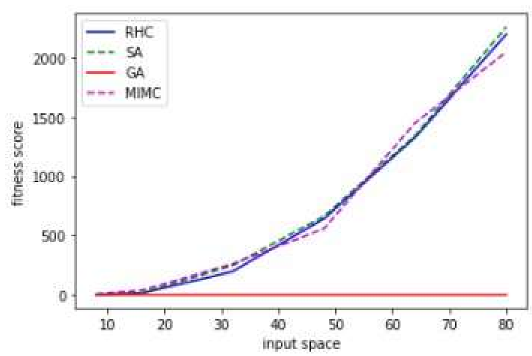
The goal is to find a way to put a queen on each columns of N*N chess board and avoid queens to attack each other. It would highlight GA.

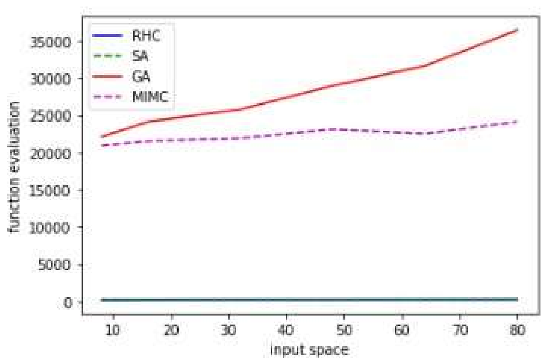




The plot on the left (fitness score under different iterations) showed that GA started with the best fitness score (when compared with the other three techniques) and found the global optimum one as the first. The plot on the right (wall clock time under different iterations) showed that the time complexity of SA and RHC behaved stable compared to MIMC and GA. However, since GA found the optimal state at using 100 iteration with less than 1 second difference. It can be concluded that GA was the best technique here.







The plot on top left (wall clock time under input space) indicated that the time complexity of MIMC was likely to be affected by input space while the other three remained stable. The last one (function evaluation under input space) showed the number of times to evaluate fitness function of GA got affected the most. However, since this is an optimization problem, the plot on top right (fitness score under input space) showed that GA had the best fitness score and best stability when input size changed.

Overall, we can see that GA was the best because it can found the state with optimal fitness score when input space change. Even though it also had the largest number of function evaluation and relatively high wall clock time, since the difference was subtle, its performance stayed the best.

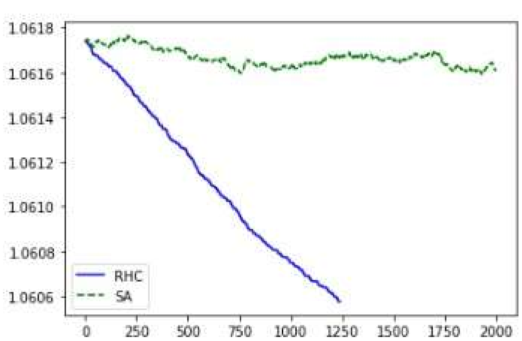
Section B – Replace backpropagation in Neural Network on weight opmization

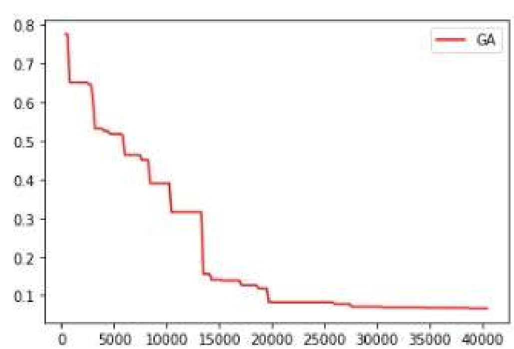
In assignment 2, MLPClassifier was used in exploring neural network with perceptron training and back propagation. At the same time, fitting the weights of a neural network problem can be viewed as an optimization problem (trying to minimize loss function along the way of trying different states of weights combination) as well.

	RHC	SA	GA	MLP
Accuracy score	0.4444444444444444	0.4666666666666667	0.9777777777777777	0.9777777777777777

Figure. Accuracy score comparison table

With the same configuration and the same dataset, other than the algorithm hyper-parameter, it can be observed that GA and MLP both obtained good accuracy score (closed to one).





The plot on the left (fitness score under function evaluation for RHC and SA) showed that SA could not obtain better weight even with bigger evaluation. At the same, there was an improvement using RHC, however, the difference was small. therefore they are not a good technique when replacing back propagation. From the plot on the right, GA started with the best fitness score (when compared with the other two techniques) and reached to a closed to 0 fitness score at the end with a decrease of 0.7. Thus, GA was the best among the three.

Conclusion

From Section A, the exploration showed that random search algorithm could help finding optimal solution. Even though it might encounter and stuck at local optimum, given more iterations and attempts, it is likely to find the global optimum. This is very useful when solving np hard problem, where huge amount of resources are needed otherwise.

From Section B, three random search algorithms were applied to find the weights of a neural network problem, with positive possibilities to apply these algorithms to any optimization problem and more areas including machine learning models.