Session : Ant Colony Optimization

Course Title: Computational Intelligence
Course Code: 19CSE422A

Course Leader:
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Objectives of this Session

I wish to:

1. Highlight some interesting facts about biological ants
2. Introduce the intelligent social foraging behavior of ants
3. Discuss the random exploration and stigmergy-based foraging
4. Discuss the simple ant colony optimization algorithm (SACO)
5. Discuss the pros and cons of the SACO algorithm
6. Discuss the ant system (AS) algorithm
7. Introduce the variants of ant colony optimization
8. Discuss the influence of the various parameters on the effectiveness of algorithm

Intended Outcomes of this Session

At the end of this session, the student will be able to:

1. Summarize the interesting facts about ants in nature
2. Discuss the stigmergy-based foraging behavior of ants
3. Develop code for ant decision process
4. Develop code for pheromone depositing and evaporation
5. Develop the simple ant colony optimization (ACO) algorithm
6. Develop the ant systems algorithm
7. Distinguish between the numerous variants of ACO
8. Choose good values of parameters of ACO and
9. List the applications of ACO

Recommended Resources for this Session

1. Engelbrecht, A. P. (2007). *Computational intelligence: An introduction*. Chichester, England, John Wiley & Sons.

2. Konar, A. (2005). *Computational Intelligence: Principles, Techniques and Applications*. Secaucus, NJ, USA, Springer-Verlag New York, Inc.

Ants and their Colonies

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- The ant has two compound eyes, each of which has many smaller eyes

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- The job of the queen is to lay eggs which the worker ants look after. Worker ants are sterile, they look for food, look after the young, and defend the nest from unwanted visitors

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- The Slave-Maker Ant raids the nests of other ants and steals their pupae. When they hatch, they work as slaves within the colony

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- The Leaf Cutter Ants are farmers. They cut out pieces of leaves which they take back to their nests. They chew them into a pulp and a special fungus grows on it

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- Models have been developed for division of labor, cooperative support, self-assembly, and cemetery organization as well

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- Algorithms developed based on studies of ant foraging are collectively called instances of the ant colony optimization (ACO) meta-heuristic
- Since ACO models the foraging behavior of ants, we start from just there

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- When an ant locates a food source, it carries food to the nest while laying pheromone along the trail

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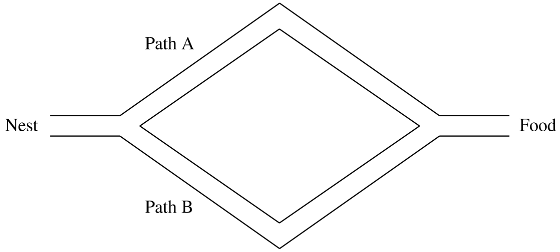
- The indirect communication where ants modify their environment by laying of pheromones to influence the behavior of other ants is referred to as **stigmergy**

Binary Bridge Experiment



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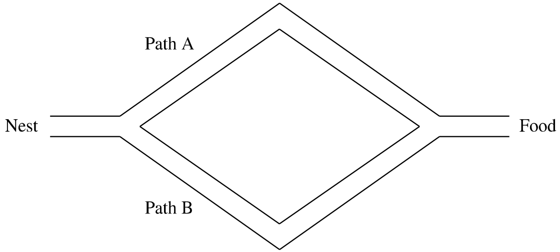

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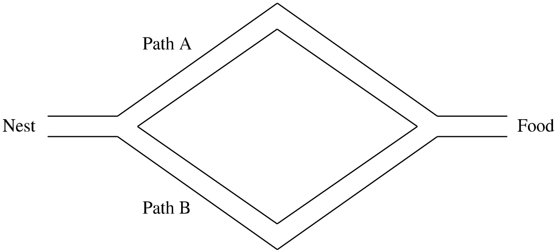

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- The selection of that branch is due to random fluctuations that caused higher concentrations on that path

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$$P_A(t+1) = \frac{(c+n_A(t))^\alpha}{(c+n_A(t))^\alpha + (c+n_B(t))^\alpha} = 1 - P_B(t+1)$$

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- Here c quantifies the degree of attraction of an unexplored branch and α is the bias to using pheromone deposits in the decision process
- The larger the value of α, the higher the probability that the next ant follows the path with a higher pheromone concentration $\alpha \approx 2$ and $c \approx 20$ matches to the observed behavior

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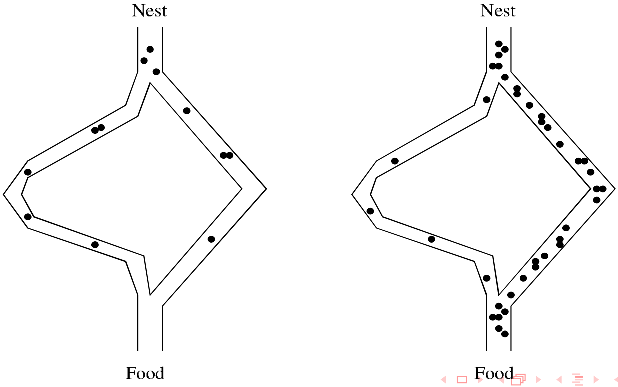
- Consider the bridge that has unequal paths



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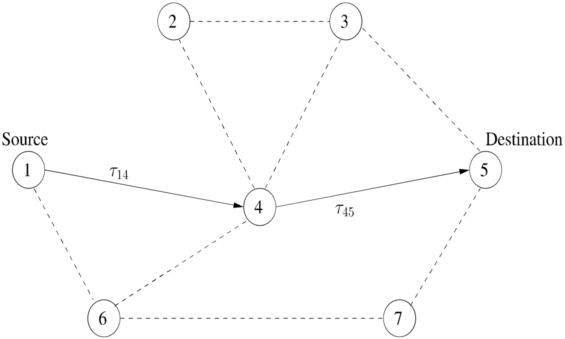
- Over time, shorter paths have stronger pheromone concentrations since they are chosen by ants most often
- Pheromone evaporates over time. The pheromone concentrations on the longer paths decrease more quickly than on the shorter paths

Artificial Ant Decision Process

Algorithm 7.1. Artificial Ant Decision Process

```
Let r ~ U(0,1);
for Each potential path A do
    Determine P_A;
    if r < P_A then
        Follow path A;
        Break;
    end if
end for
```

Simple Ant Colony Optimization (SACO)



- SACO provides solution to the problem of finding the shortest path between two nodes on a graph $G = (V, E)$. V is the set of nodes (vertexes) and E is a matrix representing the connections (edges) between nodes

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- A number of ants $k = 1, \ldots, n_k$, are placed on the source node. At each node, each ant executes a decision policy to determine the next link of the path
- Thus each ant incrementally and iteratively constructs a path to the destination

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- If ant k is currently located at node i, it selects the next node $j \in \mathcal{N}_i^k$ based on the transition probability

$$p_{ij}^k(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)}{\displaystyle\sum_{j \in \mathcal{N}_i^k} \tau_{ij}^{\alpha}(t)} & \text{if } j \in \mathcal{N}_i^k \\ 0 & \text{if } j \notin \mathcal{N}_i^k \end{cases}$$

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- Here, $j \in \mathcal{N}_i^k$ is the set of feasible nodes connected to node i, with respect to ant k. If, for any node i and ant k, $\mathcal{N}_i^k = \emptyset$, then the predecessor to node i is included in $\mathcal{N}_i^k$

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- Here, α is a positive constant used to amplify the influence of pheromone concentrations

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- Here, $\Delta\tau_{ij}^{k}(t)$ is the quality of the constructed path (its length). Any other measure of quality can be used

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- Here, $\Delta\tau_{ij}^{k}(t)$ is the quality of the constructed path (its length). Any other measure of quality can be used
- In implicit evaluation of paths, all ants deposit the same amount of pheromone. In explicit, pheromone amounts are proportional to some quality measure of constructed solutions

Simple Ant Colony Optimization

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- In implicit evaluation of paths, all ants deposit the same amount of pheromone. In explicit, pheromone amounts are proportional to some quality measure of constructed solutions
- SACO terminates when a maximum number of iterations, n_t, has been exceeded, an acceptable solution has been found, or all ants follow the same path

Simple ACO Algorithm

Algorithm 17.2 Simple ACO Algorithm

Initialize $\tau_{ij}(0)$ to small random values;
Let $t = 0$;
Place n_k ants on the origin node;
repeat
    for *each ant* $k = 1, \ldots, n_k$ **do**
        //Construct a path $x^k(t)$;
        $x^k(t) = \emptyset$;
        repeat
            Select next node based on the probability defined in equation (17.2);
            Add link (i, j) to path $x^k(t)$;
        until *destination node has been reached*;
        Remove all loops from $x^k(t)$;
        Calculate the path length $f(x^k(t))$;
    end
    for *each link* (i, j) *of the graph* **do**
        //pheromone evaporation;
        Reduce the pheromone, $\tau_{ij}(t)$, using equation (17.5);
    end
    for *each ant* $k = 1, \ldots, n_k$ **do**
        for *each link* (i, j) *of* $x^k(t)$ **do**
            $\Delta\tau^k = \frac{1}{f(x^k(t))}$;
            Update τ_{ij} using equation (17.4);
        end
    end
    $t = t + 1$;
until *stopping condition is true*;
Return the path $x^k(t)$ with smallest $f(x^k(t))$ as the solution;

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- For large values of ρ, pheromone evaporates rapidly, while for small values it evaporates slower
- The more pheromones evaporate, the more random the search becomes, facilitating better exploration. For $\rho = 1$, the search is completely random

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- For smaller α, the algorithm generally converges to the shortest path. For complex problems, large values of α result in worse convergence behavior

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- η_{ij} represents the *a priori* effectiveness (attractiveness) of the move from i to j, computed using some heuristic
- The pheromone concentrations τ_{ij} indicate how profitable it has been to make a move from i to j (memory of previous best moves)

Transition Probability: AS Versus SACO

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- If $\beta = 0$, the attractiveness (or potential benefit) of moves is neglected and the search algorithm is similar to SACO

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- For this purpose, a tabu list is usually maintained for each ant. As an ant visits a new node, that node is added to the ants tabu list
- Nodes in the tabu list are removed from $\mathcal{N}_i^k$ ensuring that no node is visited more than once

Pheromone Evaporation in AS

1. After completion of a path by each ant, the pheromone on each link is updated as $\tau_{ij}(t+1) = \tau_{ij}(t) + \Delta\tau_{ij}(t)$, with

   $$\Delta\tau_{ij}(t) = \sum_{k=1}^{n_k} \Delta\tau_{ij}^{k}(t)$$

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2. Here $\Delta\tau_{ij}^k(t)$ is the amount of pheromone deposited by ant k on link (i,j) at time step t

3. Three variants of AS exist which differ in the way $\Delta\tau_{ij}^k(t)$ is calculated (assuming a minimization problem)

Variants of AS

- **Ant-cycle AS:**

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{f(x_k(t))} & \text{if link } (i,j) \text{ occurs in path } x^k(t) \\ 0 & \text{otherwise} \end{cases}$$

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$$\Delta\tau_{ij}^{k}(t) = \begin{cases} Q & \text{if link } (i,j) \text{ occurs in path } x^k(t) \\ 0 & \text{otherwise} \end{cases}$$

- Each ant deposits the same amount of pheromone. Total pheromone is proportional to the number of ants that followed link (i,j)

Variants of AS

- **Ant-quantity AS:**

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{d_{ij}} & \text{if link } (i,j) \text{ occurs in path } x^{k}(t) \\ 0 & \text{otherwise} \end{cases}$$

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- If d_{ij} represents the distance between links, then ant-quantity AS prefers selection of the shortest links

AS Algorithm

Algorithm 17.3 Ant System Algorithm

```
t = 0;
Initialize all parameters, i.e. α, β, ρ, Q, n_k, τ_0;
Place all ants, k = 1, ..., n_k;
for each link (i, j) do
    τ_ij(t) ~ U(0, τ_0);
end
repeat
    for each ant k = 1, ..., n_k do
        x^k(t) = ∅;
        repeat
            From current node i, select next node j with probability as defined in
            equation (17.6);
            x^k(t) = x^k(t) ∪ {(i, j)};
        until full path has been constructed;
        Compute f(x^k(t));
    end
    for each link (i, j) do
        Apply evaporation using equation (17.5);
        Calculate Δτ_ij(t) using equation (17.10);
        Update pheromone using equation (17.4);
    end
    for each link (i, j) do
        τ_ij(t + 1) = τ_ij(t);
    end
    t = t + 1;
until stopping condition is true;
Return x^k(t) : f(x^k(t)) = min_{k'=1,...,n_k} {f(x^{k'}(t))};
```

Other Ant Algorithms

- **Ant Colony System:** Differs from AS in these aspects
  - A different transition rule is used
  - A different pheromone update rule is defined
  - Local pheromone updates are introduced
  - Candidate lists are used to favor specific nodes

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- **Max-Min Ant System:**
  - Address the premature stagnation problem of AS
  - Pheromone intensities are restricted within given intervals
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  - Initial pheromones are set to the max allowed value
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- **Ant-Q:** The pheromone notion is dropped to be replaced by Ant-Q value. The goal is to learn AQ-values such that the discovery of good solutions is favored in probability

Other Ant Algorithms

- **Fast Ant System:**
  - Originally developed to solve the quadratic assignment problem
  - Uses only one ant
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- **Antabu:**
  - Includes a local search using tabu search to refine solutions constructed by each iteration of AS
  - The global update rule is changed such that each ant's pheromone deposit on each link of its constructed path is proportional to the quality of the path

Other Ant Algorithms

- **AS-rank:** Modification of AS to:
  - Allow only the best ant update pheromone concentrations on the links of the global-best path
  - use elitist ants
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Other Ant Algorithms

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  - Allow only the best ant update pheromone concentrations on the links of the global-best path
  - use elitist ants
  - Let ants update pheromone on the basis of a ranking of the ants
- **ANTS:** ANTS differs from AS in:
  - The transition probability calculation
  - The global update rule, and (3) the approach to avoid stagnation

Parameter Settings

- **The number of ants n_k:** An obvious influence of n_k relates to computational complexity. The more ants used, the more paths have to be constructed, and the more pheromone deposits calculated

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- Small values of n_k may then cause sub-optimal solutions to be found, or early stagnation

- Too many ants are not necessarily beneficial. With large values of n_k, it may take significantly longer for pheromone intensities on good links to increase to higher levels

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- This may cause a bias towards the links with large initial concentrations, with links that have small pheromone values being neglected as components of the final solution

Applications of Ant Colony Optimization

- Assignment problems
- Bioinformatics
- Data clustering
- Robotics
- Routing
- Scheduling
- Sequential ordering problem
- Set covering
- Shortest common super-sequence
- Text mining

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6. Important algorithmic parameters: Number of ants, maximum number of iterations, initial pheromone, evaporation rate, etc

Any Questions?

Thank You