المركز الوطني للمتميزين
جلسة إثرائية عن:

ذكـــاء الأســـــراب
Swarm Intelligence

Presented by:
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ذكاء الأسراب هو أحد حقول علم:

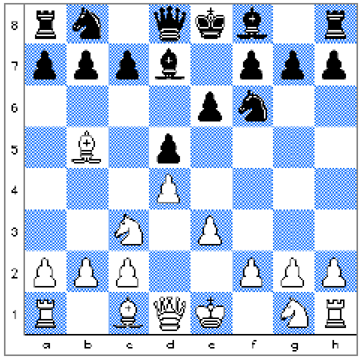
الذكاء الاصطناعي

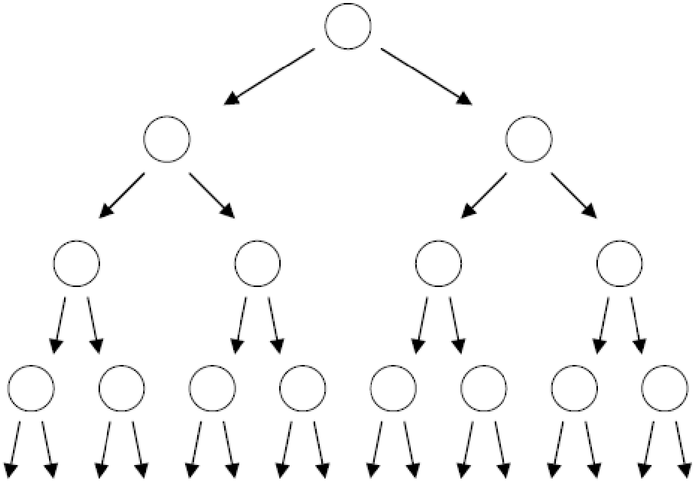
- ما هو تعريف علم الذكاء الاصطناعي؟
- هل هناك حدود لمدى ذكاء الالات؟

لماذا نحتاج الذكاء الاصطناعي؟

Computational hard problems:

- NP hard problems (Travelling Salesman Problem)
- Action-response planning (Chess playing)



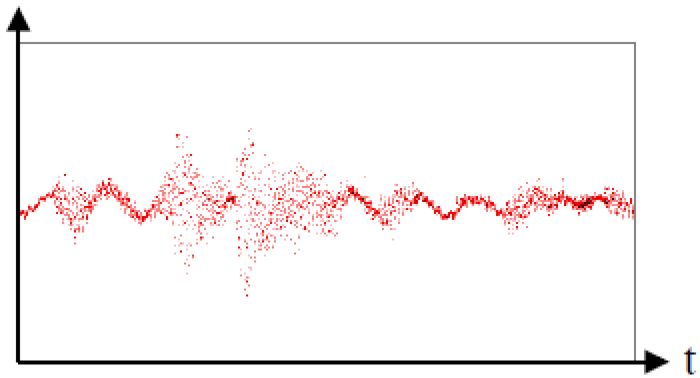


لماذا نحتاج الذكاء الاصطناعي؟

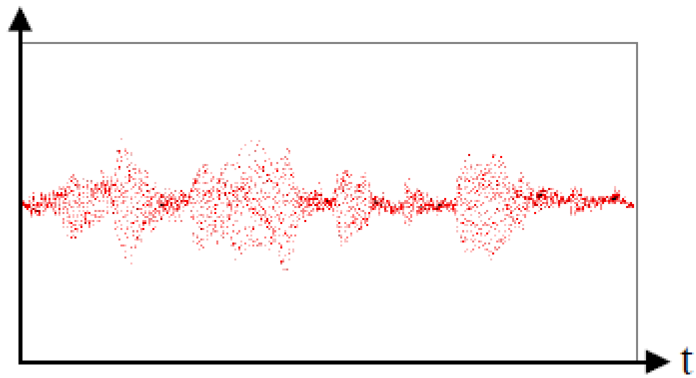
Fuzzy problems:

- Intelligent human-machine interaction
- Natural language understanding

Example: Fuzziness in sound processing



“E-vo-lu-tio-na-ry Com-pu-ta-tion”



“E-vo-lu-tio-na-ry Com-pu-ta-tion”

لماذا نحتاج الذكاء الاصطناعي؟

Hardly predictable and dynamic problems:

- Real-world autonomous robots
- Management and business planning

Japanese piano robot

Trade at the stock exchange

ما البدائل لحل المشاكل السابقة؟

- DNA based computing (chemical computation)
- Quantum computing (quantum-physical computation)
- Bio-computing (simulation of biological mechanisms)

Swarms الأسراب

- Aggregation of similar animals, generally cruising in the same direction

- Ants swarm to build colonies
- Birds swarm to find food
- Bees swarm to reproduce

Swarm Intelligence ذكاء الأسراب

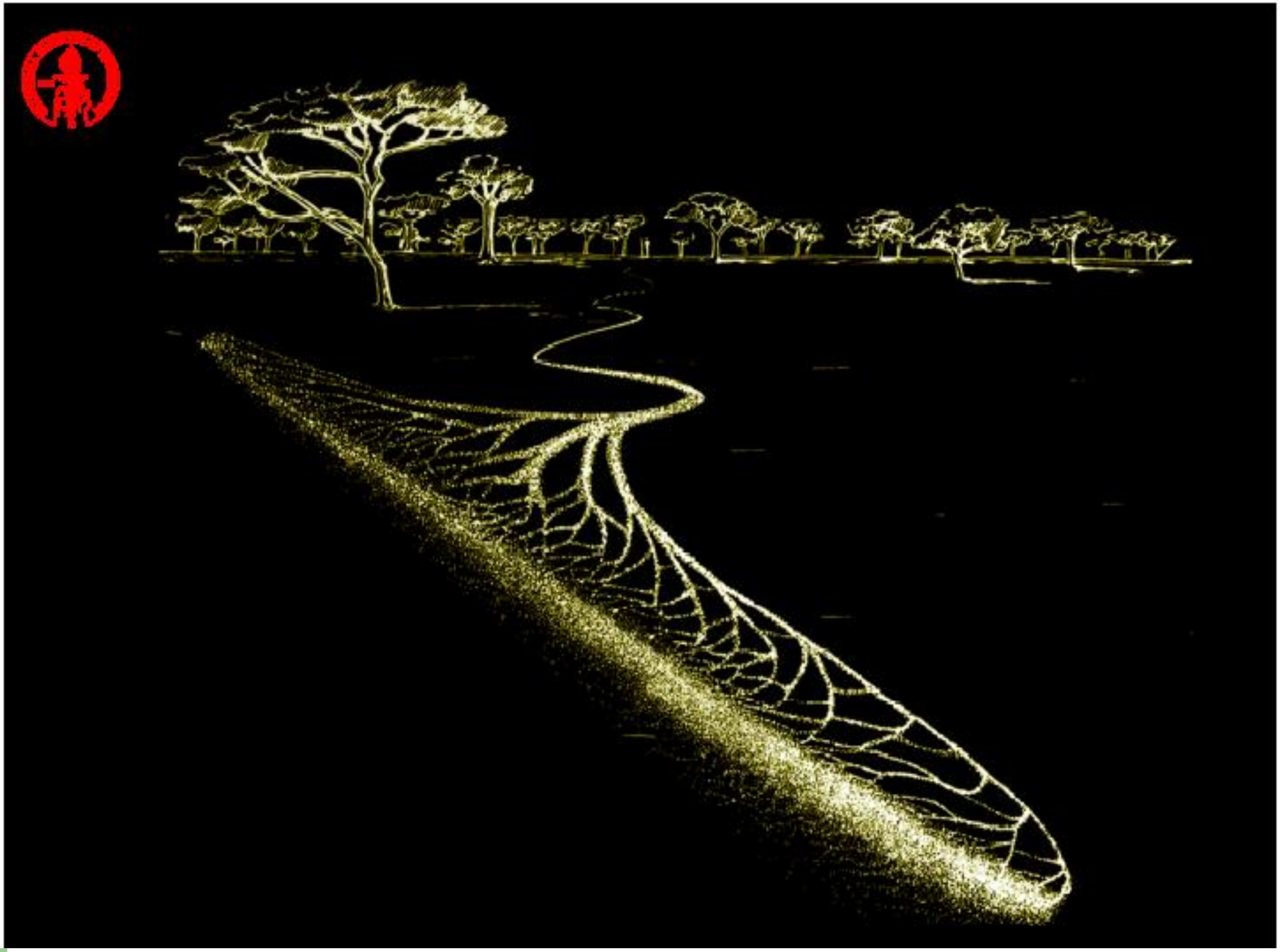
- any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies

- Solves optimization problems

Why do animals swarm?

- To forage better
- To migrate
- As a defense against predators

- Social Insects have survived for millions of years.

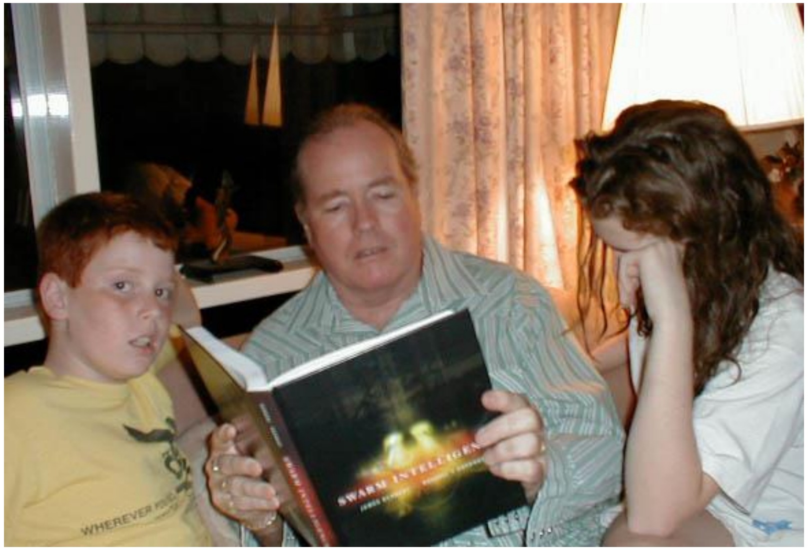


Swarm Intelligence
Particle Swarm Optimization (PSO)

Basic Concept

The Inventors

Russell Eberhart
electrical engineer

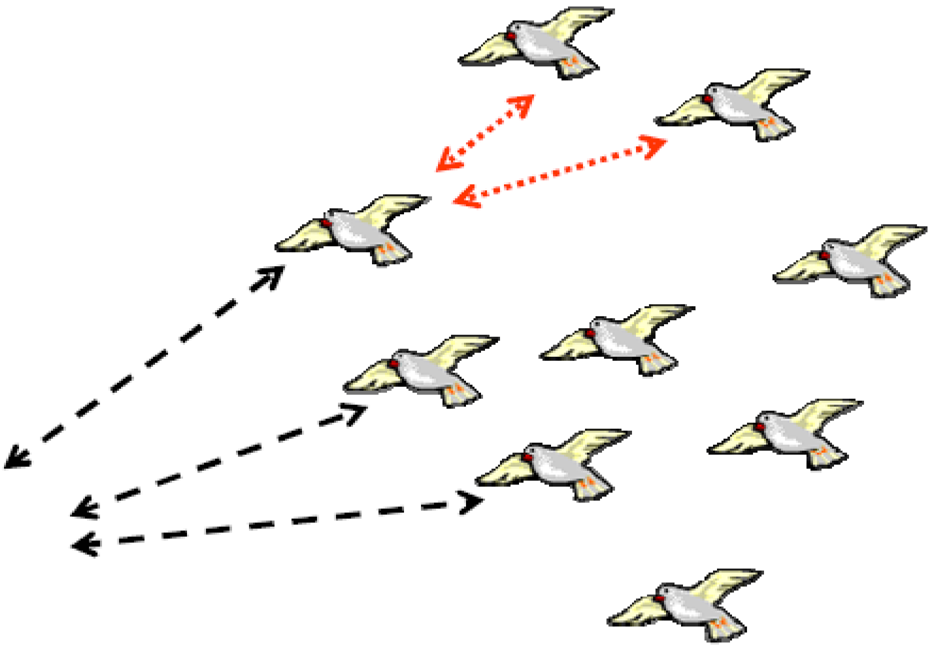


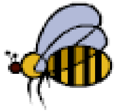
James Kennedy
social-psychologist

Particle Swarm Optimization (PSO)

- Particle swarm optimization imitates human or insects social behavior.
- Individuals interact with one another while learning from their own experience, and gradually move towards the goal.
- It is easily implemented and has proven both very effective and quick when applied to a diverse set of optimization problems.

Particle Swarm Optimization (PSO)





- Bird flocking is one of the best example of PSO in nature.
- One motive of the development of PSO was to model human social behavior.

طريقة البحث في خوارزمية PSO

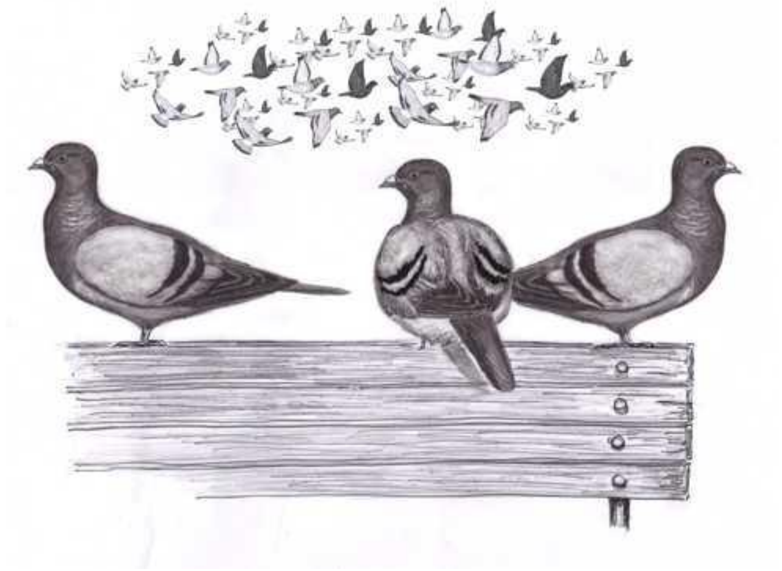
- It uses a number of agents, i.e., particles, that constitute a swarm moving around in the search space looking for the best solution.

- Each particle is treated as a point in a N-dimensional space which adjusts its "flying" according to its own flying experience as well as the flying experience of other particles.

The basic concept

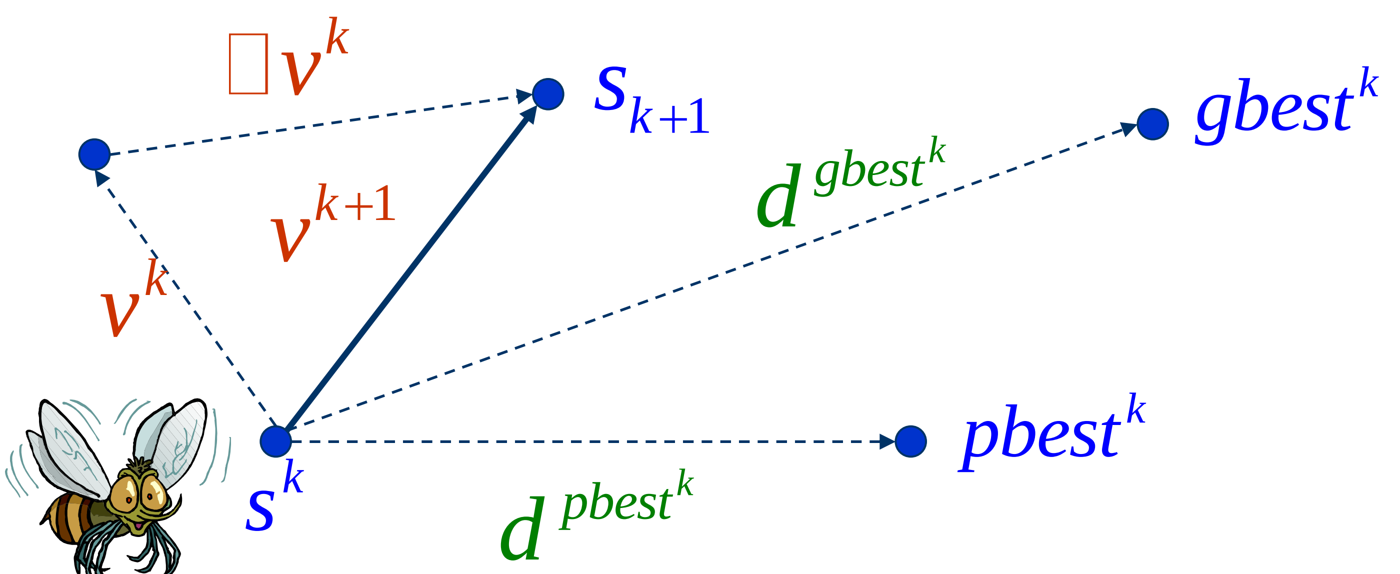
- Each agent remembers the best value of the function found so far by it (**pbest**) and its co-ordinates.
- Secondly, each agent know the globally best position that one member of the flock had found, and its value (**gbest**).

- The basic concept of PSO lies in accelerating each particle toward its **pbest** and the **gbest** locations, with a random weighted acceleration at each time.



Particle Flying Model

$$v_i^{t+1} = v_i^t + c_1 r_1^t \left[P_{best,i}^t - x_i^t\right] + c_2 r_2^t \left[G_{best} - x_i^t\right]$$



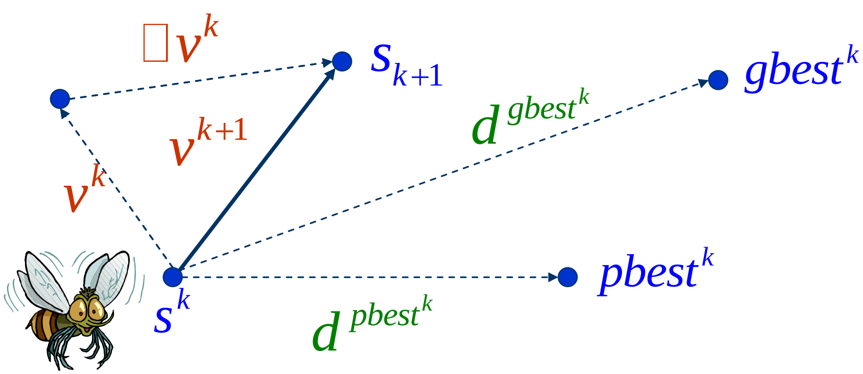
$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

Particle Flying Model

- Each particle tries to modify its position using the following information:
  - the current positions,
  - the current velocities,
  - the distance between the current position and pbest,
  - the distance between the current position and the gbest.

$$\Delta v^k = w_1 d^{pbest^k} + w_2 d^{gbest^k}$$

$$w_1 = c_1 \cdot rand()$$
$$w_2 = c_2 \cdot rand()$$



$$* \quad v_i^{k+1} = v_i^k + \Delta v_i^k$$

$$\Delta v_i^k = c_1 \cdot rand() \cdot (pbest_i^k - s_i^k) + c_2 \cdot rand() \cdot (gbest^k - s_i^k)$$

PSO Algorithm

$$** \quad s_i^{k+1} = s_i^k + v_i^k$$

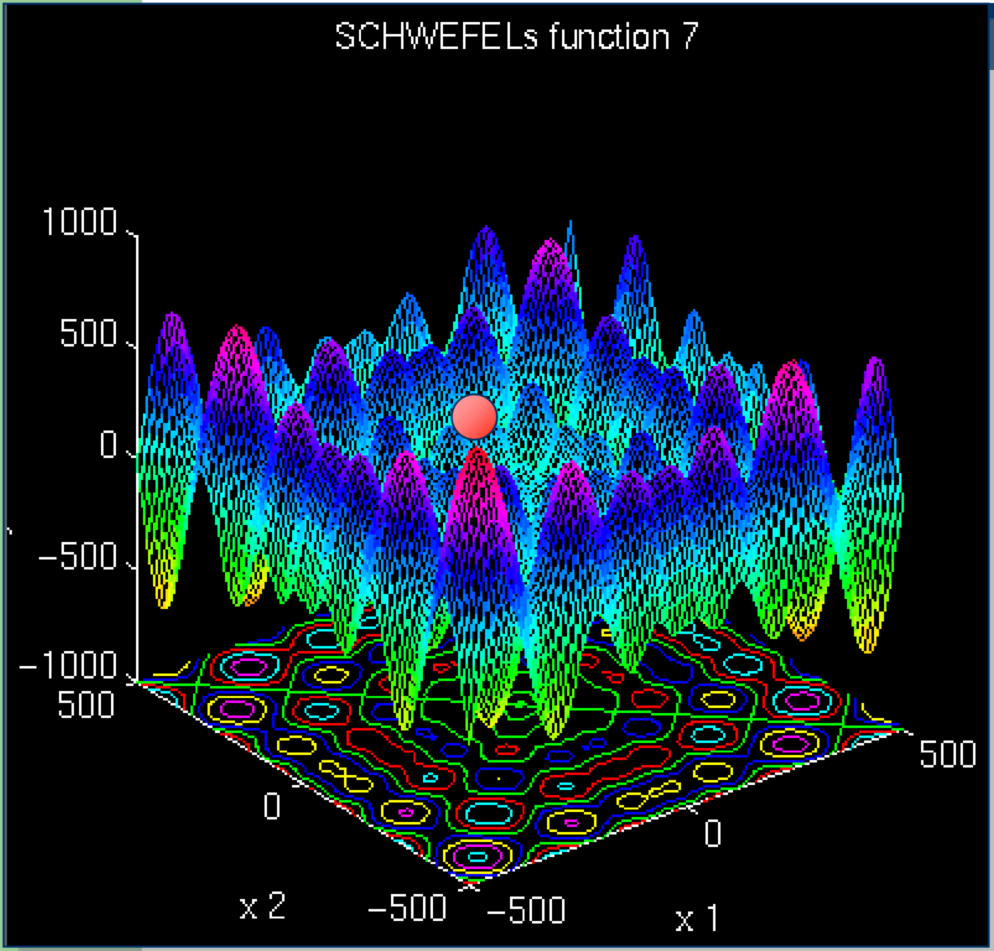
```
For each particle
    Initialize particle
END

Do
   For each particle
       Calculate fitness value
       If the fitness value is better than the best fitness value (pbest) in history
           set current value as the new pbest
   End

   Choose the particle with the best fitness value of all the particles as the gbest
   For each particle
       Calculate particle velocity according equation (*)
       Update particle position according equation (**)
   End
While maximum iterations or minimum error criteria is not attained
```

Swarm Intelligence

Particle Swarm Optimization (PSO)

Examples

Schwefel's Function



$$f(x) = \sum_{i=1}^{n} (-x_i) \cdot \sin\left(\sqrt{|x_i|}\right)$$

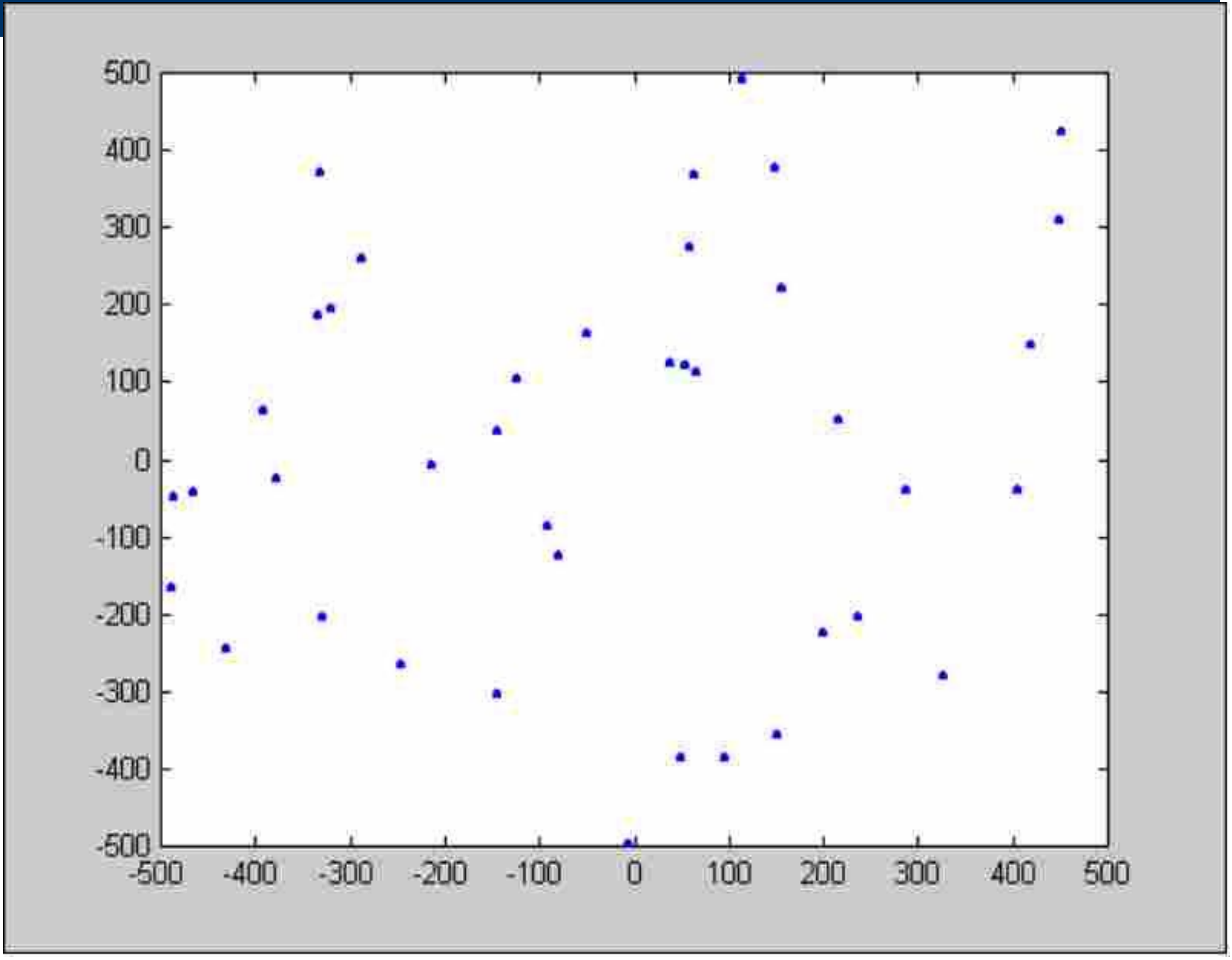
with $-500 \le x_i \le 500$

Global minimum

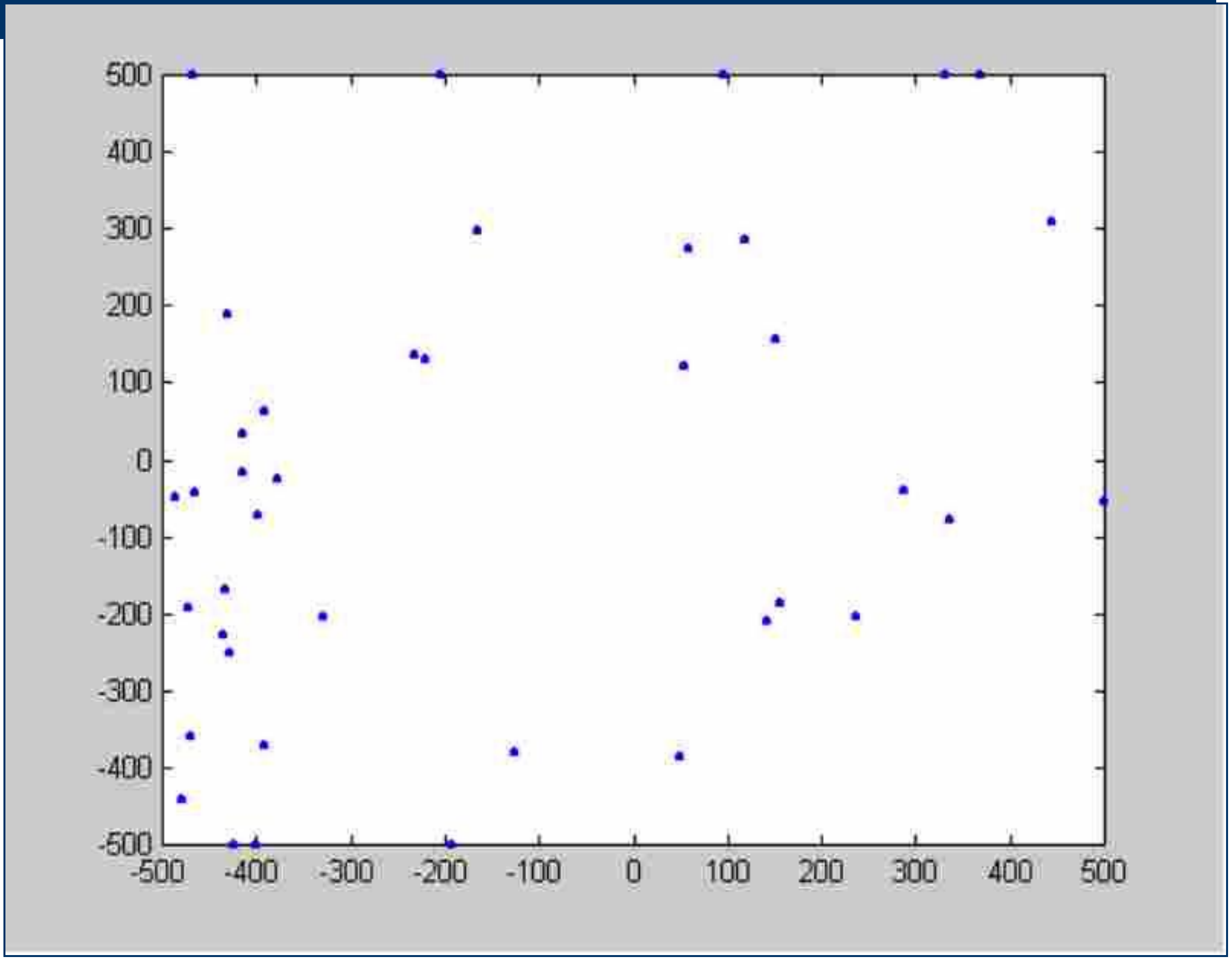
$$f(x) = n \cdot 418.9829;$$

$$x_i = -420.9687, \; i = 1 : n$$

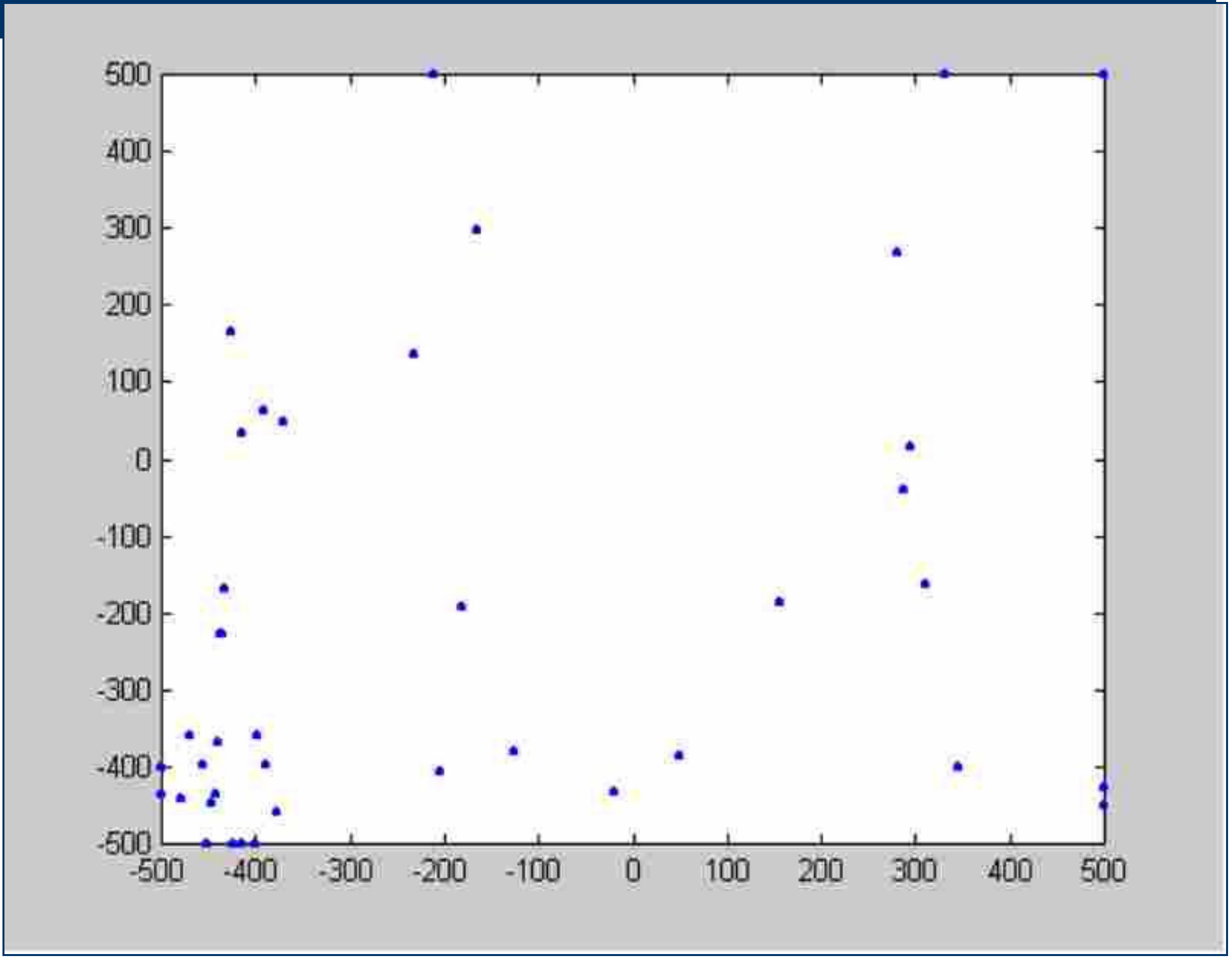
Simulation — Initialization



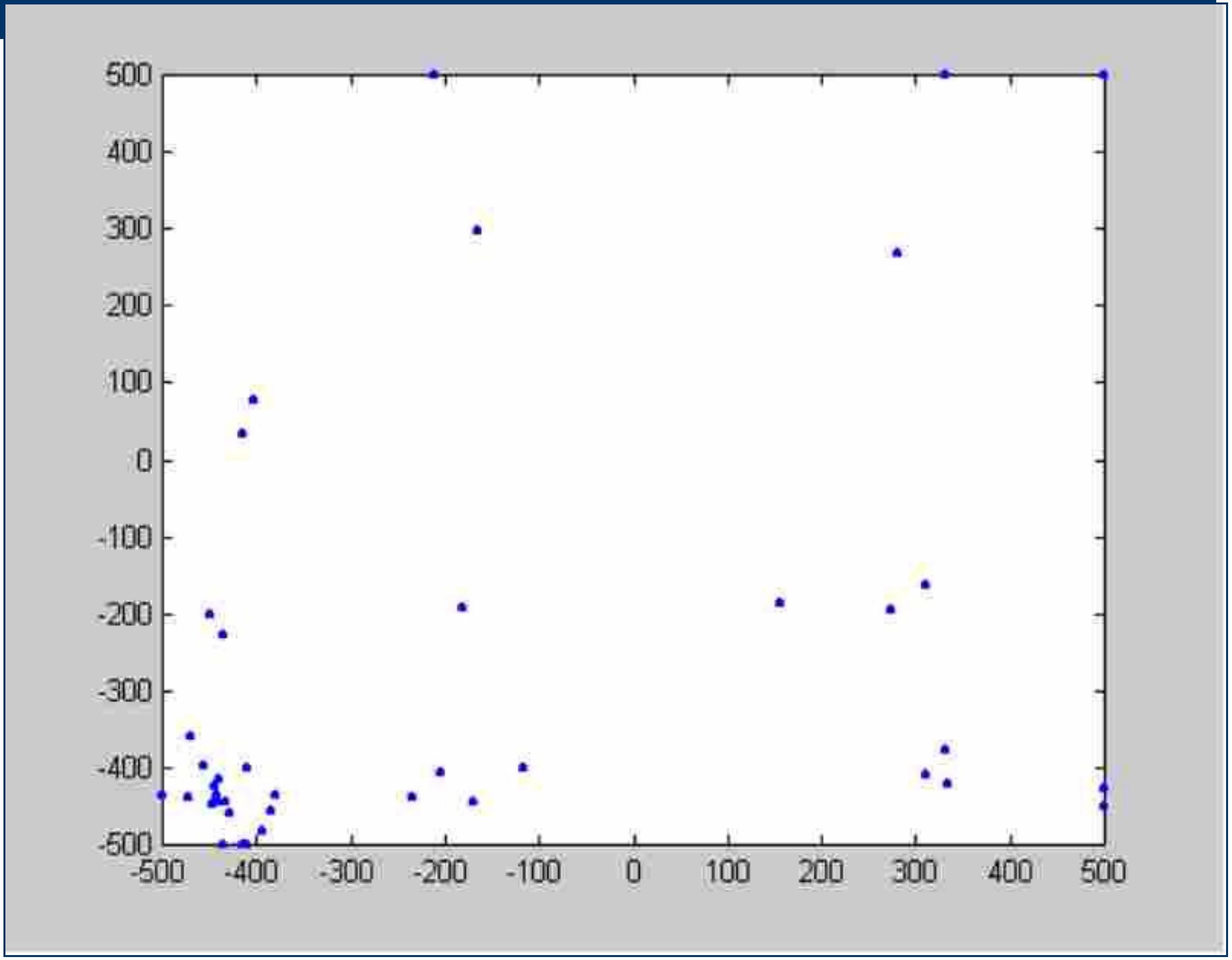
Simulation — After 5 Generations



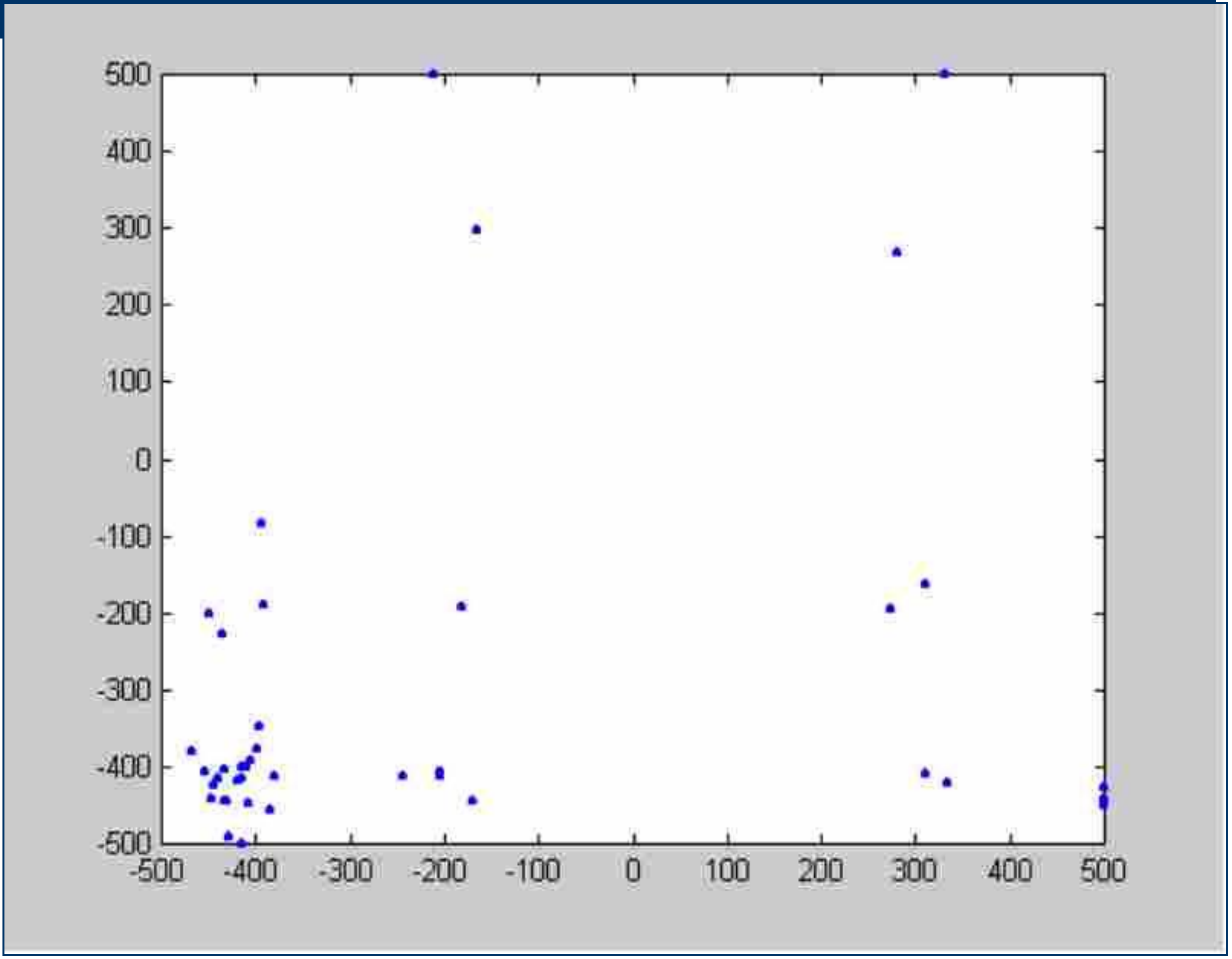
Simulation — After 10 Generations



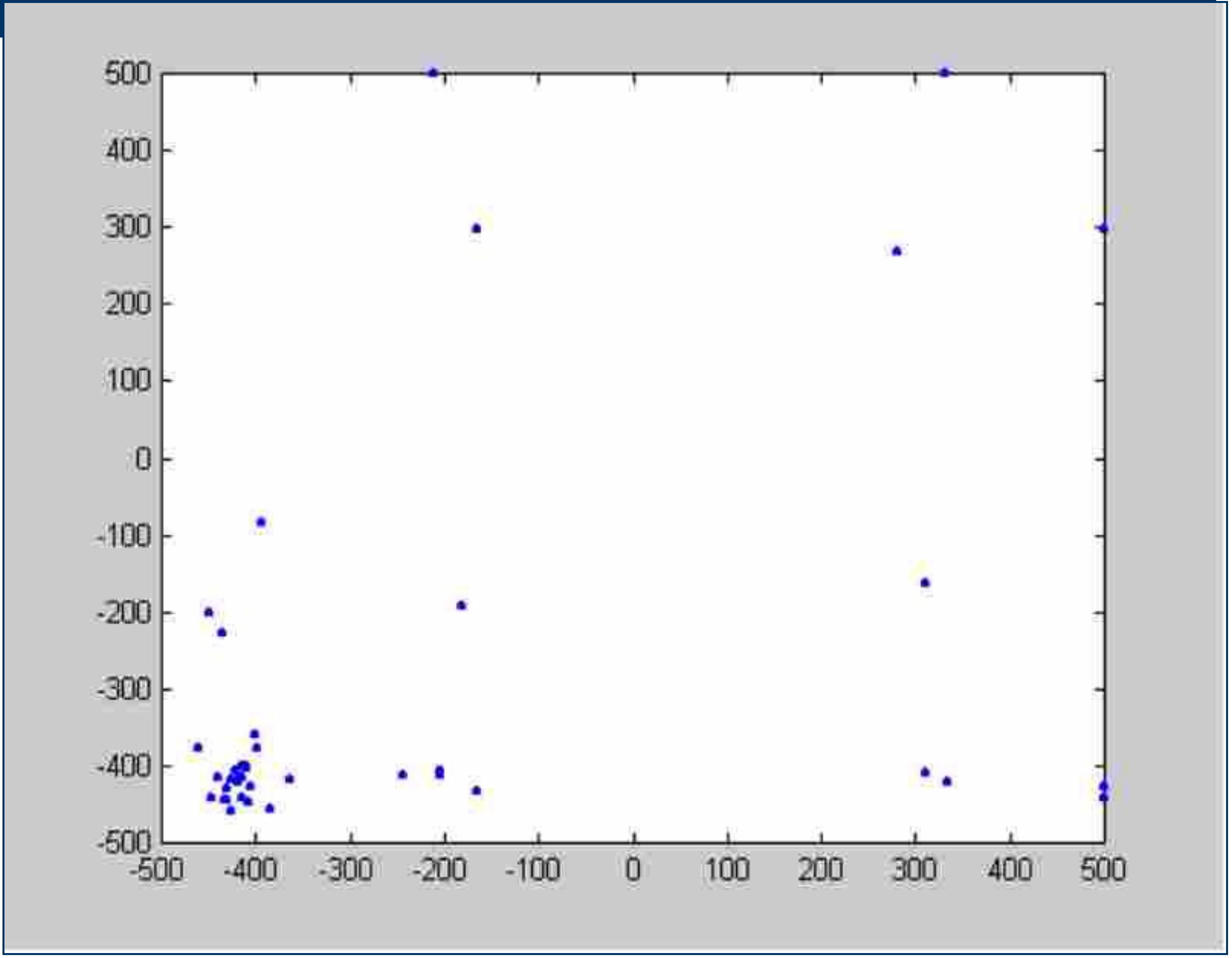
Simulation — After 15 Generations



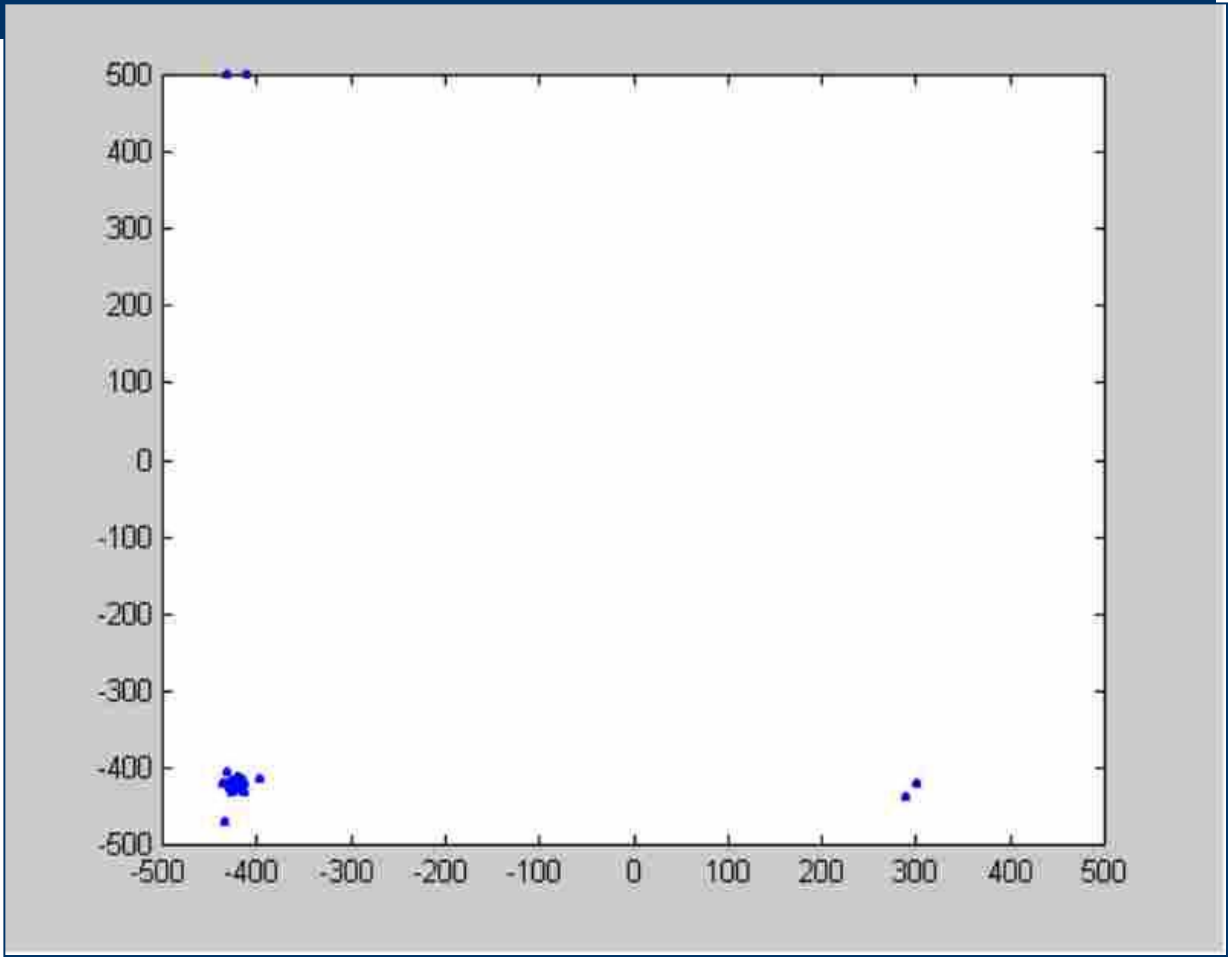
Simulation — After 20 Generations



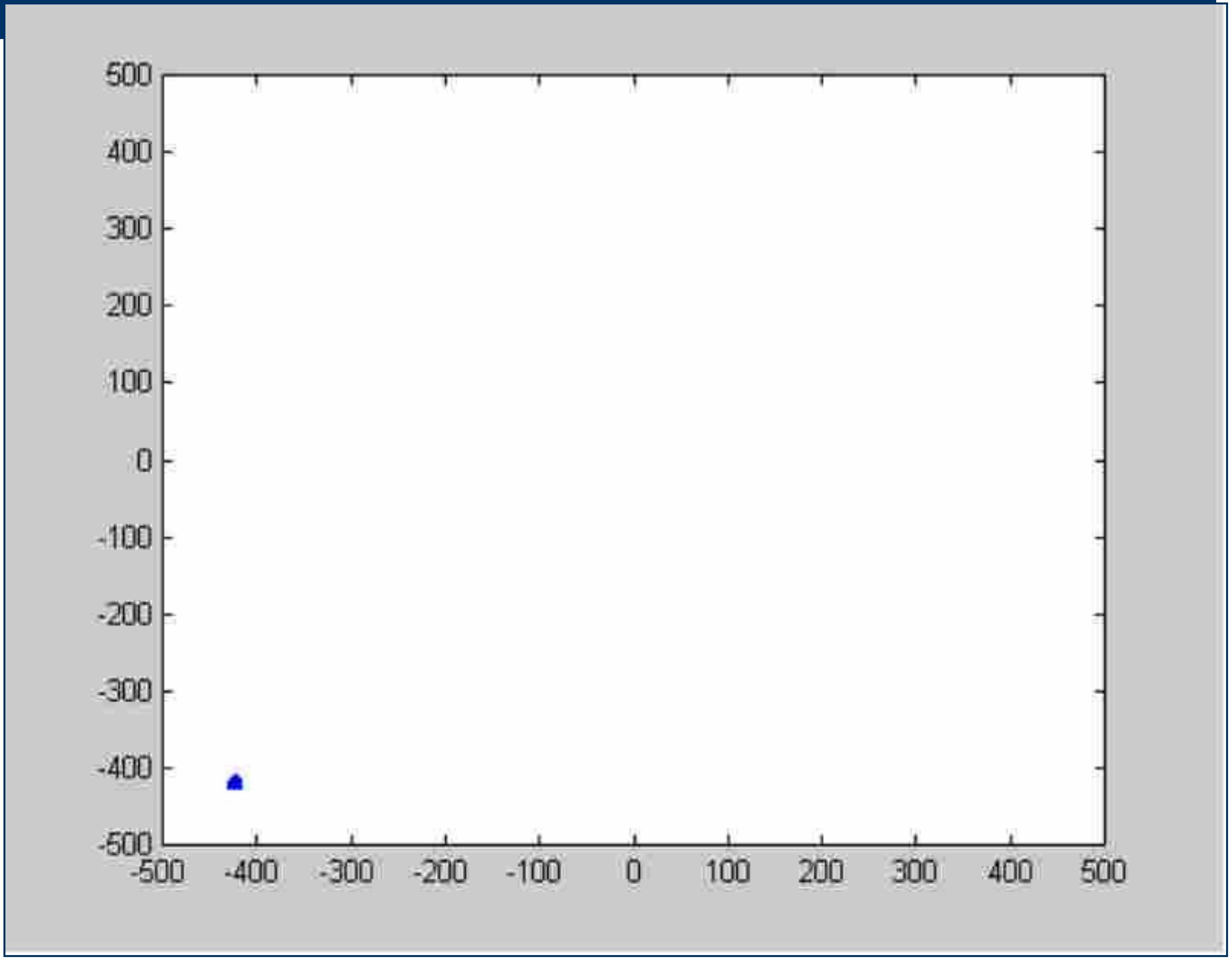
Simulation — After 25 Generations



Simulation — After 100 Generations

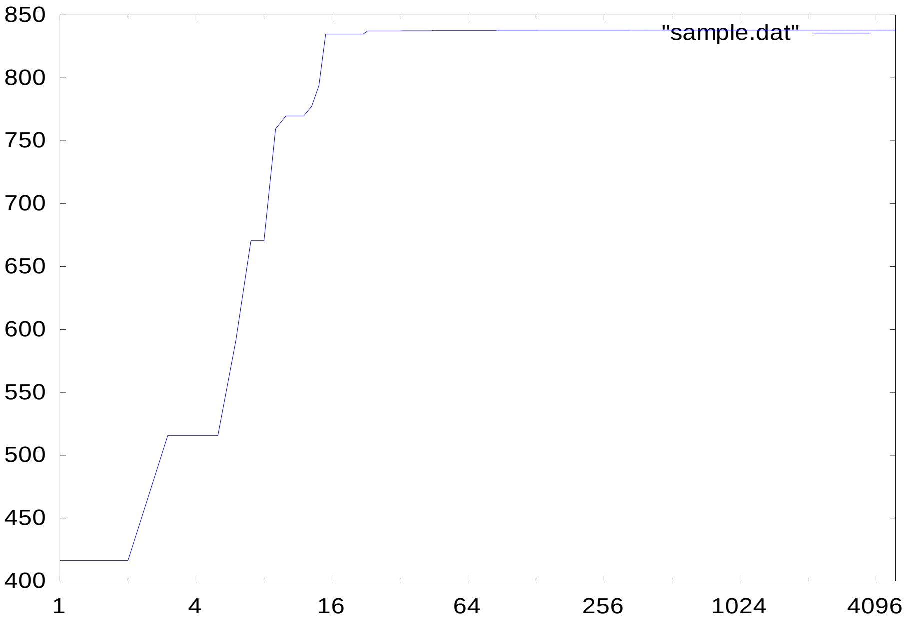


Simulation — After 500 Generations



Summary

Iterations	gBest
0	416.245599
5	515.748796
10	759.404006
15	793.732019
20	834.813763
100	837.911535
5000	837.965771
Optimun	837.9658



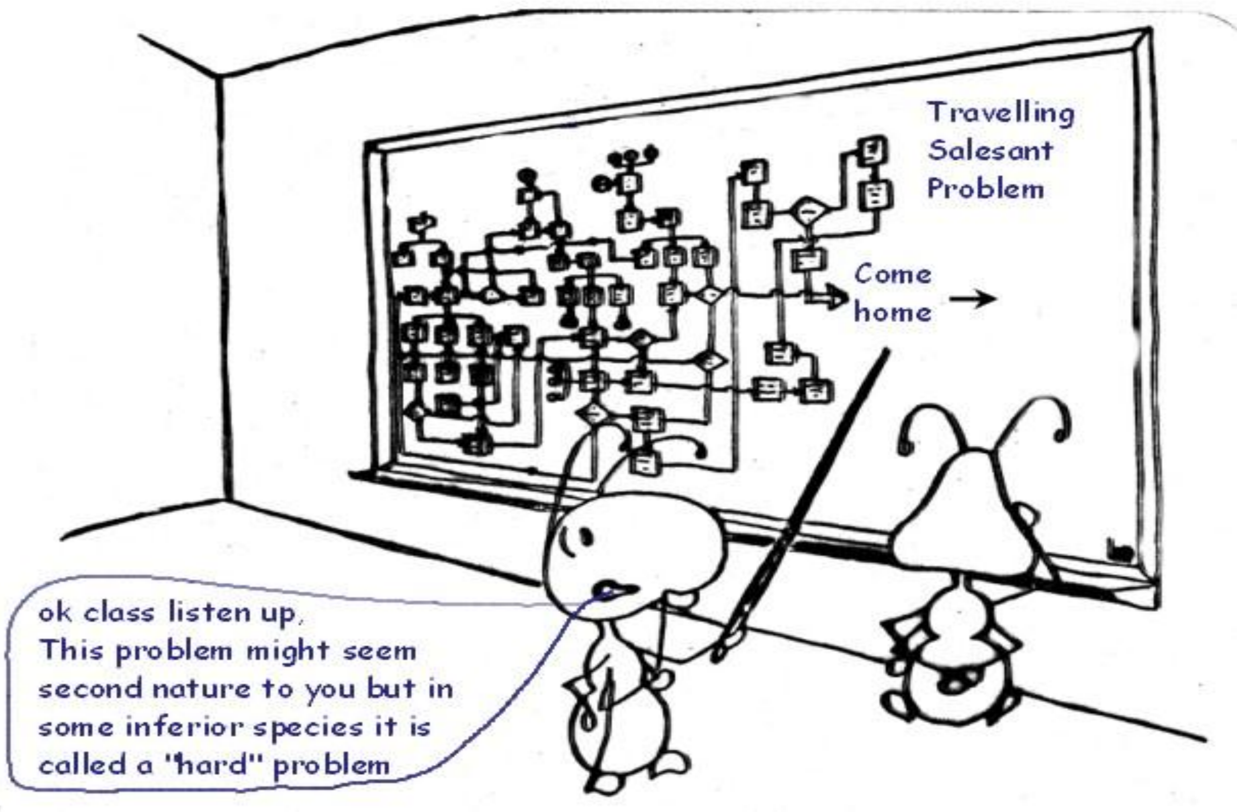
Ant Algorithm

Ant Colony
Optimization (ACO)

Facts

- Many discrete optimization problems are difficult to solve, e.g., NP-Hard
- *Soft computing techniques* to cope with these problems:
  - Simulated Annealing (SA)
    - Based on physical systems
  - Genetic algorithm (GA)
    - based on natural selection and genetics
  - Ant Colony Optimization (ACO)
    - modeling ant colony behavior

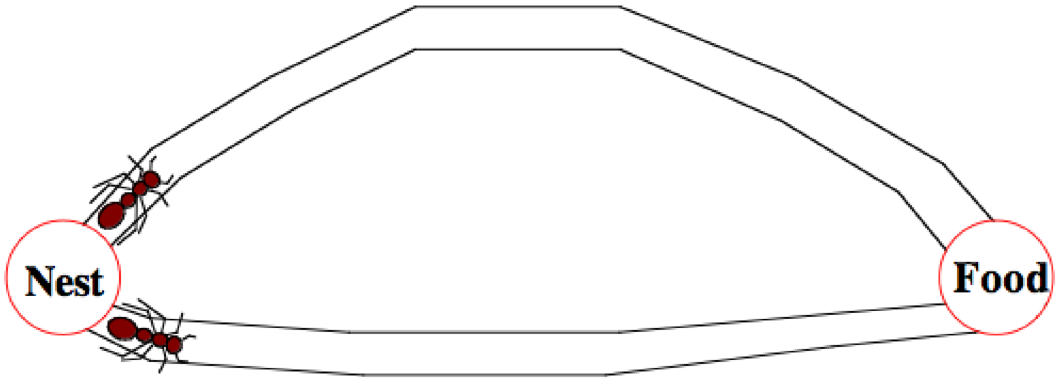
Ant Colony Optimization



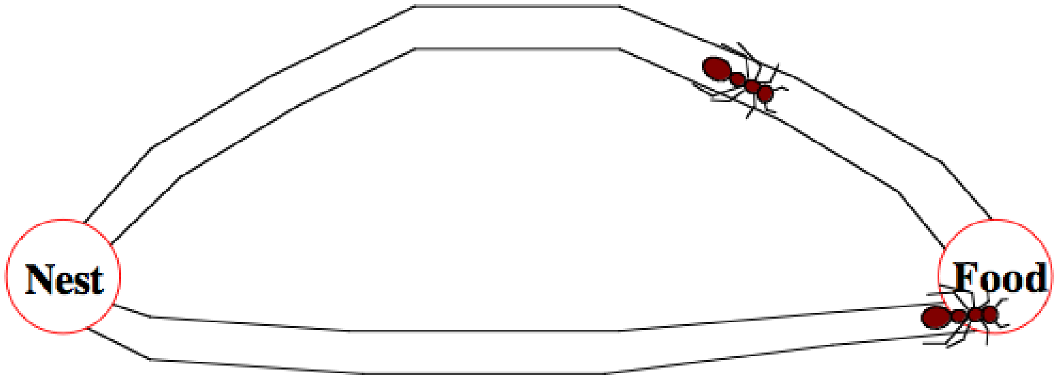
Algorithm Inspiration

- Inspired by foraging behavior of ants.
- Ants find shortest path to food source from nest.
- Ants deposit pheromone along traveled path which is used by other ants to follow the trail.
- This is a kind of indirect communication via the local environment.

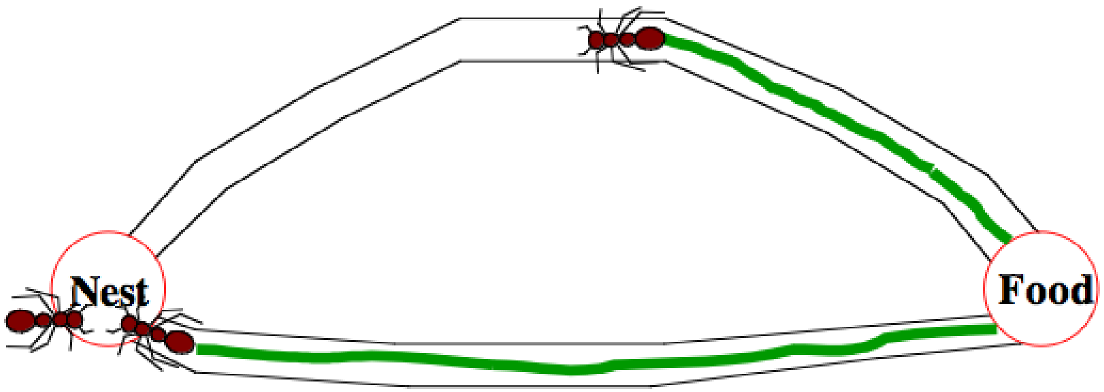
كيف نختار الطريق الأقصر إلى الطعام؟



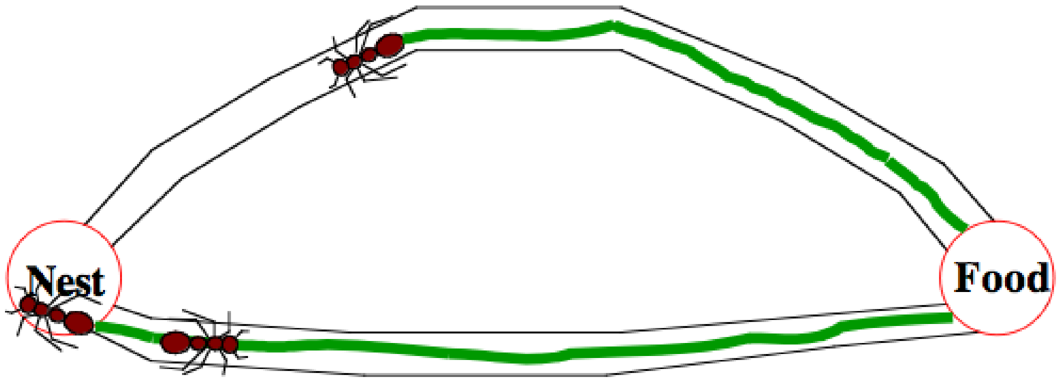
- 2 ants start with equal probability of going on either path.



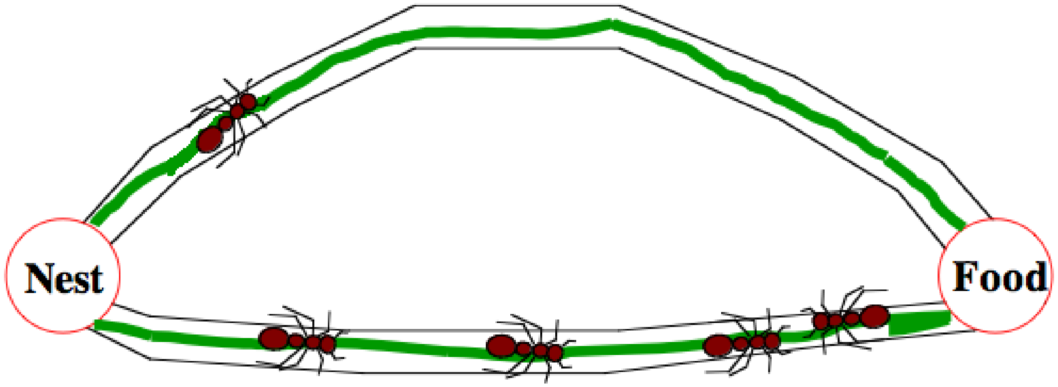
- The ant on shorter path has a shorter to-and-fro time from it’s nest to the food.



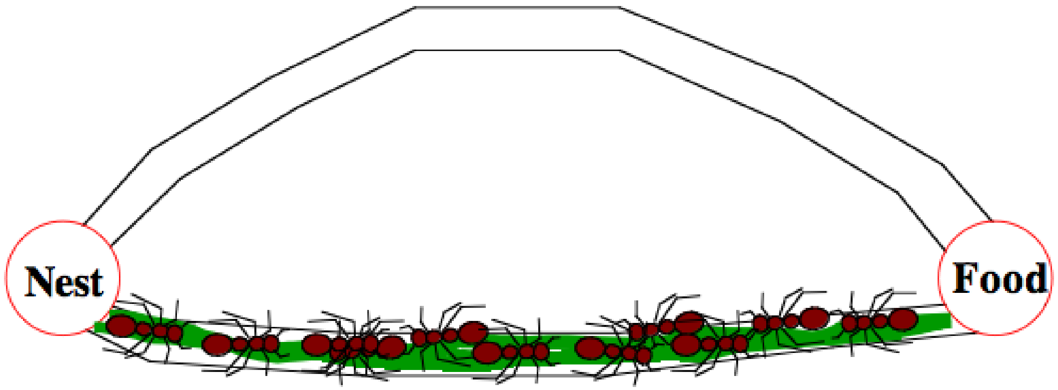
- The density of pheromone on the shorter path is higher because of 2 passes by the ant (as compared to 1 by the other).



- The next ant takes the shorter route.

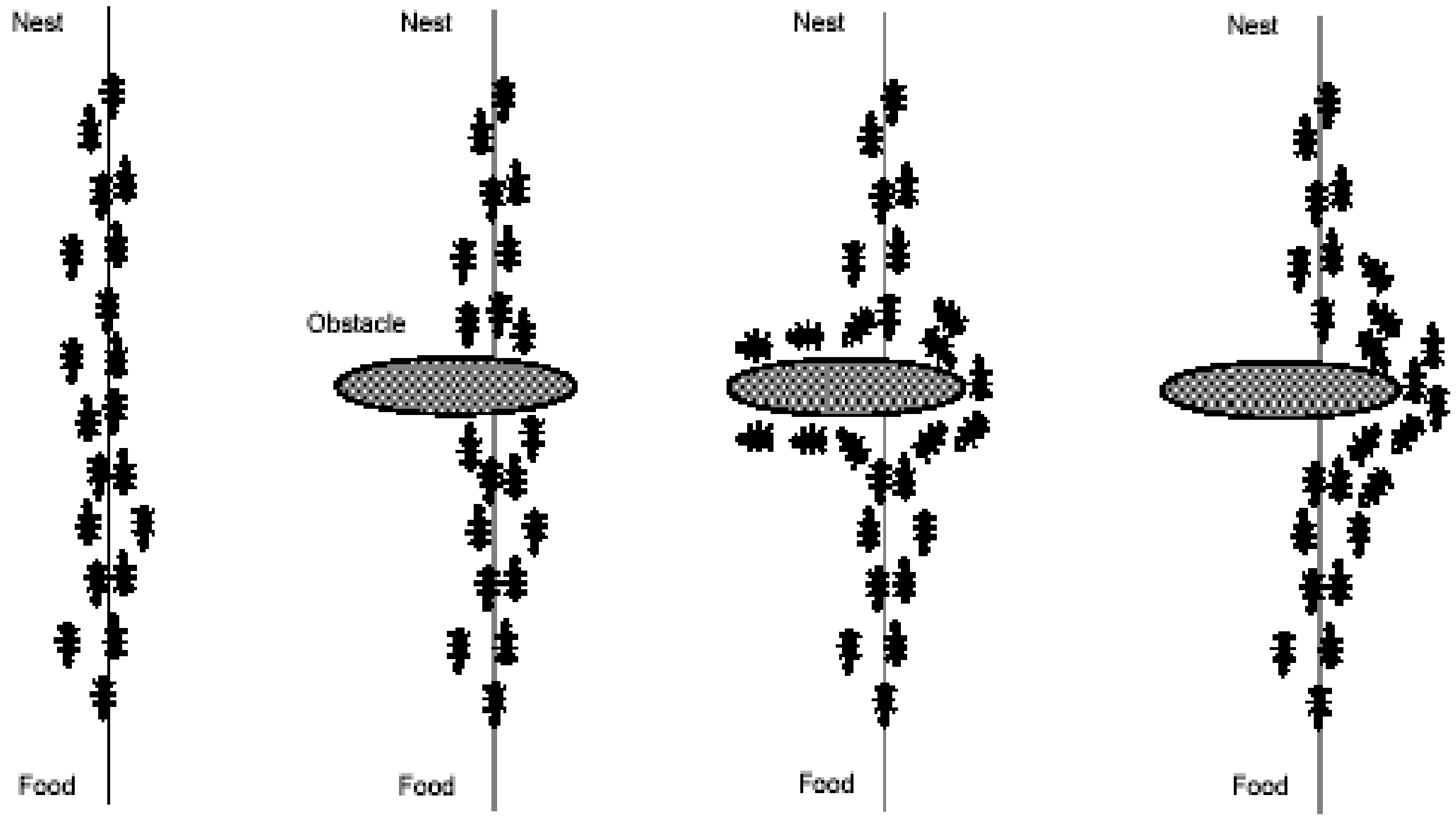


- Over many iterations, more ants begin using the path with higher pheromone, thereby further reinforcing it.



- After some time, the shorter path is almost exclusively used.

Natural Behavior of Ant



Typical Applications

- TSP — Traveling Salesman Problem
- Quadratic assignment problems
- Scheduling problems
- Dynamic routing problems in networks

ACO Concept

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

ACO System

- Virtual “trail” accumulated on path segments
- Starting node selected at random
- Path selection philosophy
  - 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 goal, e.g., starting node for TSP, reached
- Finished “tour” is a solution

ACO System, cont.

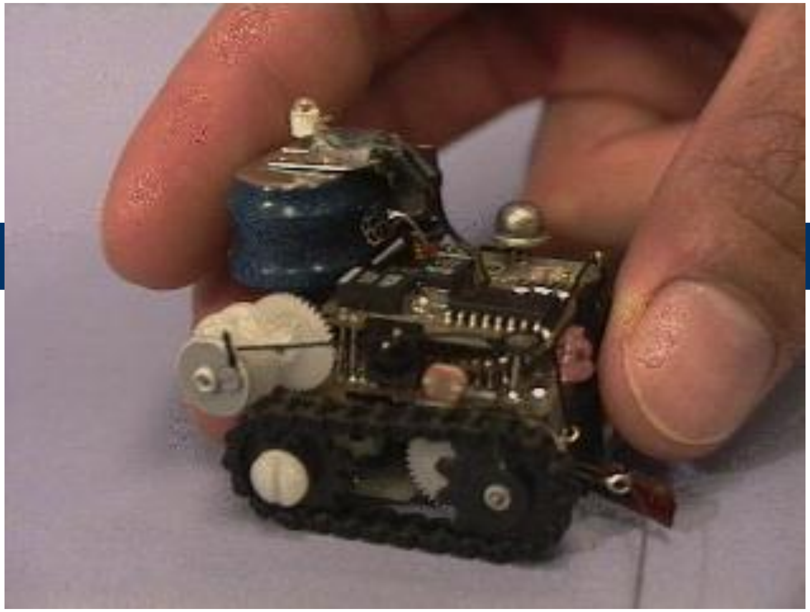
- A completed tour is analyzed for optimality
- “Trail” amount adjusted to favor better solutions
  - better solutions receive more trail
  - worse solutions receive less trail

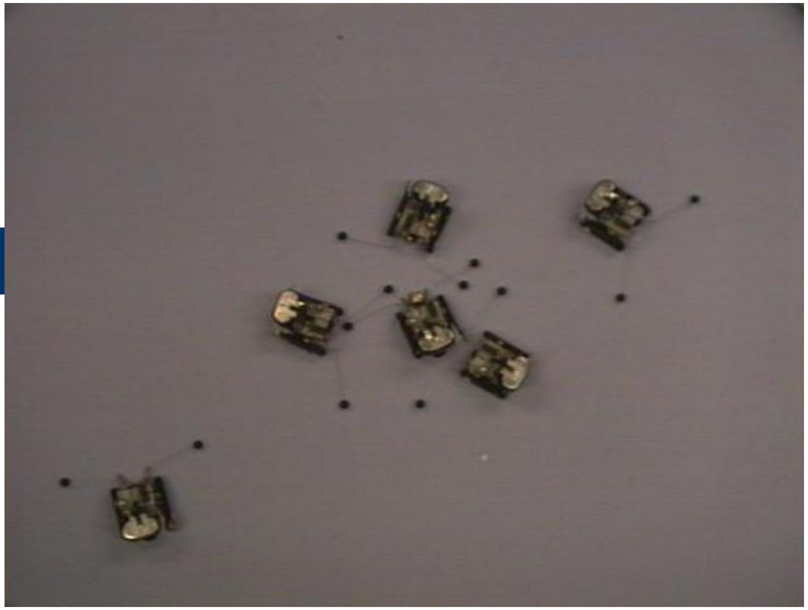
  ⇒higher probability of ant selecting path that is part of a better-performing tour
- New cycle is performed
- Repeated until most ants select the same tour on every cycle (convergence to solution)

Ant Algorithm for TSP

```
Randomly position m ants on n cities
Loop
    for step = 1 to n
        for k = 1 to m
            Choose the next city to move by applying
            a probabilistic state transition rule (to be described)
        end for
    end for
    Update pheromone trails
Until End_condition
```

Robots



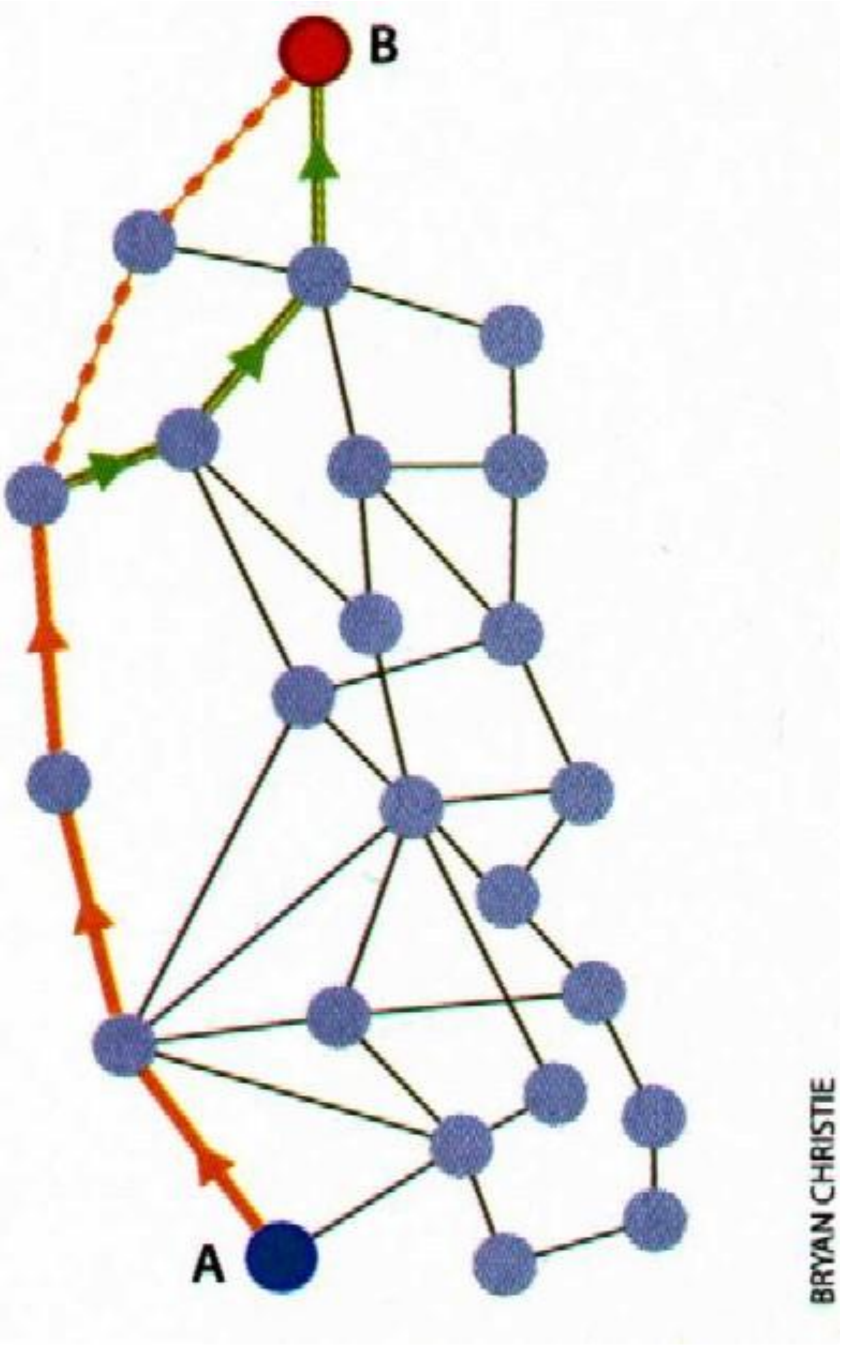


- Collective task completion
- No need for overly complex algorithms
- Adaptable to changing environment

Communication Networks

- Routing packets to destination in shortest time
- Similar to Shortest Route
- Statistics kept from prior routing (learning from experience)

- Shortest Route
- Congestion
- Adaptability
- Flexibility



Pheromone Intensity

$$\tau_{ij}(t)$$

$$\tau_{ij}(0) = C, \ \forall i, j$$

Ant Transition Rule

Probability of ant k going from city i to j:

$$p_{ij}^{k}(t) = \frac{\left[\tau_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}\right]^{\beta}}{\sum_{l \in J_i^k} \left[\tau_{il}(t)\right]^{\alpha} \cdot \left[\eta_{il}\right]^{\beta}}$$

$$\alpha, \beta \geq 0$$

$$\eta_{ij} \propto 1/d_{ij}$$

visibility

J_i^k : the set of nodes applicable to ant k at city i

Ant Transition Rule

Probability of ant k going from city i to j:

$$p_{ij}^{k}(t) = \frac{\left[\tau_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}\right]^{\beta}}{\sum_{l \in J_i^k} \left[\tau_{il}(t)\right]^{\alpha} \cdot \left[\eta_{il}\right]^{\beta}}$$

$$\alpha, \beta \geq 0$$

$$\eta_{ij} \propto 1/d_{ij}$$

- $\alpha = 0$: a greedy approach
- $\beta = 0$: a rapid selection of tours that may not be optimal.
- Thus, a tradeoff is necessary.

Pheromone Update

$$\Delta\tau_{ij}^{k}(t)=\begin{cases} Q/L^{k}(t) & (i,j)\in T^{k}(t) \\ 0 & otherwise \end{cases}$$

Q: a constant
$T^k(t)$: the tour of ant k at time t
$L^k(t)$: the tour length for ant k at time t

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

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

مجالات استخدام ذكاء الأسراب

- Routing
- Controlling unmanned vehicles
- Satellite Image Classification
- Movie effects

شكرا لإصغائكم

إعداد:

علي عروس

كلية الهندسة المعلوماتية – السنة الخامسة

قسم البرمجيات ونظم المعلومات

6/4/2015

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