Genetic Algorithms

THE TRAVELING SALESMAN PROBLEM

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Introduction

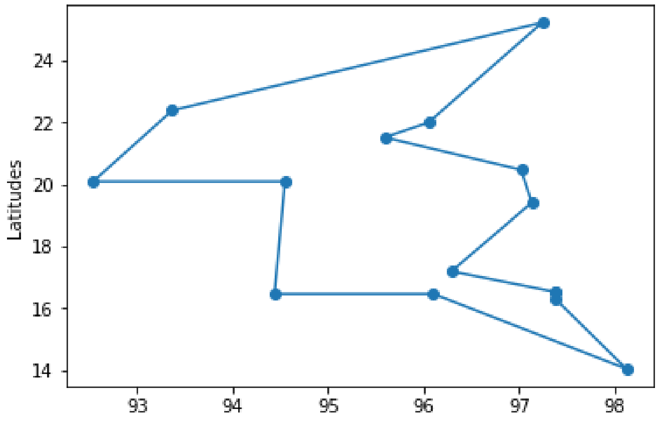
The travelling salesman problem (TSP) asks the following question: Given a list of cities and the distances between each pair of cities, what is the shortest possible route that visits each city exactly once and returns to the origin city? It is an NP-hard problem in combinatorial optimization, important in operations research and theoretical computer science.

In Machine Learning course, we were asked to resolve a TSP problem given fourteen latitudes and longitudes located in Burma, after some training on simple genetic algorithms problems. Those simple problems leaded us to imagine, create and test a solution for this problem

Our solution tends to test a lot of possibilities, we tested mutation, crossover, population size and number of generations.

Our shortest path

```
0: (16.47, 94.44)
1: (20.09, 94.55)
2: (20.09, 92.54)
3: (22.39, 93.37)
4: (25.23, 97.24)
5: (22.0, 96.05)
6: (21.52, 95.59)
7: (20.47, 97.02)
8: (19.41, 97.13)
9: (17.2, 96.29)
10: (16.53, 97.38)
11: (16.3, 97.38)
12: (14.05, 98.12)
13: (16.47, 96.1)
```

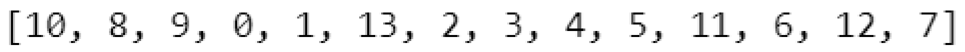


1 : Solution of the shortest tour

After running tests this solution has proven to be the best, with the vincenty formula for the distance, it's 3346,762 Km long. Our fitness solution was to sum the distance between the cities, in the order of the tour. We can't verify if it's the shortest path, we could have run a script that test all the possible paths, but it would take us 4 days, this is due to the fact that the TSP is a NP-complete problem. We managed to ask our collaborators and it seems to be the shortest path found among our peers.

Our solution

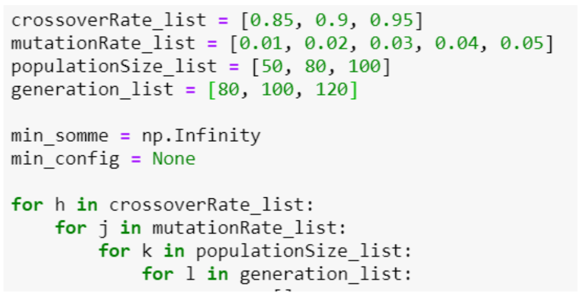
Our chromosome would look like a list of number between 0 and 13 which one represent the 14 cities. So, it would represent in which order the tour is to make.



```
[10, 8, 9, 0, 1, 13, 2, 3, 4, 5, 11, 6, 12, 7]
```

2: example of one of our chromosome

We made 5-nested loops to test 4 parameters and run the experience a multiple time to compute the mean of an experience. We change the parameters during the practical work, we searched a way not to have always a best solution, but the quickest way to have a good solution, while decreasing the population size and the number of generations



```
crossoverRate_list = [0.85, 0.9, 0.95]
mutationRate_list = [0.01, 0.02, 0.03, 0.04, 0.05]
populationSize_list = [50, 80, 100]
generation_list = [80, 100, 120]

min_somme = np.Infinity
min_config = None

for h in crossoverRate_list:
    for j in mutationRate_list:
        for k in populationSize_list:
            for l in generation_list:
```

One of the best results was with these parameters :

Crossover rate	Mutation rate	Population size	Generation nb	Score (mean)
0.9	0.05	80	100	3403.011365
0.95	0.03	100	120	3405.802383
0.9	0.05	100	80	3408.707522
0.85	0.05	100	80	3409.995064
0.9	0.03	50	120	3410.844585

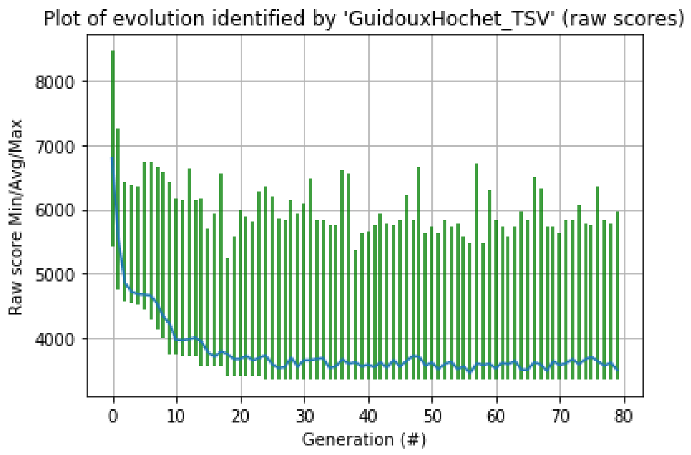
But as this is not determinist, it sometimes gives us the best solution, but sometimes doesn't, which is why we provide multiple solutions.

Results

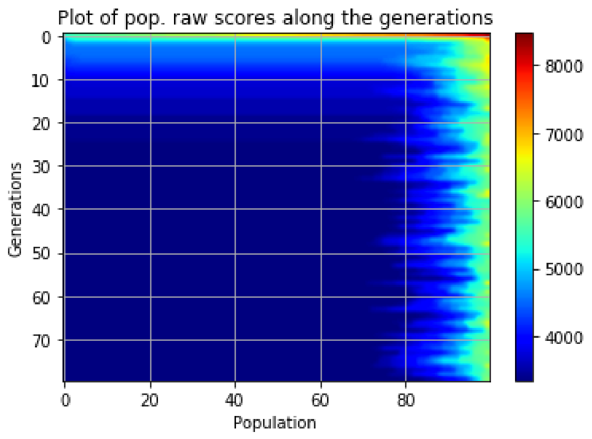
These plots show when we test with those parameters:

Crossover rate	Mutation rate	Population size	Generation nb
0.95	0.02	100	80

The blue line seen in the plot above represents the shortest path in km for each generation. In our fitness function, there is no penalty, like a really bad score if path cross each over. Therefore the range varies a lot.



This heatmap represents the plot of population scores by the number of generations. There's a lot of variations, but we see that the more there's generation



Conclusion

It would have taken us 4 days to compute all the 6227020800 tour possibilities, but with the solutions it took us only a bunch of seconds. This has proven to be very efficient and powerful, and it is very satisfying to see that the algorithm delivers good results. We didn't took the time to display a real map, or to do