Mandatory assignment 1: Traveling Salesman Problem [INF4490]

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Contents

1	Introduction	1
2	Exhaustive search	1
3	Hill Climbing	2
4	Genetic algorithm	3
5	Hybrid algorithm	5
	5.1 Lamarckian learning model	
	5.2 Baldwinian learning model	7

1 Introduction

This report documents the results of implementing different algorithms to solve the 'Traveling salesman problem'. Four different algorithms are tested: exhaustive search, hill climbing, a genetic algorithm and a hybrid algorithm using elements from the genetic- and the hill climbing algorithm.

All the algorithms are more or less inspired by the examples and pseudo codes in [1] and [2]

2 Exhaustive search

For $n_cities = 6$:

This algorithm was made based on [2, chapter 9.4.1]. The program ineffectively searches every permutation of the number of cities, which means it searches permutations that in reality represents the same distances ([1, 2, 3], [2, 3, 1], [3, 2, 1], etc.)

Start the program

\$ python3 exhaustive.py european_cities.csv

The program will find the shortest tour between 6 - 10 cities. The program outputs

```
For n_{\text{cities}} = 9:
```

Best distance: 6678.549999999999

Best sequence: (2, 6, 8, 3, 7, 0, 1, 4, 5)

Best order of travel: Berlin Copenhagen Hamburg Brussels Dublin

Barcelona Belgrade Bucharest Budapest Berlin

For $n_cities = 10$:

Best distance: 7486.309999999999

Best sequence: (6, 8, 3, 7, 0, 1, 9, 4, 5, 2)

Best order of travel: Copenhagen Hamburg Brussels Dublin Barcelona

Belgrade Istanbul Bucharest Budapest Berlin Copenhagen

Time spent [seconds]: [0.002037, 0.015967, 0.134317, 1.310069, 13.964733]

The time used by the algorithm to find the best distance was measured. The time spent on solving TSP for six, seven, eight, nine and ten cities is shown in the last two lines of the program output and in figure 1.

Time taken as function of how many cities visited

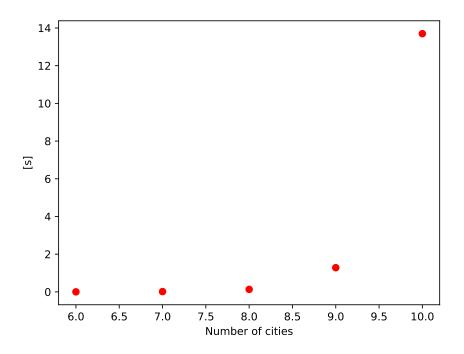


Figure 1: Time spent for the TSP algorithm

It can be seen that time spent by the algorithm searching for an optimal solution in TSP for n cities is roughly the time spent on searching for n-1 cities multiplied by n. The time spent by the algorithm (on my laptop) to search for the optimal solution in TSP for 24 cities can be calculated with

$$t_{10} \frac{24!}{10!} \approx 14s \cdot \frac{24!}{10!} \approx 2.4 \cdot 10^{18}$$

which is around 76 billion years.

3 Hill Climbing

This algorithm was made based on [2, chapter 9.4.3].

Start the program with

\$ python3 hill_climber.py european_cities.csv

The program will try to find the shortest route between 10 and the shortest route between 24 cities. The program outputs

For 10 cities:

Running the algorithm 20 **times** Number of searches per round: 10000 Best distance: 7503.09999999999

Worst distance: 8324.82 Average distance: 7835.56 Standard deviation: 229.896

Time taken per search [seconds]: 0.145487

For 24 cities:

Running the algorithm 20 times Number of searches per round: 10000 Best distance: 19413.89999999998 Worst distance: 22341.170000000006

Average distance: 21236.6 Standard deviation: 751.52

Time taken per search [seconds]: 2.017303

The best result of 20 hill climber runs gets close to the solution computed by the exhaustive search (7503 vs 7486). Results of 7486 have a been observed during test runs.

The hill climber uses 10000 iterations each run, using a total of 200000 iterations to find this result. The exhaustive search on the other hand uses 10! = 3628800 iterations.

Increasing the iterations used by the hill climber reduces the standard deviation and increases the chances of it finding the optimal distance.

When searching 24 cities, the hill climber uses around two seconds every run, resulting in a total of around 40 seconds for the whole run. This is in strong contrast to the 76 billion years of the exhaustive search. However, the result found is quite far from the optimal one, but gets better if number of iterations increases.

4 Genetic algorithm

This algorithm was made based on [1, chapter 3 - 6]. All in all, the algorithm consist of:

- An initializer: random permutations computed using numpy.
- A parent selector: using a linear ranking scheme with s = 1.5.
- A crossover algorithm: cycle crossover.
- A mutating scheme: inversion of subset of cities in the children. Probability of mutation: 50%
- Survivor selector: GENITOR. The n weakest parents are replaced by n children. I have chosen n=4 for all my runs.

The program was tested with a population of 10, 50 and 100.

Start the program with

```
$ python3 genetic_algorithm.py european_cities.csv
```

The program will try to find the shortest distance between 24 cities using the three different population sizes, and then do the same with 10 cities. The program outputs:

 $Search:\ 24\ cities\ ,\ population\ size:\ 10\,,\ number\ of\ generations:\ 500\,,$

number of rounds: 20, number of children: 4:

Best distance: 13340.920000000002

Worst distance: 17002.0 Average distance: 15437.6 Standard deviation: 851.065 Time [seconds]: 4.982695 Best order of travel:

Prague Berlin Warsaw Kiev Moscow Stockholm Saint Petersburg Hamburg Copenhagen Dublin London Brussels Paris Madrid Barcelona Rome Milan Munich Belgrade Istanbul Bucharest Sofia Budapest Vienna Prague

Search: 24 cities, population size: 50, number of generations: 500,

number of rounds: 20, number of children: 4:

Best distance: 15607.64 Worst distance: 19076.97 Average distance: 17500.1 Standard deviation: 839.583 Time [seconds]: 10.528968 Best order of travel:

Rome Milan Munich Budapest Prague Hamburg Copenhagen Stockholm Warsaw Sofia Istanbul Bucharest Kiev Moscow Saint Petersburg Vienna Belgrade Madrid Barcelona Paris Brussels Dublin London Berlin Rome

Search: 24 cities, population size: 100, number of generations: 500,

number of rounds: 20, number of children: 4:

Best distance: 16469.68 Worst distance: 21342.51 Average distance: 19425.3 Standard deviation: 1086.04 Time [seconds]: 17.520685

Best order of travel:

Budapest Kiev Moscow Stockholm Warsaw Saint Petersburg Prague Paris Dublin Munich Rome Bucharest Belgrade Vienna Berlin Hamburg Copenhagen Brussels London Milan Madrid Barcelona Sofia Istanbul Budapest

Search: 10 cities, population size: 10, number of generations: 500,

number of rounds: 20, number of children: 4:

Best distance: 7486.309999999999

Worst distance: 7503.1 Average distance: 7490.51 Standard deviation: 7.27028 Time [seconds]: 2.610346 Best order of travel:

Brussels Hamburg Copenhagen Berlin Budapest Bucharest Istanbul Belgrade Barcelona Dublin Brussels

Search: 10 cities, population size: 50, number of generations: 500,

number of rounds: 20, number of children: 4:

Best distance: 7486.3099999999999 Worst distance: 7663.510000000001

Average distance: 7498.53 Standard deviation: 38.433 Time [seconds]: 6.380234 Best order of travel:

Hamburg Brussels Dublin Barcelona Belgrade Istanbul Bucharest Budapest Berlin Copenhagen Hamburg

Search: 10 cities, population size: 50, number of generations: 500,

number of rounds: 20, number of children: 4:

Best distance: 7486.309999999999

Worst distance: 7603.24 Average distance: 7501.36 Standard deviation: 34.5993 Time [seconds]: 6.684515 Best order of travel:

Belgrade Istanbul Bucharest Budapest Berlin Copenhagen Hamburg Brussels Dublin Barcelona Belgrade

A plot of the average fitness of the best individual of each generation can be seen in figure 2.

Average fitness of best fit individual in each generation

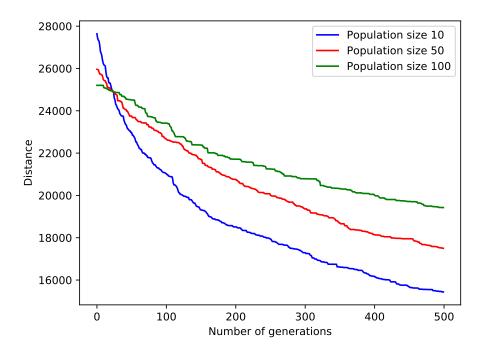


Figure 2: Average fitness result for the genetic algorithm

As shown in the plot and the output, the algorithm converges slower as population size increases. A reason for this might be because the survivor selection do not scale with the population size (n = 4 for all population sizes). For this setup, the smaller population size (or the bigger ratio between n and population size) gives the most effective and fruitful search.

The genetic algorithm is run 500 times, generating 500 generations of data. When looking at how the results from running the genetic algorithm with 10 cities compares with exhaustive search and hill climber, we see that it finds the optimal solution from exhaustive search, but using far less iterations that the hill climber,

5 Hybrid algorithm

The algorithm was made by modifying the genetic algorithm, adding a number of iterations of the hill climber to the parent selection. This was done by using the hill climber on every parent, then sorting the parents based on the new fitness values. For the Lamarckian learning model, the pre hill climb values were discarded and the new ones kept, while for the Baldwinian learning, the new fitness values were discarded amd the old ones kept. For this run I used hill climber with 3 iterations and the same population sizes as the genetic algorithm.

Start the program with

\$ python3 hybrid_algorithm.py european_cities.csv

5.1 Lamarckian learning model

The part of the programming testing the Lamrarckian learning model outputs:

```
LAMARCKIAN LEARNING MODEL ——
Search: 24 cities, population size: 10, number of generations: 500, number of rounds: 20, number of children: 4, number of hill climb iterations: 3:
Best distance: 12384.21999999998
Worst distance: 14111.69
Average distance: 13115.3
Standard deviation: 501.122
Time [seconds]: 23.187871
Best order of travel:
```

Moscow Saint Petersburg Stockholm Copenhagen Hamburg Dublin London Paris

Brussels Munich Milan Madrid Barcelona Rome Sofia Istanbul Bucharest Belgrade Budapest Vienna Prague Berlin Warsaw Kiev Moscow

Search: 24 cities, population size: 50, number of generations: 500, number of rounds: 20, number of children: 4, number of hill climb iterations: 3: Best distance: 12384.22 Worst distance: 13501.650000000001 Average distance: 12900.0 Standard deviation: 288.045 Time [seconds]: 99.415685 Best order of travel: Moscow Kiev Bucharest Istanbul Sofia Belgrade Rome Milan Barcelona Madrid Paris Dublin London Brussels Hamburg Copenhagen Stockholm Berlin Prague Munich Vienna Budapest Warsaw Saint Petersburg Moscow Search: 24 cities, population size: 100, number of generations: 500, number of rounds: 20, number of children: 4, number of hill climb iterations: 3: Best distance: 12325.930000000002 Worst distance: 13476.58999999998 Average distance: 12827.5 Standard deviation: 275.802 Time [seconds]: 199.236898 Best order of travel: Copenhagen Berlin Warsaw Stockholm Saint Petersburg Moscow Kiev Istanbul Bucharest Sofia Belgrade Budapest Vienna Prague Munich Milan Rome Barcelona Madrid Paris Brussels London Dublin Hamburg Copenhagen Search: 10 cities, population size: 10, number of generations: 500, number of rounds: 20, number of children: 4, number of hill climb iterations: 3: Best distance: 7486.309999999995 Worst distance: 7503.099999999999 Average distance: 7488.83 Standard deviation: 5.99523 Best order of travel: Dublin Brussels Hamburg Copenhagen Berlin Budapest Bucharest Istanbul Belgrade Barcelona Dublin Search: 10 cities, population size: 50, number of generations: 500, number of rounds: 20, number of children: 4, number of hill climb iterations: 3: Best distance: 7486.309999999999 Worst distance: 7486.309999999995 Average distance: 7486.31 Standard deviation: 5.85938e-05 Time [seconds]: 64.33309 Best order of travel: Hamburg Brussels Dublin Barcelona Belgrade Istanbul Bucharest Budapest Berlin Copenhagen Hamburg Search: 10 cities, population size: 100, number of generations: 500, number of rounds: 20, number of children: 4, number of hill climb iterations: 3: Best distance: 7486.309999999999 Worst distance: 7486.309999999999 Average distance: 7486.31 Standard deviation: 5.85938e-05

Time [seconds]: 128.094541 Best order of travel: Istanbul Bucharest Budapest Berlin Copenhagen Hamburg Brussels Dublin Barcelona Belgrade Istanbul

A plot of the average fitness of the best individual of each generation can be seen in figure 3.

Average fitness of best fit individual in each generation

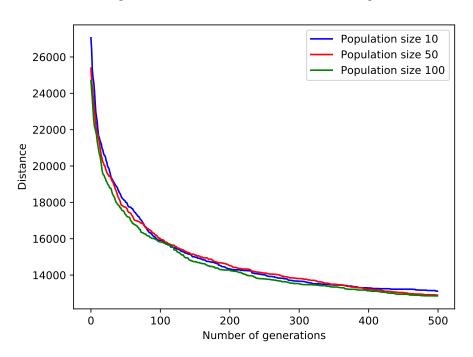


Figure 3: Average fitness result for the hybrid algorithm with a Lamarckian learning model

As shown in the plot and the output, the algorithms converges faster than the genetic algorithm when using the same number of generations. The three populations converges approximately at the same speed. The standard deviation decreases as the population size increases.

5.2 Baldwinian learning model

The part of the programming testing the Baldwinian learning model outputs:

```
—— BALDWINIAN LEARNING MODEL —— Search: 24 cities, population size: 10, number of generations: 500, number of rounds: 20, number of children: 4, number of hill climb iterations: 3:

Best distance: 24573.85

Worst distance: 33081.719999999994

Average distance: 28469.5

Standard deviation: 2413.0

Time [seconds]: 28.799268
```

Best order of travel:
Bucharest Istanbul Rome Dublin London Berlin Milan Prague Copenhagen
Warsaw Saint Petersburg Kiev Moscow Stockholm Vienna Brussels Paris

Warsaw Saint Petersburg Kiev Moscow Stockholm Vienna Brussels Paris Munich Belgrade Sofia Barcelona Budapest Hamburg Madrid Bucharest

Search: 24 cities, population size: 50, number of generations: 500, number of rounds: 20, number of children: 4,

number of hill climb iterations: 3:

Best distance: 22539.57 Worst distance: 32637.84 Average distance: 27822.1 Standard deviation: 2372.2 Time [seconds]: 131.015888 Best order of travel:

Hamburg Stockholm Warsaw Munich Milan Madrid Budapest Kiev Moscow Belgrade Istanbul Saint Petersburg London Berlin Sofia Vienna Rome Brussels Bucharest Paris Dublin Barcelona Prague Copenhagen Hamburg

Search: 24 cities, population size: 100, number of generations: 500,

number of rounds: 20, number of children: 4,

number of hill climb iterations: 3:

Best distance: 24413.59

Worst distance: 31961.60999999999

Average distance: 26829.1 Standard deviation: 1923.99 Time [seconds]: 268.707197

Best order of travel:

Milan Madrid Copenhagen Stockholm Sofia Istanbul Hamburg Paris Prague Berlin Saint Petersburg Moscow Warsaw Rome Vienna London Bucharest Budapest Kiev Belgrade Brussels Munich Barcelona Dublin Milan

Search: 10 cities, population size: 10, number of generations: 500,

number of rounds: 20, number of children: 4,

number of hill climb iterations: 3:

Best distance: 8895.97 Worst distance: 14540.27 Average distance: 11162.9 Standard deviation: 1312.17 Time [seconds]: 16.562146 Best order of travel:

Brussels Belgrade Istanbul Bucharest Dublin Barcelona Budapest Hamburg Copenhagen Berlin Brussels

Search: 10 cities, population size: 50, number of generations: 500,

number of rounds: 20, number of children: 4,

number of hill climb iterations: 3:

Best distance: 8304.14

Worst distance: 14255.750000000002

Average distance: 10502.8 Standard deviation: 1614.64 Time [seconds]: 82.029157 Best order of travel:

Brussels Dublin Barcelona Hamburg Istanbul Bucharest Belgrade Budapest Berlin Copenhagen Brussels

Search: 10 cities, population size: 100, number of generations: 500,

number of rounds: 20, number of children: 4,

number of hill climb iterations: 3: Best distance: 8514.890000000001 Worst distance: 14829.510000000002

Average distance: 10811.2 Standard deviation: 2013.73 Time [seconds]: 159.45777 Best order of travel:

Budapest Bucharest Dublin Belgrade Hamburg Istanbul Brussels Copenhagen Berlin Barcelona Budapest

A plot of the average fitness of the best individual of each generation can be seen in figure 4.

Average fitness of best fit individual in each generation

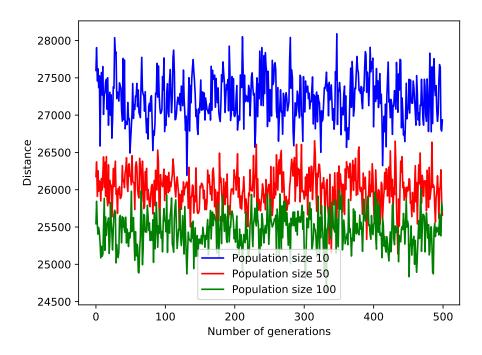


Figure 4: Average fitness result for the hybrid algorithm with a Baldwinian learning model

As shown in the plot and output, the Baldwinian learning model fails

References

- [1] A.E Eiben, J.E Smith, Introduction to Evolutionary Computing, Springer, London, 2nd edition, 2015.
- [2] Stephen Marsland, *Machine Learning An Algorithmic Perspective*, Chapman and Hall/CRC, Boca Raton/London/New York, 2nd edition, 2015.