

## MSE Algorithms

# L05: Ant Colony Optimization, Work on Santas Challenge

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# Course Overview

1. Introduction: Basic problems and algorithms
2. Constructive methods: Random building, Greedy
3. Local searches
4. Randomized methods
5. Threshold accepting, Simulated Annealing
6. Decomposition methods: Large neighborhood search
7. Learning methods for solution improvement: Tabu search
8. Application: Santa's Challenge
9. **Learning methods for solution building: Artificial ant systems**
10. Methods with a population of solutions: Genetic algorithms
11. Work on Santa's Challenge
12. Final Lecture

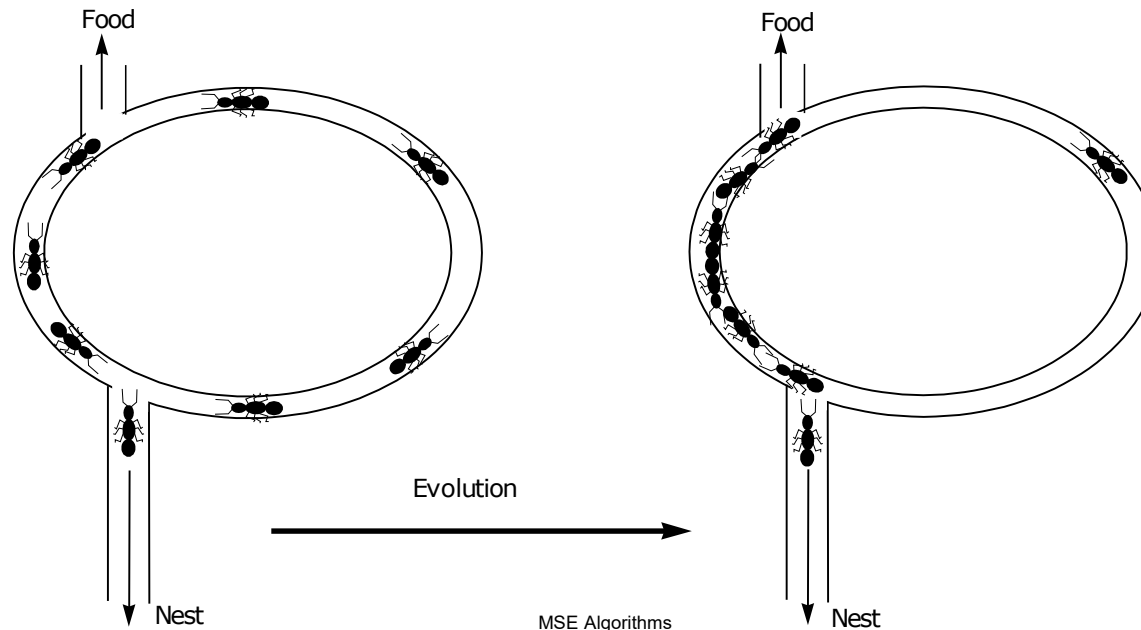


# Ant Colony Optimization (ACO)

**Ant Systems** are used to **CONSTRUCT** solutions

# Ants can find Shortest Paths

- Ants leave a "pheromone trail" on their way from the nest to a target (e.g. food)
- The more pheromone on a segment, the more likely a next ant is to use this segment
- Experiments have shown that ants can find shortest path between source and target (2-bridge-experiment)
- Ant Colony Optimization simulates behaviour of ants to solve combinatorial problems



# Meta-Heuristic: Ant Colony Optimization (ACO)

Set parameters

Initialize pheromone trails

**Do**

Let artificial Ants construct solutions

Apply Local Search (optional)

Update Pheromones

Keep best solution so far

**While** termination condition not met

ACO is a Constructive  
Method, i.e. it generates  
new solutions

# Components of an ACO System

## Memory

- Associate a value  $\tau_e$  (pheromone trail) to each element  $e$  constituting a solution
- $\tau_e$  depends on the number of times  $e$  has been used **and** on the quality of solutions using  $e$

## Construct Ant Solutions (building phase)

- Let  $m$  artificial ants build solutions in parallel, starting from empty solutions
- For each partial solution, ants choose a feasible next element  $e$  with a probability proportional to  $\tau_e^\alpha \cdot c(s, e)^\beta$ , where  $c(s, e)$  is an incremental cost function that measures the quality of adding element  $e$  to partial solution  $s$
- Parameters  $\alpha \geq 0$  and  $\beta \leq 0$  balance the importance of learning versus greedy choice

## Update Pheromones

- **Evaporate:** Multiply all  $\tau_e$  by  $1 - \rho$ , where  $0 \leq \rho \leq 1$  is a parameter to simulate pheromone evaporation
- **Reinforcement:** For each element  $e$  belonging to a solution  $s$  at a given iteration, add  $Q / f(s)$  to  $\tau_e$ , where  $Q$  is a parameter and  $f(s)$  the cost of solution  $s$ . This simulates the leaving of pheromone marks on trails by ants

# Ant System for TSP

## Data

Distance matrix  $D = (d_{ij})$  between cities

Trace matrix  $T = (\tau_{ij})$

Parameters  $\alpha, \beta, \rho, \tau_0, Q, m, \text{max\_iter}$

## Initialisation

$\tau_{ij} = \tau_0$  **for all**  $i, j$

## Repeat for $\text{max\_iter}$ iterations

$R = (r_{ij}) = 0$

**For each**  $k = 1, \dots, m$

$L = 0$

Choose a city  $i$  at random

**Repeat, while** all cities have not been visited

Choose a city  $j$  not yet visited with probability proportional to  $\tau_{ij}^\alpha \cdot d_{ij}^\beta$

$L = L + d_{ij}$

$i = j$

**For all** arc  $(i, j)$  of the tour just built, set

$r_{ij} = r_{ij} + Q/L$

$T = (1-\rho)T + R$  // Update pheromone trail after having built  $m$  solutions

**Return** The best tour found

// Edge reinforcement

// Ant  $k$  build a new solution

// Tour length

// Current city :  $i$

Note:  $\beta \leq 0$

The shorter a tour of ant  $k$ , the higher the reinforcement value  $r_{ij}$  for the edges on this tour.



1. What is the effect if we set  $\alpha = 0$ .
2. Same for  $\beta = 0$ .

# Ant Algorithm Variants

<i>Algorithm</i>	<i>Authors</i>	<i>Year</i>
Ant System (AS)	Dorigo et al.	1991
Elitist AS	Dorigo et al.	1992
Ant-Q	Gambardella & Dorigo	1995
Ant Colony System	Dorigo & Gambardella	1996
<i>MAX-MIN</i> AS	Stützle & Hoos	1996
Rank-based AS	Bullnheimer et al.	1997
ANTS	Maniezzo	1999
BWAS	Cordón et al.	2000
Hyper-cube AS	Blum et al.	2001

Source: Marco Dorigo et al, Ant Colony Optimization, 2006

## Resources:

- *Ant Colony Optimization – Artificial Ants as a Computational Intelligence Technique* by Marco Dorigo, Mauro Birattari, and Thomas Stützle, 2006.
- [https://www.researchgate.net/publication/230660829\\_Ant\\_Colony\\_Optimization\\_Artificial\\_Ants\\_as\\_a\\_Computational\\_Intelligence\\_Technique](https://www.researchgate.net/publication/230660829_Ant_Colony_Optimization_Artificial_Ants_as_a_Computational_Intelligence_Technique)

# META-HEURISTIC: MaxMin Ant System (MMAS)

## MMAS is one of the most successful ACO variants

### Changes in comparison to Classical ACO:

- Only the best ant is used to update the pheromone trails
- Maintains lower and upper bounds  $\tau_{\min}$  and  $\tau_{\max}$  for pheromone values  $\tau_e$ . Updates to  $\tau_e$  cannot exceed or fall below these boundaries.
- Pheromone is updated only for elements of the "best" solution found. "Best" solution could be smallest of solutions from current iteration, or "best-so-far", the best solution ever found.
- Update depends on the cost of the best solution (e.g. proportional to  $1/f(s)$ )

# MMAS for TSP with Nearest Neighbors

## Standard parameter settings

$\alpha = 1$ ,  $\beta = -2$ ,  $\rho = 0.98$ ,  $Q = 1$ ,  $b = 20$ ,  $m = \text{problem size}$

$\tau_{min} = \dots$ ,  $\tau_{max} = \dots$ ,  $max\_iter = \dots$

// Problem dependent

## Initialisation

$\tau_{ij} = \tau_{max}$  for all arc  $(i, j)$

## Repeat for $max\_iter$ iterations

For each ant  $k = 1, \dots, m$

$s_k = \emptyset$

// Solution built by ant  $k$

Choose a city  $i$  at random

// Current city :  $i$

Repeat, while all cities have not been visited

If there is a city  $j$  not yet visited among  $b$  nearest neighbours of  $i$

Choose a city  $j$  among them with probability proportional to  $\tau_{ij}^\alpha \cdot d_{ij}^\beta$

Else Choose a city  $j$  not yet visited with maximum  $\tau_{ij}^\alpha \cdot d_{ij}^\beta$

$s_k = s_k + (i, j)$

$i = j$

Improve solution  $s_k$  with a local search

For all arc  $(i, j)$  of the best tour  $s^*$  among  $s_1, s_2, \dots, s_m$

$\tau_{ij} = \max(\tau_{min}, \min(\tau_{max}, (1 - \rho)\tau_{ij} + Q/\text{Length}(s^*)))$

Return The best tour found

# MMAS for TSP: Pherome Update

**For all** arc  $(i, j)$  of the best tour  $s^*$  among  $s_1, s_2, \dots, s_m$   
 $\tau_{ij} = \max(\tau_{min}, \min(\tau_{max}, (1 - \rho)\tau_{ij} + Q/Length(s^*) ) )$



# Steiner Tree Problem

# Definition: Steiner Tree Problem

## Problem Definition:

Given a network  $G = (V, E, C)$  with

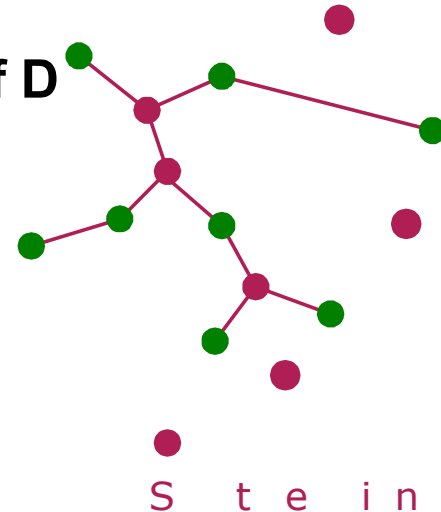
$V$  set of vertices

$E$  set of (undirected) edges

$C$  a function that specifies the weights of the edges  
and a subset  $D \subseteq V$ ,

find a tree of minimum weight that contains **all vertices of  $D$**   
(and may include additional vertices of  $V$  not in  $D$ ).

The optional nodes (which are not in  $D$ ) are called Steiner nodes.  
The nodes in  $D$  are called terminals.



Which problem is "easier" to solve?

- a) Minimum Spanning Tree
- b) Steiner Tree
- c) Both are equal



# Steiner Tree vs. MST

Join at [menti.com](https://menti.com) | use code **8283 7649**



Which problem is "easier" to solve?



0  
MST

0  
Both are same



# SOLUTION: Steiner Tree vs. MST

- If  $D = V$  in the Steiner Tree Problem, then we have an MST-Problem. Thus, in general if  $D \neq V$  the Steiner Tree Problem is harder.
- In fact, the Steiner Tree Problem is NP-hard, while MST is solvable in linear time (Prim's algorithm, with respect to the edges).
- Remark: If  $|D|=2$ , then the Steiner Tree Problem is equivalent to the shortest path problem and thus solvable in linear time (Dijkstra's algorithm, with respect to the edges).

# Steiner Tree Problem: Real World Applications

- Layout of electrical networks, water distribution networks, etc.: The edges of the input graph typically correspond to segments in the local street map, with vertices representing street intersections and the location of potential customers (terminals). The cost  $c$  associated with an edge is the cost of laying the pipe or cable on the corresponding street segment.
- Efficient point to multipoint transfers across multiple datacenters in cloud services (see e.g. <https://www.usenix.org/system/files/conference/hotcloud17/hotcloud17-paper-noormohammadpour.pdf>)

## ACO for Steiner Tree Problem

Propose an ACO for the Minimum Steiner Tree problem.  
Describe how to choose the pheromone trails and how they are exploited.

# SOLUTION: ACO for Steiner Tree



**IMPORTANT:** there is no need  
in ACO that the "ants" really  
follow a "consecutive" path

## ACO for Steiner Tree Problem

- Element  $e$  of a partial solution = edge of a tree
- An edge can only be selected as next element if it does not create a cycle
- Probability to choose edge  $e$  depends on lengths of  $e$  (in the graph) and on pheromone trail on  $e$
- Stop building as soon as all mandatory nodes are in the solution and solution is a tree

## ACO for Numerical Problems

In graph-based problems such as TSP or Steiner Tree Problem, it is usually obvious what a "step" of an ant is: Choosing an edge to the next city or node.

What about problems that are **not** graph-based, such as the Knapsack Problem? What would a "step" of an ant be here?

# SOLUTION: ACO for Knapsack

## ACO for Numerical Problems

For Knapsack Problem with items  $a_1, \dots, a_n$ :

- Start with empty solution.
- Partial solution is a selection of  $k$  items.
- Potential next steps are taking any of the items that are not yet in the knapsack and which still fit in.
- Options: Either use value or ratio of value/weight to select the next item.
- Probability to choose item  $a$  depends on value (or value/weight) of  $a$  and on pheromone trail on  $a$ .

# Santa's Challenge

