# Implementing Ant Colony Optimization (ACO) algorithm for a given Symmetric traveling salesman problem (TSP)

Yefferson A. Marín Cantero
Artificial intelligence course
Systems Engineering Programa
Universidad Tecnológica de Bolívar
Cartagena de Indias, D.T. y C - Bolívar
1p-2020

## **Definitions**

## **Ant Colony Optimization (ACO)**

It is an **optimization algorithm** used to find the shortest path between points or nodes. It is developed by observing the behaviour of ants when they follow a path to their food source. Ants are essentially blind so they follow pheromone trails left behind by other ants on the path. This algorithm follows the same approach by using the probability of going to the next node as the distance to the node and the amount of pheromones.

## Symmetric traveling salesman problem (TSP)

Given a set of **n** nodes and distances for each pair of **nodes**, find a roundtrip of minimal total length visiting each node exactly once. The distance from node *i* to node *j* is the same as from node *i*.

## Introduction

This algorithm is done using the following requirements:

- Python (https://python.org)
- Numpy (https://numpy.org)
- Matplotlib (https://matplotlib.org)

And its taking as data the **The 100-city problem A** kroA100.tsp by *Krolak/Felts/Nelson* (and additional results for **52 locations in Berlin** berlin52.tsp by *Groetschel*). The purpose is to find the shortest path to travel in a closed path between all the locations (nodes), and plot space and path.

# **Steps**

#### 1. Initialize Ants

First its required to select a given (or arbitrary) number of ants, placed in random positions of the given TSP space.

# 2. Ants moving via probability

Then for each of the ants we complete a closed path i.e. from start, covering all the nodes and without repeating any of the nodes. To move an ant from one node to the next we use the following formula.

$$P_{ij}(t) = rac{ au_{ij}^lpha + \eta_{ij}^eta}{\sum ( au^lpha + \eta^eta)}$$

Where  $\tau$  (tau) is the amount of pheromones and  $\eta$  (eta) is the inverse of the distance (1/d).

 $\alpha$  (alpha) and  $\beta$  (beta) are the algorithm's parameters. They are used to give more or less weight to the distance or pheromones while selecting the next node.

## 3. Deposit of Pheromones

When an ant moves from a node to the next, it leaves a trail for the next ant to follow, the more ants follow the same path, the stronger the pheromone trail gets. Pheromone trails are incremented by.

$$au^{(i+1)} = au^i + \Delta au$$

Where  $\Delta \tau$  (*delta tau*) is a prameter and i is the iteration number.

#### 4. Evaporation of Pheromones

After each iteration the pheromones also tend to evaporate. The evaporation of pheromones are given as.

$$\tau^{(i+1)} = (1-\rho)\tau^i$$

where  $\rho$  (*rho*) is the evaporation rate.

## 5. Ending condition

We can use any condition to terminate the search, such as a distance below a certain threshold. In this implementation, the ending condition will be the number of iterations.

# **Implementation**

Initially we import the library.py and matplotlib, as it follows:

```
In [1]: from library import *
  import matplotlib.pyplot as plt
```

#### TSP file

A Symmetric traveling salesman problem (TSP) file has the following structure:

```
1- NAME : <string>
 2- TYPE : <string>
 3- COMMENT : <string>
 4- DIMENSION : <integer>
 5- EDGE WEIGHT TYPE : <string>
 6- NODE COORD SECTION : <integer> <real> <real>
 7- EOF
 1- Identifies the data file
 2- Specifies the type of the data (TSP: Data for a symmetric traveling salesman problem)
 3- Additional comments (usually the name of the contributor or creator of the problem instance is given h
ere).
 4- For a TSP the dimension is the number of its nodes
 5- Specifies how the edge weights (or distances) are given (EUC 2D: Weights are Euclidean distances in 2-
D)
 6- Node coordinates are given in this section. Each line is of the form
 7- Terminates the input data. This entry is optional.
```

As some functions has been defined in libraries.py, we can call a method that reads our TSP file and store its data in order to use later. To start, we will use the **The 100-city problem A** ( kroA100.tsp ) by *Krolak/Felts/Nelson*).

```
In [2]: # Get TSP data
TSP = getTspData('data/kroA100.tsp')

# Display TSP file headers
displayTspHeaders(TSP)

Name: kroA100
Type: TSP
Comment: 100-city
Dimension: 100
Edge Weight Type: EUC_2D
```

## **Space**

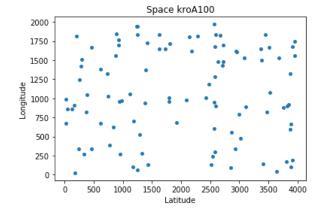
We can use now its coordenates pairs to plot nodes, this representation is what is called **space**.

```
In [3]: # Get Space
    space = np.array(TSP['node_coord_section'])

# Plot nodes
plt.scatter(space[:, 0], space[:, 1], s = 15)

# Plot properties
plt.title('Space {}'.format(TSP['name']))
plt.xlabel('Latitude')
plt.ylabel('Longitude')

# Show plot
plt.show()
plt.close()
```



Then we call the algorithm as it follows. By default our algorithm parameters will be:

But they can be changed passing them as argument to the runAcoTsp() function like:

```
iterations = 100
    colony = 25
    alpha = 1.2
    beta = 1.5
    del_tau = 2
    rho = 0.2

# Call passing arguments
min_path, min_distance = runAcoTsp(space, iterations, colony, alpha, beta, del_tau, rho)
```

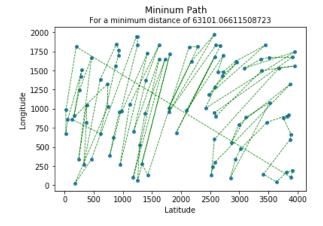
In this case we will run it as default, by using runAcoTsp(space).

```
In [4]: # Run ACO
    min_path, min_distance = runAcoTsp(space)

# Plot path
    plt.scatter(space[:, 0], space[:, 1], marker='o', s=15)
    plt.plot(space[min_path, 0], space[min_path, 1], c='g', linewidth=0.8, linestyle="--")

# Plot properties
    plt.suptitle('Mininum Path')
    plt.title('For a minimum distance of {}'.format(min_distance), fontsize = 10)
    plt.xlabel('Latitude')
    plt.ylabel('Longitude')

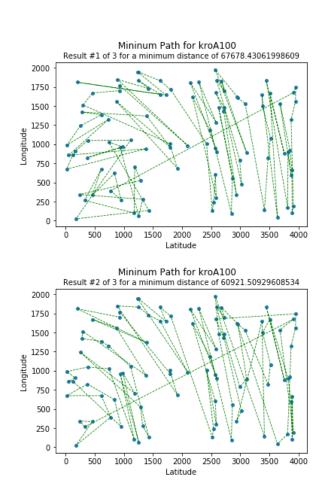
# Show plot
    plt.show()
    plt.close()
```

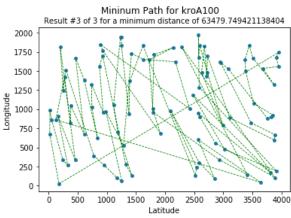


As it shows in last plot, after perform the number of iteration (our ending condition), the shortes path is represented by the green line, and it minimum distance is calculated as well.

In order to watch the algorith initial points randomness, we will perform it again, but a total of 3 times to to get an average minimum distance.

```
In [5]: # Vars
        n = 3
        average = 0
        # Repeat
        for i in range(n):
            # Call
            min_path, min_distance = runAcoTsp(space)
            average += min_distance
            # Plot path
            plt.scatter(space[:, 0], space[:, 1], marker='o', s=15)
            plt.plot(space[min_path, 0], space[min_path, 1], c='g', linewidth=0.8, linestyle="--")
            # Plot properties
            plt.suptitle('Mininum Path for {}'.format(TSP['name']))
            plt.title('Result #{} of {} for a minimum distance of {}'.format(i + 1, n, min_distance), fontsiz
            plt.xlabel('Latitude')
            plt.ylabel('Longitude')
            plt.show()
            plt.close()
        # Show Average
        print('Min Distance Average for the last {} results is {}'.format(n, average/n))
```





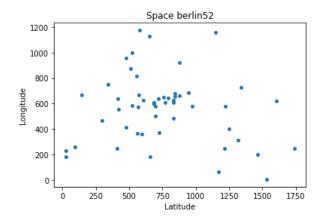
Min Distance Average for the last 3 results is 64026.56311240327

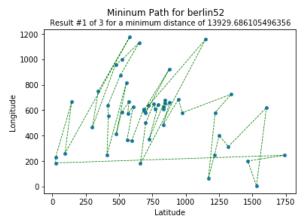
## **Extras**

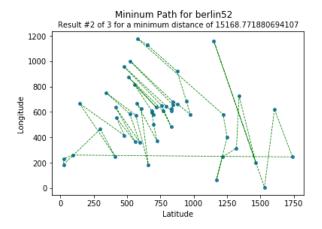
The same functions can be used to and additional results for **52 locations in Berlin** ( berlin52.tsp ) by *Groetschel* but using a differente set of algorithm parameters.

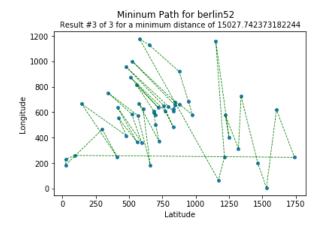
```
In [6]: # Get TSP data
        TSP = getTspData('data/berlin52.tsp')
        # Display TSP file headers
        displayTspHeaders(TSP)
        # Get Space
        space = np.array(TSP['node_coord_section'])
        plt.scatter(space[:, 0], space[:, 1], s = 15)
        # Plot properties
        plt.title('Space {}'.format(TSP['name']))
        plt.xlabel('Latitude')
        plt.ylabel('Longitude')
        # Show plot
        plt.show()
        plt.close()
        # Algorithm Parameters
        iterations = 50
        colony = 25
        alpha = 1
        beta = 1
        del_tau = 1.5
        rho = 0.5
        # Vars
        average = 0
        # Repeat
        for i in range(n):
            # Run
            min_path, min_distance = runAcoTsp(space, iterations, colony, alpha, beta, del_tau, rho)
            average += min_distance
            # Plot path
            plt.scatter(space[:, 0], space[:, 1], marker='o', s=15)
            plt.plot(space[min_path, 0], space[min_path, 1], c='g', linewidth=0.8, linestyle="--")
            # Plot properties
            plt.suptitle('Mininum Path for {}'.format(TSP['name']))
            plt.title('Result #{} of {} for a minimum distance of {}'.format(i + 1, n, min_distance), fontsiz
        e = 10)
            plt.xlabel('Latitude')
            plt.ylabel('Longitude')
            plt.show()
            plt.close()
        # Show Average
        print('Min Distance Average for the last {} results is {}'.format(n, average/n))
```

Name: berlin52 Type: TSP Comment: 52 Dimension: 52 Edge Weight Type: EUC\_2D









Min Distance Average for the last 3 results is 14708.733453124236

#### **Generate files**

Additionally, within our **library.py** there is also a **testing.py**, by typing in console:

```
py testing.py
```

We are going to get generated files for a number *n* of results:

- tsp-space.png With the nodes representation
- tsp-path-n.png For each path result
- tsp-results.txt For a summary of results (min distances) + average (avg min distance) result

The command will output some contextual messages ir order to know the execution process:

```
[Testing ACO_TSP] Computing 3 times for kroA100

[Testing ACO_TSP] results/kroA100-space.png generated

[Testing ACO_TSP] results/kroA100-path-1.png generated

[Testing ACO_TSP] results/kroA100-path-2.png generated

[Testing ACO_TSP] results/kroA100-path-3.png generated

[Testing ACO_TSP] results/kroA100-results.txt generated

[Testing ACO_TSP] Computing 3 times for berlin52

[Testing ACO_TSP] results/berlin52-space.png generated

[Testing ACO_TSP] results/berlin52-path-1.png generated

[Testing ACO_TSP] results/berlin52-path-2.png generated

[Testing ACO_TSP] results/berlin52-path-3.png generated

[Testing ACO_TSP] results/berlin52-results.txt generated

[Testing ACO_TSP] results/berlin52-results.txt generated
```

All those generated files, will be availables at /results in projects root.

## Source code

All code has been deployed at Github and its available at yammadev/aco-tsp (https://github.com/yammadev/aco-tsp).