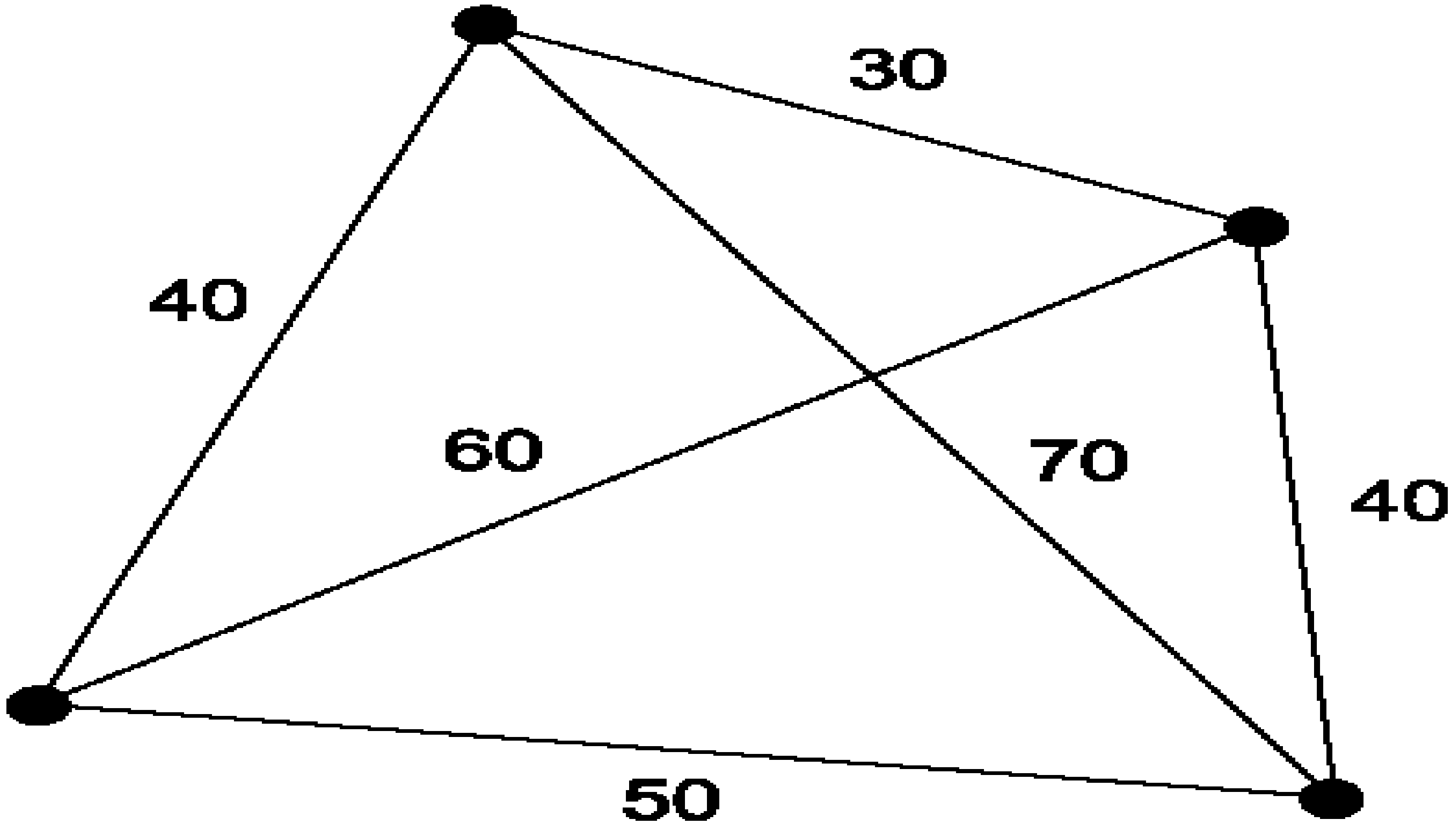
Ant Colony Optimization to solve Traveling Salesman Problem



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Topics

1. History of Ant Colony Optimization (ACO)
2. Real Ant’s Behavior
3. The Concept of Ant System
4. ACO System Concept
5. Pheromone Update Formula
6. Ant Colony Optimization Algorithm
7. Apply Ant Colony Optimization Algorithm to solve Traveling Salesman Problem
8. Example of a Simple AS to solve TSP
9. Application of ACO
10. Advantage and Disadvantages

History of Ant Colony Optimization

- The first ACO system was introduced by Marco Dorigo in his Ph.D. thesis (1992),
- It was called Ant System (AS).
- AS was initially applied to the traveling salesman problem.
- Applied later to various hard optimization problems

Macro Dorigo

Gambardella

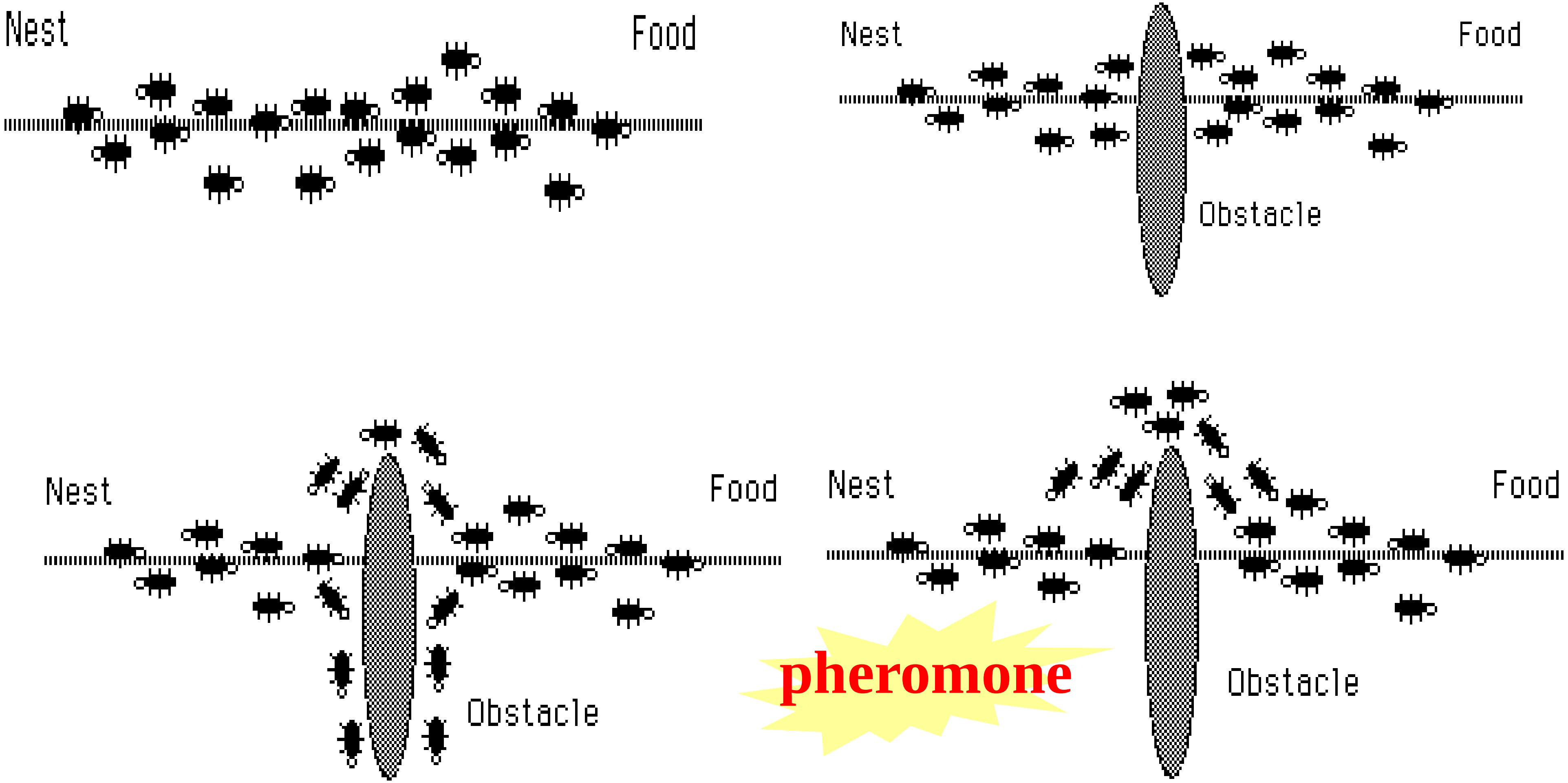
Real Ant’s Behavior

- Natural behavior of ants have inspired scientists to mimic insect operational methods to solve real-life complex problems.

- By observing ant behavior, scientists have begun to understand their means of communication.

- Ants choose paths depending on pheromone
- After collecting food, paths are marked
- Pheromone accumulation is faster on the shorter path
- After some time, the shortest path has the highest probability

Real Ant’s Behavior



The Concept of Ant System

- Ants (blind) navigate from nest to food source
- Shortest path is discovered via pheromone trails
  - each ant moves at random
  - pheromone is deposited on path
  - ants detect lead ant's path, inclined to follow
  - more pheromone on path increases the probability of path being followed

- These pheromones evaporate with time.

The Concept of Ant System

- The shorter path will be reinforced by the pheromones further.
- Finally , the ants arrive at the shortest path.
- Starting node selected at random
- Path selected at random
  - based on amount of “trail” present on possible paths from starting node
  - higher probability for paths with more “trail”
- Ant reaches next node, selects next path
- Continues until reaches starting node
- Finished “tour” is a solution

The Concept of Ant System

- A completed tour is analyzed for optimality
- “Trail” amount adjusted to favor better solutions
  - better solutions receive more trail
  - worse solutions receive less trail
  - higher probability of ant selecting path that is part of a better-performing tour
- New cycle is performed
- Repeated until most ants select the same tour on every cycle

Ant Colony Algorithms

- Algorithm was inspired by observation of real ant colonies.
- Ants are essentially blind, deaf and dumb.
- Q: how can ants find the shortest path to food sources?
- Ants deposit *pheromones* on ground that form a trail. The trail attracts other ants.

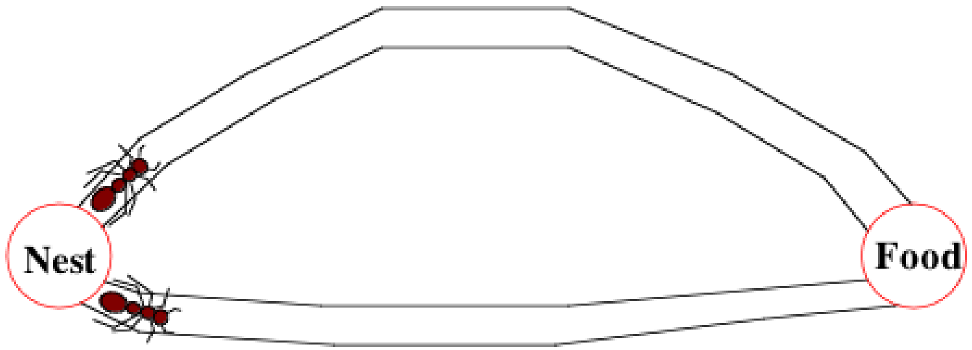
- The ants evaluate the cost of the paths they have traversed.
- The shorter paths will receive a greater deposit of pheromones.
- An evaporation rule will be tied with the pheromones, which will reduce the chance for poor quality solutions.

How Ants find foods

How Ants find foods

Ant foraging

Cooperative search by pheromone trails



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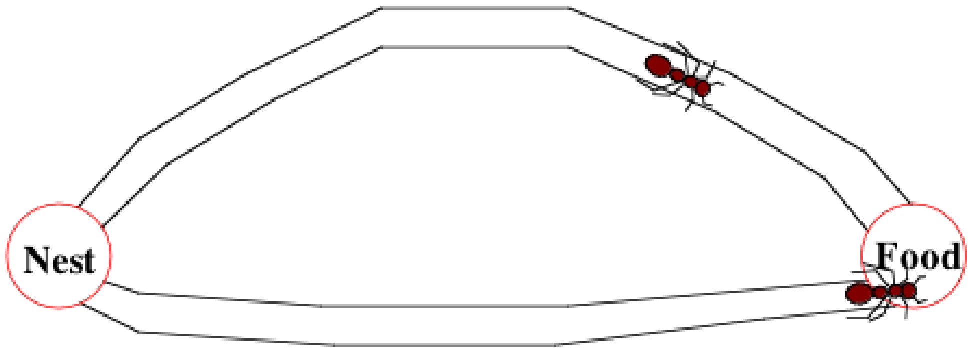

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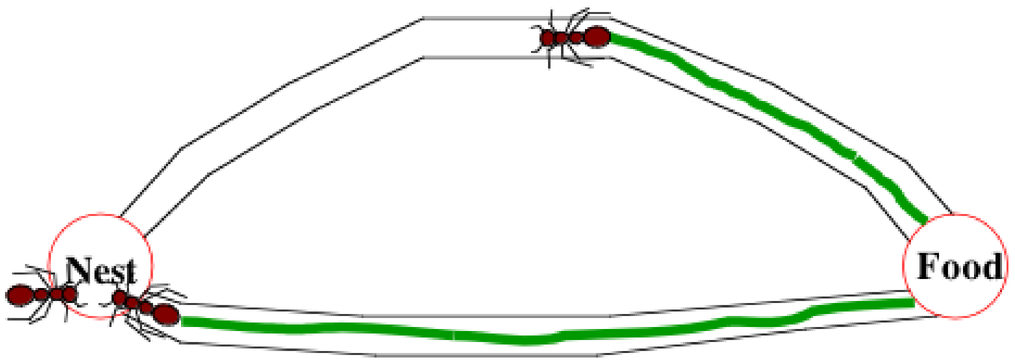

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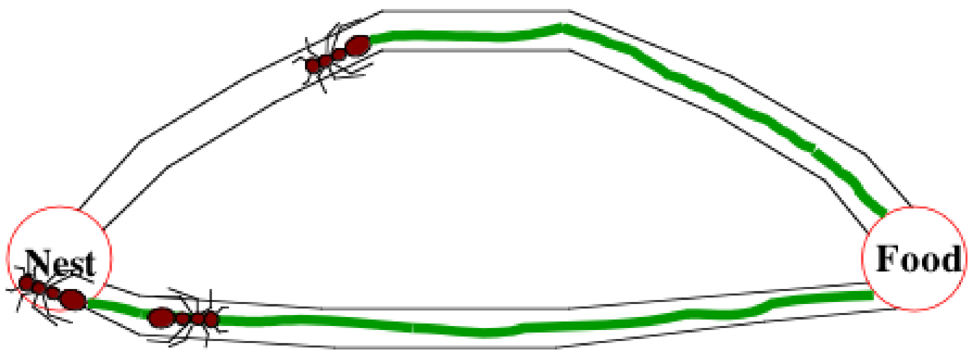

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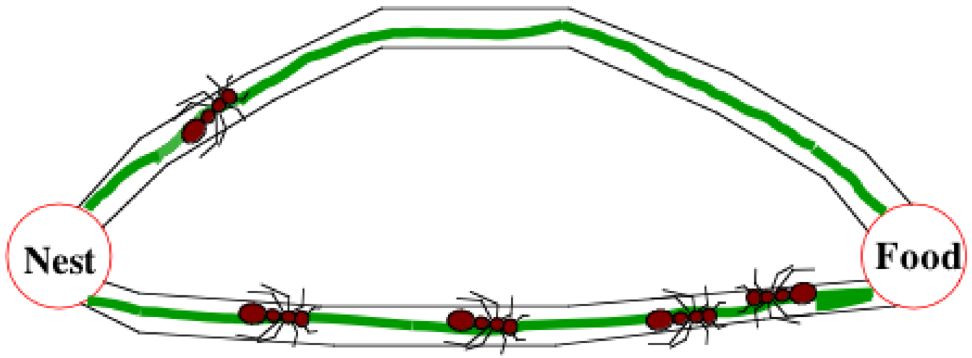

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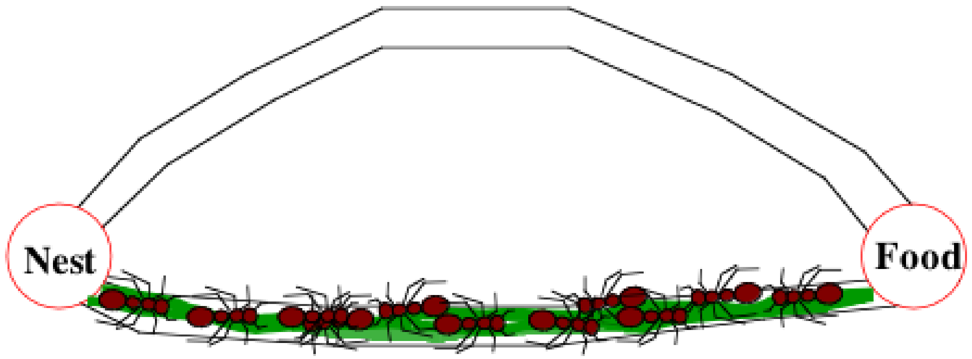


Ant System (AS)

- Three different versions are proposed:
  - Ant Density
  - Ant quantity
  - Ant cycle

Pheromone updated after each move of ant from one city to another

Pheromone updates after all ants construct tour

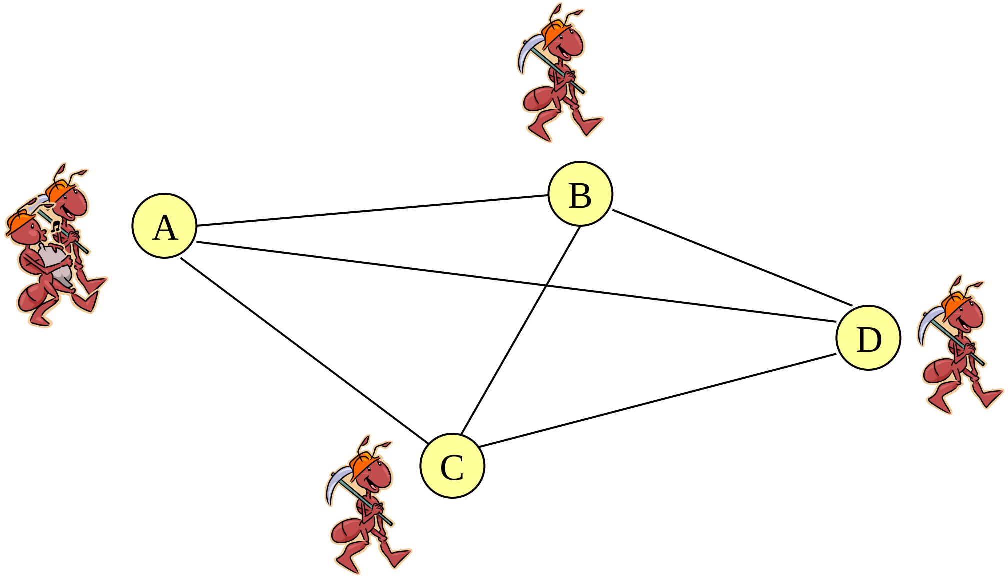
Ant cycle in performed mush better than other two.
We will present Ant-cycle algorithm

Ant Systems for TSP:

Graph (N,E): where N = cities/nodes, E = edges

= *the tour cost from city i to city j (edge weight)*

Ant move from one city i to the next j with some transition probability.



Tour Construction

1. Initially, each ant is put on some randomly chosen city.
2. Tabu list: N_i^k set of all cities that ant k has not visited
3. $n_{ij} = 1/d_{ij}$, **visibility**: Heuristic desirability of choosing city j when in city i.
4. **Pheromone trail**: $T_{ij}(t)$ This is a global type of information

Transition probability: Ant *k*, currently at city *i*, chooses to go to city *j* at *t* th iteration is:

$$P_{ij}^{k}(t) = \frac{[T_{ij}(t)]^{\alpha} \cdot [n_{ij}]^{\beta}}{\sum_{l \in J_i^k} [T_{lk}(t)]^{\alpha} \cdot [n_{lk}]^{\beta}} \quad \text{If } j \in N_i^k$$

Closest cities are selected based on pheromone and distance.

- α,β determines relative influence of pheromone trail and heuristic information
- If α=0, closest cities are more likely to be selected. Approaches to greedy algorithm
- If β=0, only pheromone amplification is at work

Pheromone Update Rule

- After all ants constructed their tours, pheromone trails are updated.
- It is done by
  - Firstly, lowering the pheromone strength on all arcs by a constant factor
  - Secondly, allowing each ant to add pheromone on the arcs it has visited.

$$\tau_{ij}(t+1) = (1-\rho)\cdot\tau_{ij}(t) + \sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t)$$

(Trail pheromone decay)

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} 1/L^{k}(t) \quad \text{or } Q/L & \text{if arc } (i,j) \text{ is used by ant } k \\ 0 & \text{otherwise} \end{cases}$$

$L^{k}(t)$ is length of *k*th ant's tour. 0 < ρ <= 1 is pheromone trail evaporation.

- ➢ The better the ant's tour is, more pheromone is received by arcs belonging to the tour.
- ➢ In general, arcs used by many ants and contained in shorter tours will receive more pheromone.

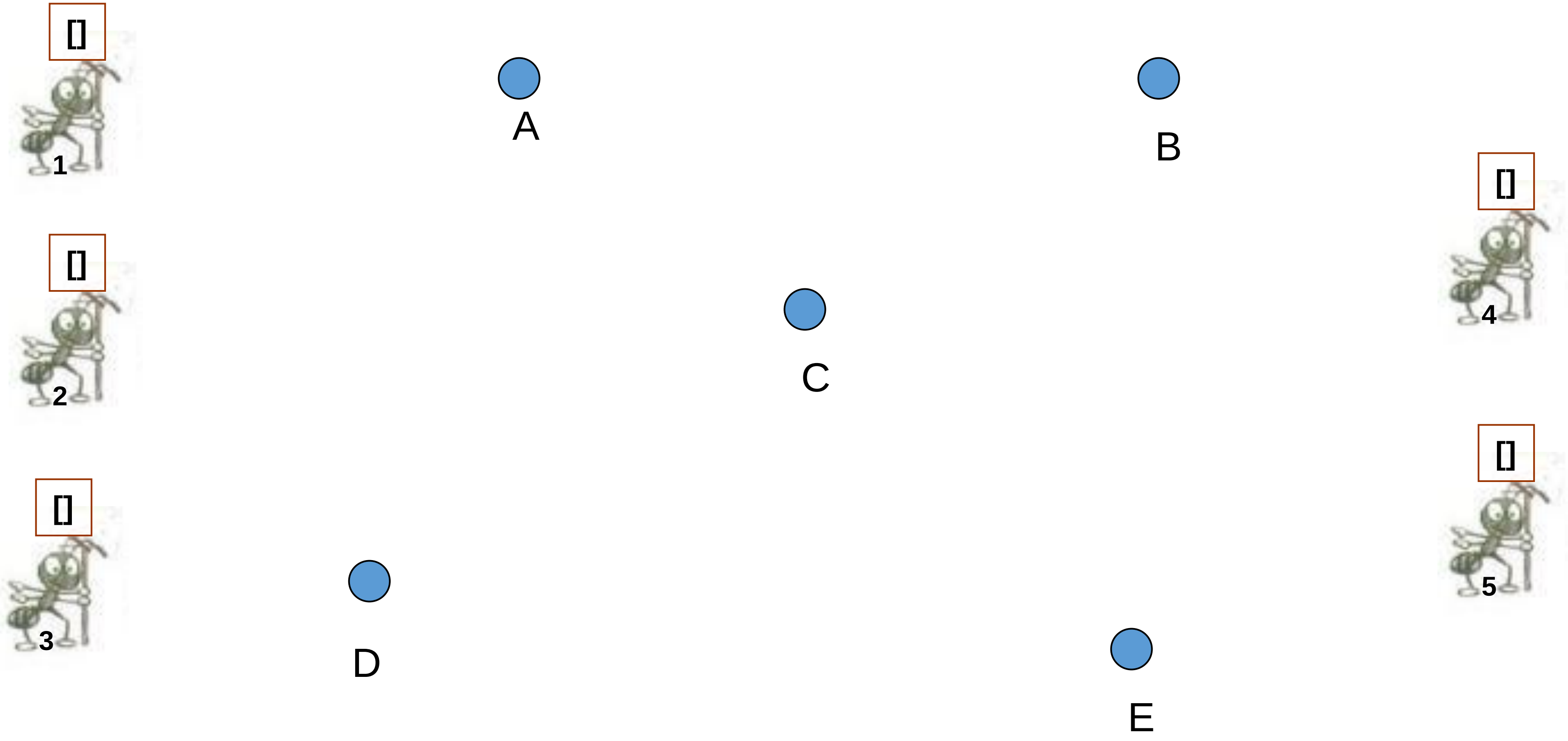
Key Parameters

$$P_{ij}^{k}(t) = \frac{[T_{ij}(t)]^{a} \cdot [n_{ij}]^{\beta}}{\sum_{l \in J_i^k} [T_{lk}(t)]^{a} \cdot [n_{lk}]^{\beta}}$$

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t)$$

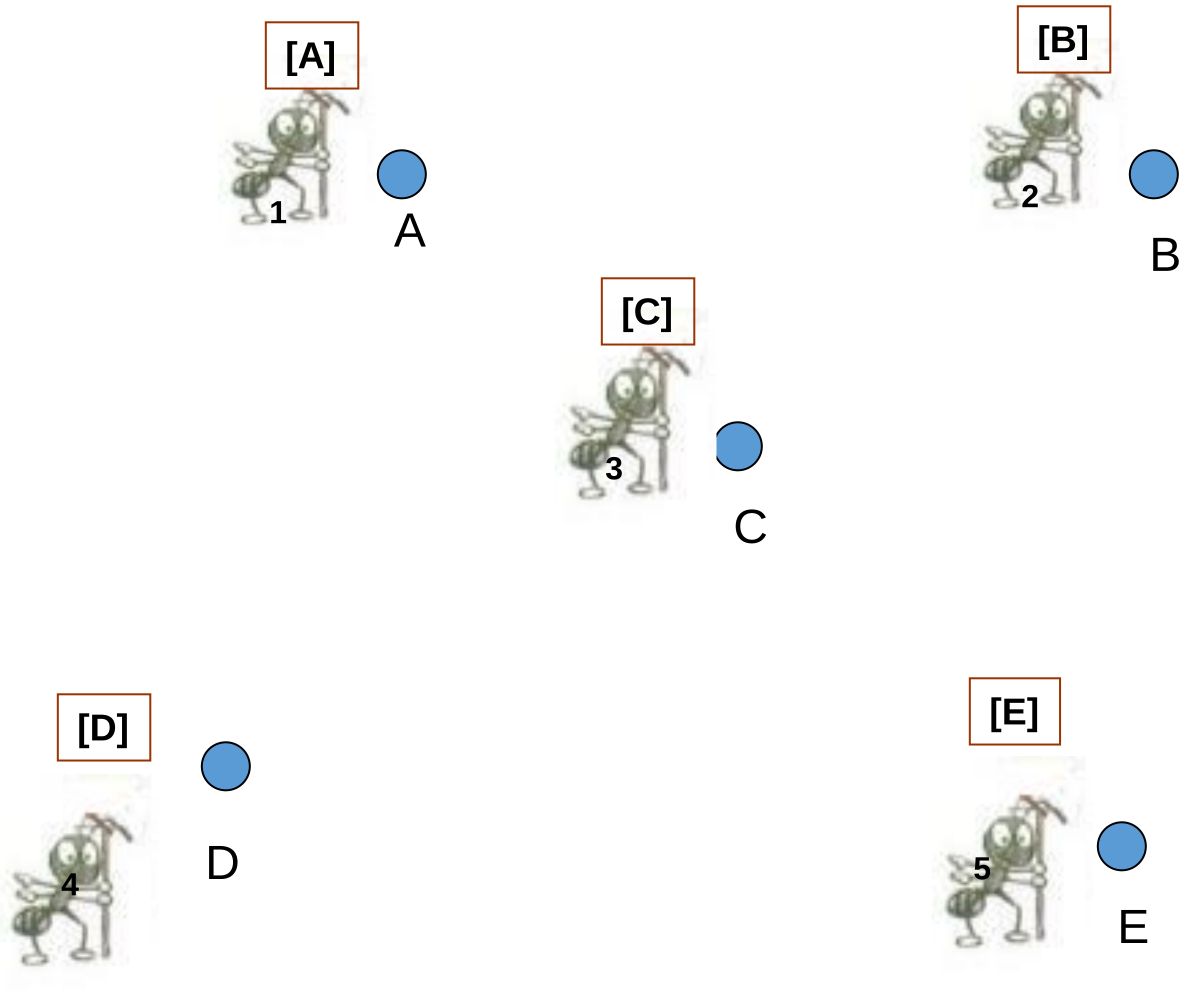
- Trail intensity is given by value of τ_{ij} which indicates the intensity of the pheromone on the trail segment, (*ij*)
- Trail visibility is $\eta_{ij} = 1/d_{ij}$: a heuristic function of the desirability of adding edge (d_{ij} is distance from i to j)
- importance of the intensity in the probabilistic transition is α
- The importance of the visibility of the trail segment is β
- The trail persistence or evaporation rate is given as ρ
- *Q* is a constant and the amount of pheromone laid on a trail segment employed by an ant (for $\Delta\tau_{ij}^{(k)} \leftarrow Q/L_k$)
- Initial pheromone is a small amount on all edges

Example of a Simple AS to solve TSP

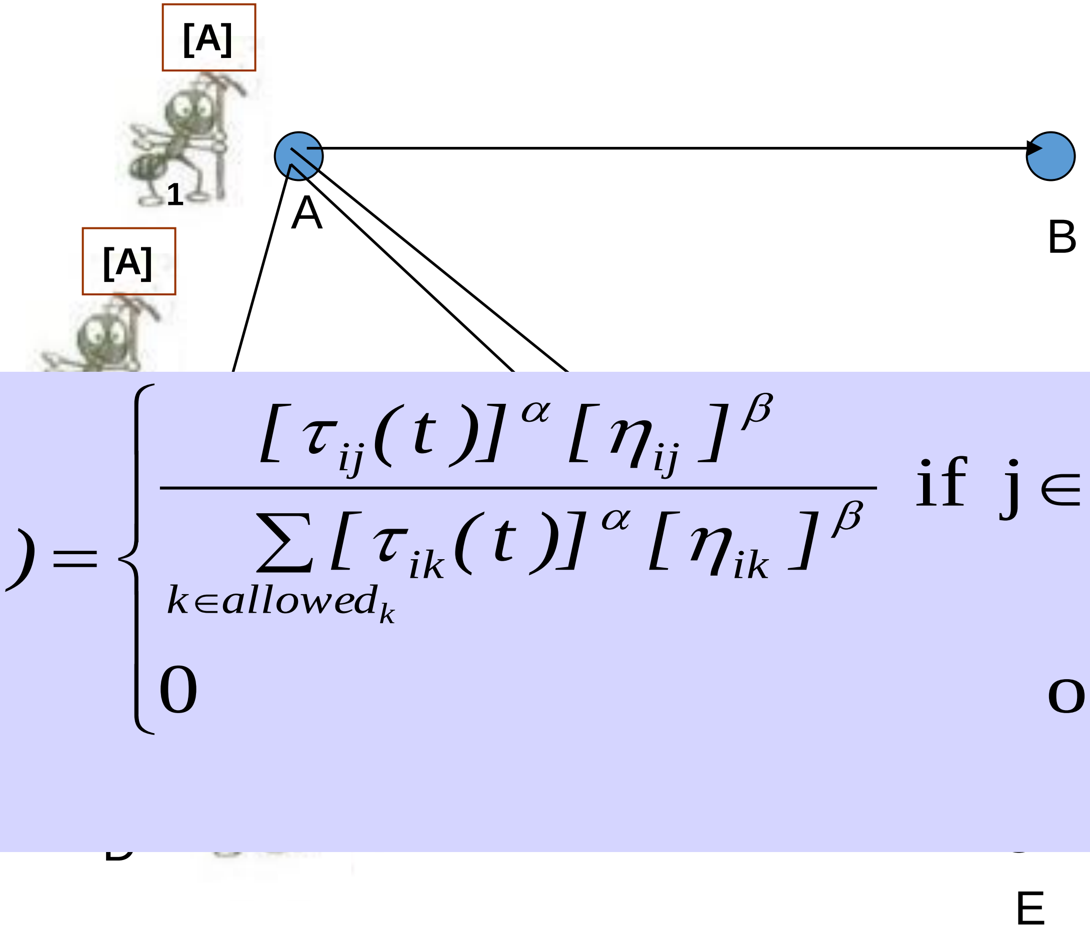


d_{AB} =100;d_{BC} = 60…;d_{DE} =150

Example of a Simple AS to solve TSP

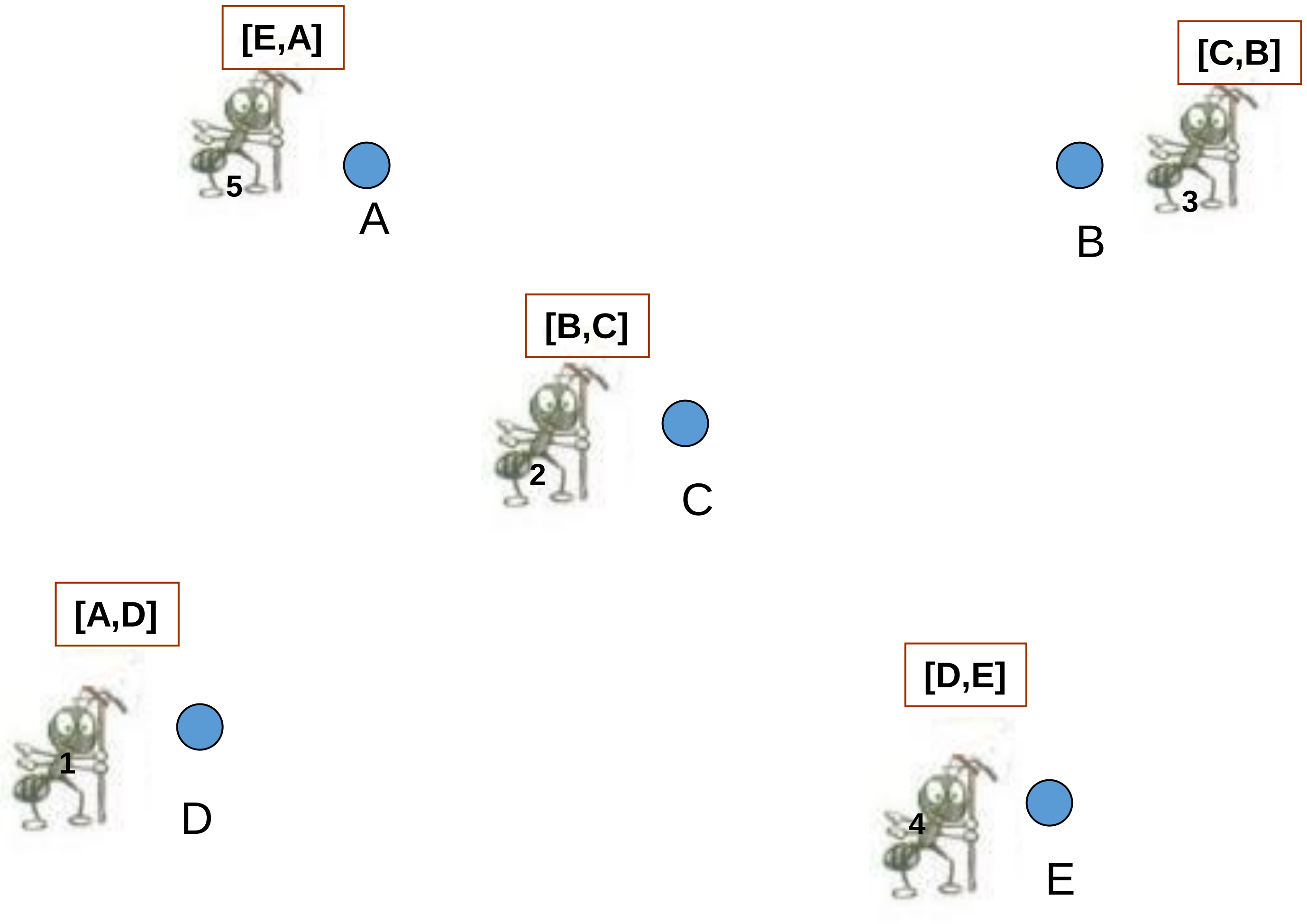


Example of a Simple AS to solve TSP

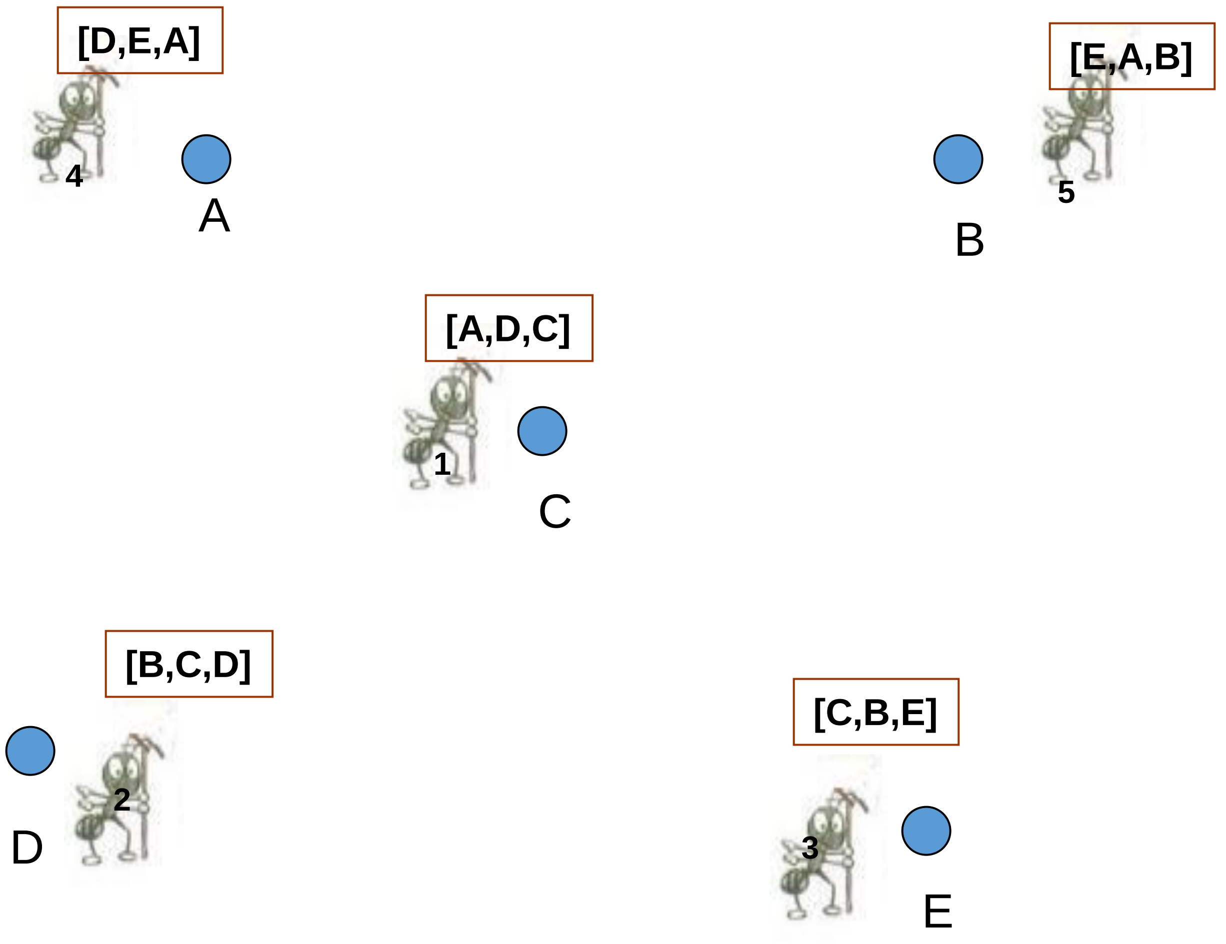


$$p_{ij}^{k}(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum\limits_{k\in allowed_k}[\tau_{ik}(t)]^{\alpha}[\eta_{ik}]^{\beta}} & \text{if } j\in \text{allowed}_{k}\\ 0 & \text{otherwise}\end{cases}$$

Example of a Simple AS to solve TSP



Example of a Simple AS to solve TSP



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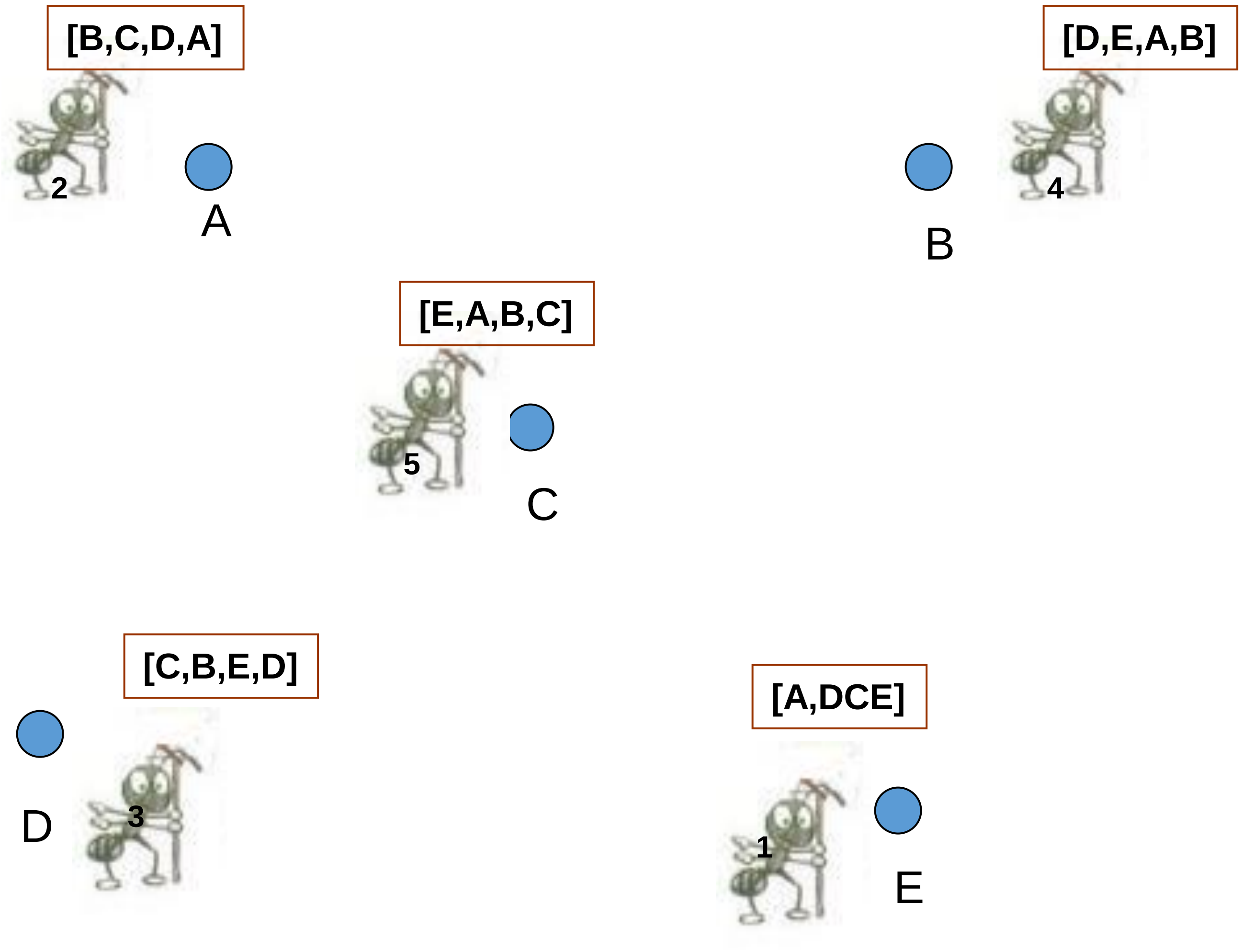

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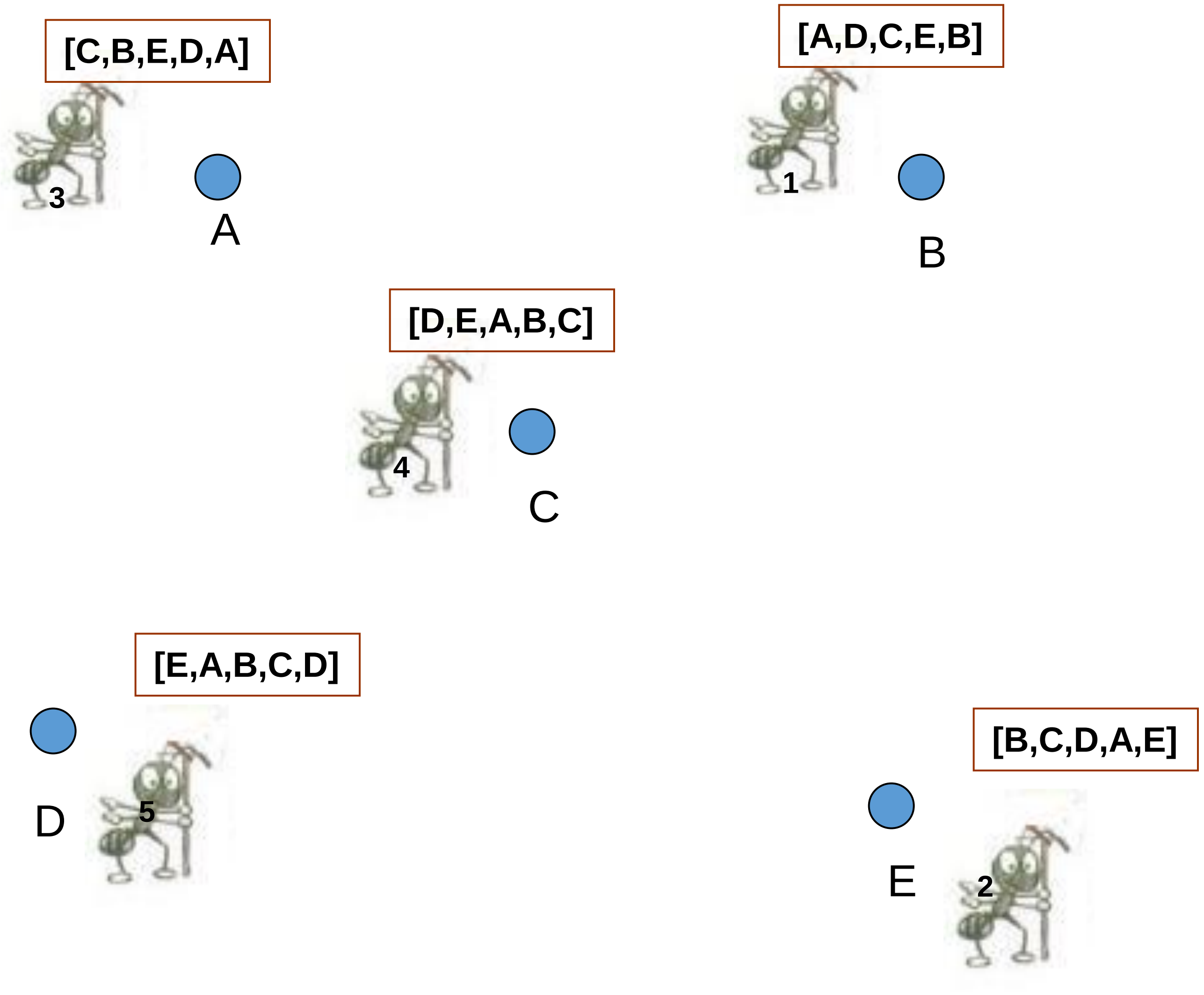
Example of a Simple AS to solve TSP



Example of a Simple AS to solve TSP

[A,D,C,E,B]

L_1 =300

[B,C,D,A,E]

L_2 =450

$$\Delta\tau_{i,j}^{k} = \begin{cases} \dfrac{Q}{L_k} & if\,(i,j) \in \text{tour} \\ 0 & \text{otherwise} \end{cases}$$

[C,B,E,D,A]

$$\Delta\tau_{A,B}^{total} = \Delta\tau_{A,B}^{1} + \Delta\tau_{A,B}^{2} + \Delta\tau_{A,B}^{3} + \Delta\tau_{A,B}^{4} + \Delta\tau_{A,B}^{5}$$

[D,E,A,B,C]

L_4 =280

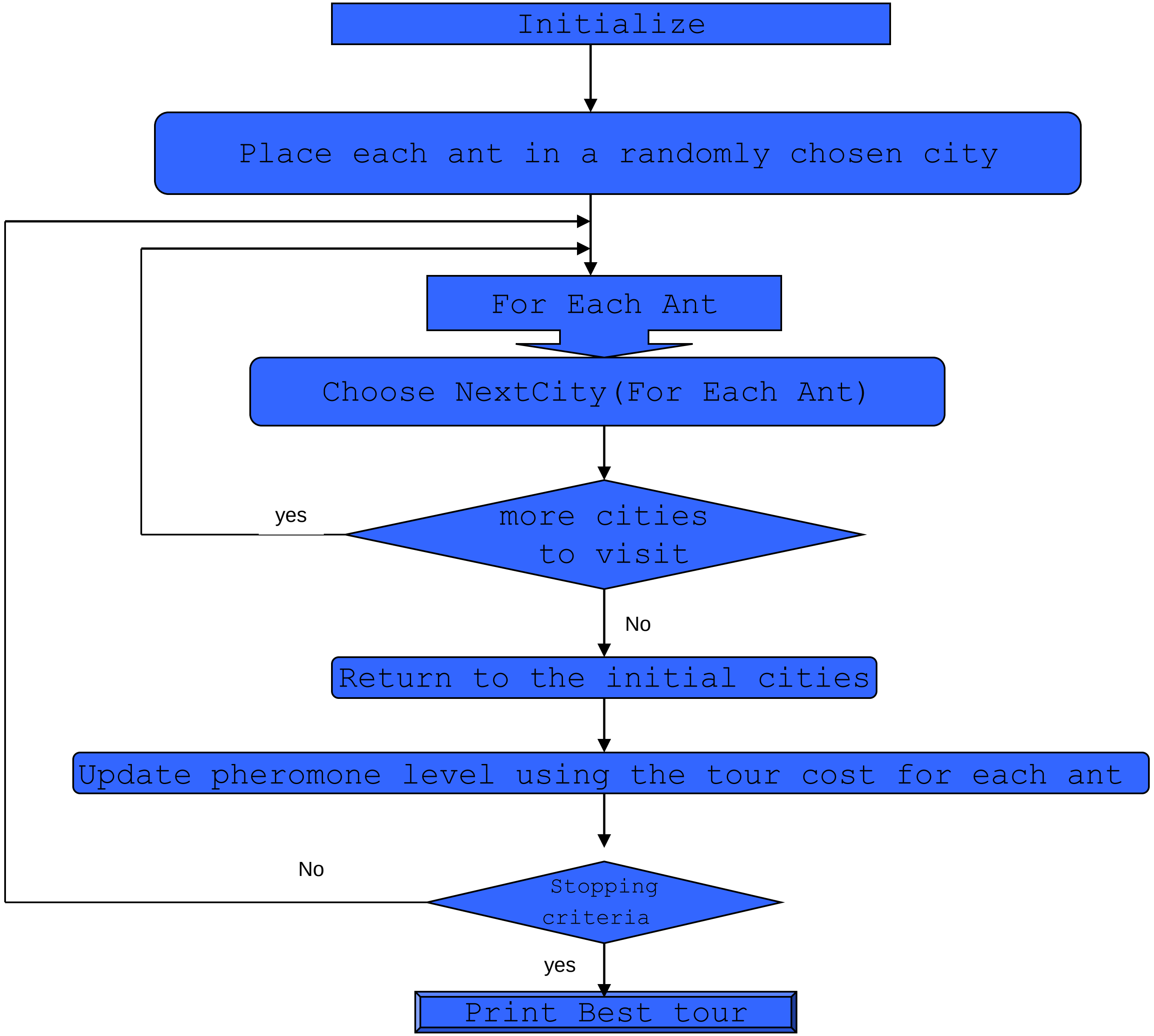
[E,A,B,C,D]

L_5 =420

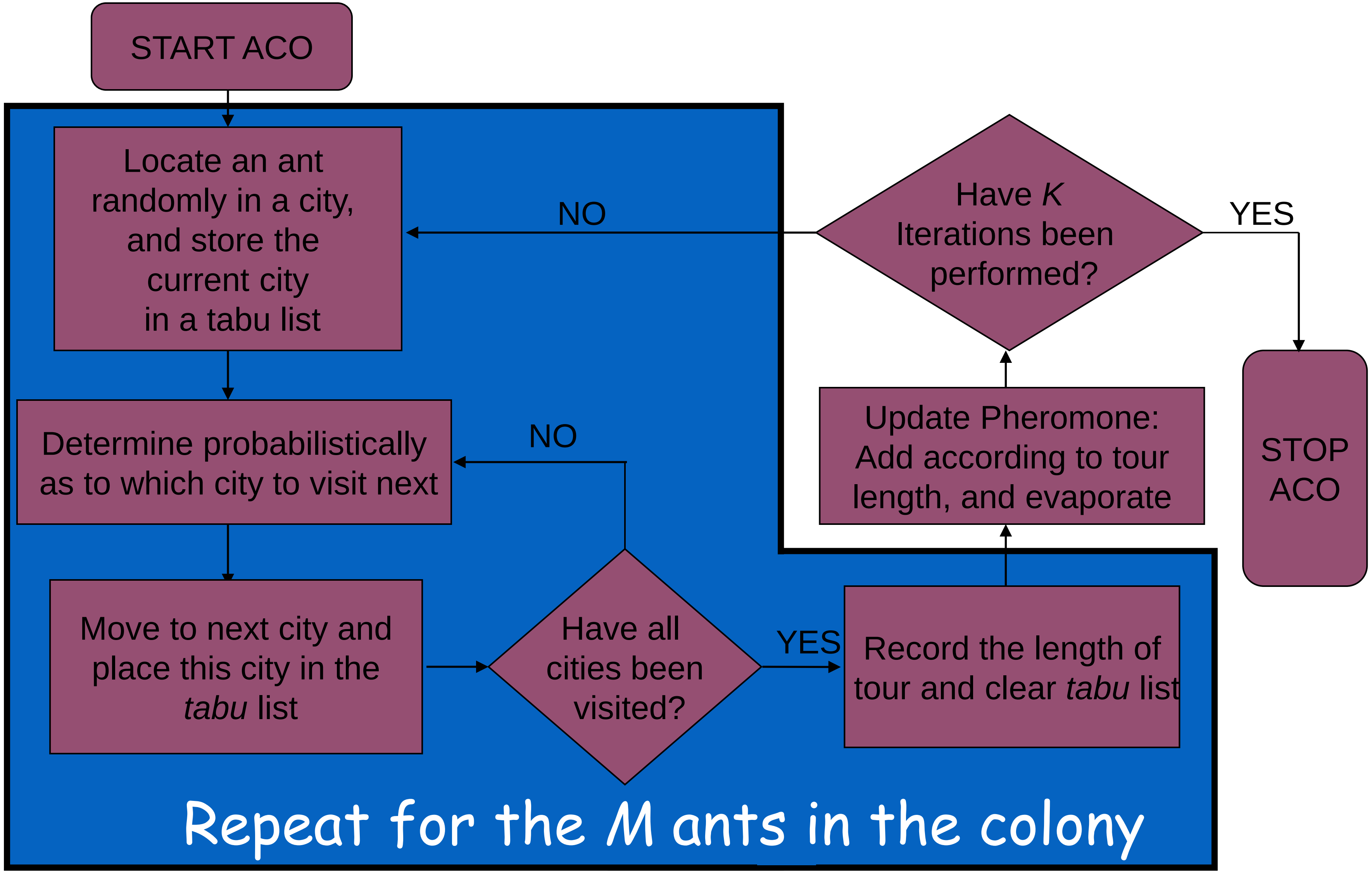
Application of ACO

- Traveling Salesman Problem (TSP)
- Class Scheduling Problem (CSP)
- Function Optimization
- Vehicle Routing
- Sequential Ordering
- Graph Coloring
- Frequency Assignment
- Train Time Scheduling
- Water Distribution Network
- Quadratic assignment problems (QAP)
- Dynamic routing problems in networks and so on…

Ant Systems Algorithm for TSP



Another ACO Flowchart for TSP



ACO Algorithm for TSP

n = number of cities
α, β = relative importance of pheromones vs. heuristic information
Q = deposition constant
ρ = evaporation rate $\in (0, 1)$
$\tau_{ij} = \tau_0$ (initial pheromone between cities i and j) for $i \in [1, n]$ and $j \in [1, n]$
d_{ij} = distance between cities i and j for $i \in [1, n]$ and $j \in [1, n]$
While not(termination criterion)
    For $q = 1$ to $n - 1$
        For each ant $k \in [1, N]$
            Initialize the starting city c_{k1} of each ant $k \in [1, N]$
            Initialize the set of cities visited by ant k: $C_k \leftarrow \{c_{k1}\}$ for $k \in [1, N]$
            For each city $j \in [1, n]$, $j \notin C_k$
                probability $p_{ij}^{(k)} \leftarrow \left(\tau_{ij}^{\alpha}/d_{ij}^{\beta}\right) / \left(\sum_{m=1, m \notin C_k}^{n} \tau_{im}^{\alpha}/d_{im}^{\beta}\right)$
            Next j
            Let ant k go to city j with probability $p_{ij}^{(k)}$
            Use $c_{k,q+1}$ to denote the city selected in the previous line
            $C_k \leftarrow C_k \cup \{c_{k,q+1}\}$
        Next ant
    Next q
    $L_k \leftarrow$ total path length constructed by ant k, for $k \in [1, N]$
    For each city $i \in [1, n]$ and each city $j \in [1, n]$
        For each ant $k \in [1, N]$
            If ant k went from city i to city j
                $\Delta\tau_{ij}^{(k)} \leftarrow Q/L_k$
            else
                $\Delta\tau_{ij}^{(k)} \leftarrow 0$
            End if
        Next ant
        $\tau_{ij} \leftarrow (1 - \rho)\tau_{ij} + \sum_{k=1}^{N} \Delta\tau_{ij}^{(k)}$
    Next city pair
Next generation

Figure 10.6 A simple ant system (AS) for solving a TSP. Each generation, some of the pheromone between cities i and j evaporates, but the pheromone also increases due to ants that travel between the two cities.

ACO Algorithm for TSP

Algorithm 6.3.1: Pseudocode for Ant System.

Input: ProblemSize, $Population_{size}$, m, ρ, α, β
Output: P_{best}

$P_{best} \leftarrow$ `CreateHeuristicSolution(`ProblemSize`)`;
$Pbest_{cost} \leftarrow$ `Cost(`S_h`)`;
Pheromone $\leftarrow$ `InitializePheromone(`$Pbest_{cost}$`)`;
while $\neg$`StopCondition()` **do**
    Candidates $\leftarrow \emptyset$;
    for $i = 1$ **to** m **do**
        $S_i \leftarrow$ `Probabilis` … `truction(`Pheromone, ProblemSize, α, β`)`;
        $Si_{cost} \leftarrow$ `Cost(`S_i`)`;
        if $Si_{cost} \leq Pbest_{cost}$ **then**
            $Pbest_{cost} \leftarrow Si_{cost}$;
            $P_{best} \leftarrow S_i$;
        end
        Candidates $\leftarrow S_i$;
    end
    `DecayPheromone(`Pheromone, ρ`)`;
    foreach $S_i \in$ Candidates **do**
        `UpdatePheromone(`Pheromone, S_i, Si_{cost}`)`;
    end
end
return P_{best};

$$\Delta\tau_{ij}^{(k)} \leftarrow Q/L_k$$

ACO Algorithm for TSP

// Initialize pheromone trails
for (every edge i, j) {
$\tau = \tau_0$
ng town for every ant
++) {
on a randomly chosen city
t tour and length
our found from the beginning
the best tour

// Initialize pheromone trails
for (every edge i, j) {
$\tau = \tau_0$
}
// Choose the starting town for every ant
for ($k = 1; k \leq m; k{+}{+}$) {
Place ant k on a randomly chosen city
}
// Initialize the best tour and length
T^+ = the shortest tour found from the beginning
L^+ = the length of the best tour
// Main loop
for ($t = 1; t \leq Tmax; t{+}{+}$) {
// Compute a tour for every ant
for ($k = 1; k \leq m; k{+}{+}$) {
Build tour $T_k(t)$ by applying $n - 1$ times the following step:
Choose the next node (city) j with the probability
$p_{ij}^k(t) = \frac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}{\sum_{l \in J_i^k} [\tau_{il}(t)]^\alpha \cdot [\eta_{il}(t)]^\beta}$, if $j \in J$
$p_{ij}^k(t) = 0$, if $j \notin J$
where i is the current city.
}
// Compute the tour lengths for all ants
for ($k = 1; k \leq m; k{+}{+}$) {
Compute the length $L_k(t)$ of the tour $T_k(t)$ produced by ant k
}
// Update the best tour if an improved tour is found
if (an improved tour is found) {
Update T^+ and L^+
print T^+ and L^+
}

// Global update for the pheromone trails
for (every edge i, j) {
Update the pheromone trails by applying the rule:
$\tau_{ij}(t) = (1 - \rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t) + e \cdot \tau_{ij}^e(t)$, where
$\Delta\tau_{ij}(t) = \sum_{k=1}^m \Delta\tau_{ij}^k(t)$
$\Delta\tau_{ij}^k(t) = \left\{ \frac{Q/L^k(t), if (i,j) \in T^k(t)}{0, otherwise} \right\}$
and
$\tau_{ij}^e(t) = \left\{ \frac{Q/L^+ \ if (i,j) \in T^+}{0, otherwise} \right\}$
}
// Calculate the intensity of the pheromone for next iteration
for (every edge i, j) {
$\tau_{ij}(t + 1) = \tau_{ij}(t)$
}
}

$_{ij}(t) = \sum_{k=1}^m \Delta\tau_{ij}^k(t)$
$_{ij}^k(t) = \left\{ \frac{Q/L^k(t), if (i,j) \in T^k(t)}{0, otherwise} \right\}$
d
$(t) = \left\{ \frac{Q/L^+ \ if (i,j) \in T^+}{0, otherwise} \right\}$
the intensity of the pheromone for next iteration
edge i, j) {
$_{ij}(t + 1) = \tau_{ij}(t)$

Advantage and Disadvantages

- For TSPs (Traveling Salesman Problem), relatively efficient
  - for a small number of nodes, TSPs can be solved by exhaustive search
  - for a large number of nodes, TSPs are very computationally difficult to solve (NP-hard) – exponential time to convergence

- Performs better against other global optimization techniques for TSP (neural net, genetic algorithms, simulated annealing)

- Compared to GAs (Genetic Algorithms):
  - retains memory of entire colony instead of previous generation only
  - less affected by poor initial solutions (due to combination of random path selection and colony memory)

Advantage and Disadvantages

- Can be used in dynamic applications (adapts to changes such as new distances, etc.)
- Has been applied to a wide variety of applications
- As with GAs, good choice for constrained discrete problems (not a gradient-based algorithm)

- Theoretical analysis is difficult:
  - Due to sequences of random decisions (not independent)
  - Probability distribution changes by iteration
  - Research is experimental rather than theoretical
- Convergence is guaranteed, but time to convergence uncertain

Advantage and Disadvantages

- Tradeoffs in evaluating convergence:
  - In NP-hard problems, need high-quality solutions quickly – focus is on quality of solutions
  - In dynamic network routing problems, need solutions for changing conditions – focus is on effective evaluation of alternative paths

- Coding is somewhat complicated, not straightforward
  - Pheromone "trail" additions/deletions, global updates and local updates
  - Large number of different ACO algorithms to exploit different problem characteristics

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