TSP Dataset - http://mistic.heig-vd.ch/taillard/problemes.dir/tsp/tsp.html

- Split into training and test datasets, two datasets with 50 and 100 cities
- Real world dataset or collected through a process not random, in form of coordinates
- Optimal solution given as in each instance cities are optimally ordered, size of dataset is large
- Very easy to use, complexity of dataset can be handled with GPU, each instance is (50, 2) or (100, 2) shape, output is a sequence of optimally ordered cities in shape (50, 1) and an optimal cost (Euclidean distance is used)

Methods the dataset was tested on –

- 2 opt – local search algorithm, iteratively swaps pairs of edges in a tour to reduce the total distance, compares every possible valid combination of swapping algorithm, it basically examines pairs of edges. It starts with an initial tour given by any constructive method like nearest neighbour then it chooses any two edges, calculates and compares the total distance. If there is an improvement it swaps otherwise not, iteratively performs many swapping until no further upgrade is there.
- City swap – Similar to 2 opt algorithm but no constructive algorithm is used, cities are randomly sorted and a starting solution is created, tries to swap all cities with nested loops.
- Genetic – iterative optimization process that uses selection, crossover and mutation to improve the solution of the problem, each individual represents a potential tour, initialization is random, then evaluation and selection is done, combines several potential tours and initiates random changes, mutation can swap two cities, insert or delete a city or any other modification. Termination can be when no further improvement is left or a fixed number of iterations.
- Simulated annealing algorithm – iteratively explores the optimal solutions search space by taking both better and worse solutions, not a greedy approach, used a temperature-controlled probability, if it decreases, algorithm converges towards better solution and vice-versa. Various parameters include setting initial temperature, cooling schedule, stopping conditions. Modifications are accepted with a certain probability, allows for exploration of different solutions, gradually the probability of accepting worse solutions decreases as we temperature is reduced according to cooling schedule.

Comparing the running times and optimal solution gap of an instance of 50 cities dataset –

- Optimal solution given - 568331.5477299746

	2-opt	City-swap	Genetic	Simulated annealing
Absolute difference	12537.14227003	403437.36131	55292.95499	235214.573914
Relative difference	2.2%	70.98%	9.72%	41.38%
Running time	0.07543039321 sec	35.3535213 sec	164.5090782 sec	195.11731052 sec

Comparing the running times and optimal solution gap of an instance of 100 cities dataset –

- Optimal solution given - 793766.5150408885

	2-opt	City-swap	Genetic	Simulated annealing
Absolute difference	29862.77495	686543.896734	236060.608419	666537.436607
Relative difference	3.76%	86.49%	29.73%	83.97%
Running time	0.2482123374 sec	305.153501272 sec	529.55376815 sec	657.88147449 sec

Remarks: Most heuristic methods are random hence above data can have differences in different runs.