Part B

Ants (Natural and Artificial)
Read Flake chs. 16–17
Real Ants

(especially the black garden ant, Lasius niger)
Adaptive Significance

- Selects most profitable from array of food sources
- Selects shortest route to it
  - longer paths abandoned within 1–2 hours
- Adjusts amount of exploration to quality of identified sources
- Collective decision making can be as accurate and effective as some vertebrate individuals
Observations on Trail Formation

• Two equal-length paths presented at same time: ants choose one at random
• Sometimes the longer path is initially chosen
• Ants may remain “trapped” on longer path, once established
• Or on path to lower quality source, if it’s discovered first
• But there may be advantages to sticking to paths
  – easier to follow
  – easier to protect trail & source
  – safer
Process of Trail Formation

1. Trail laying
2. Trail following
Trail Laying

• On discovering food, forager lays chemical trail while returning to nest
  – only ants who have found food deposit pheromone
• Others stimulated to leave nest by:
  – the trail
  – the recruiter exciting nestmates (sometimes)
• In addition to defining trail, pheromone:
  – serves as general orientation signal for ants outside nest
  – serves as arousal signal for ants inside
Additional Complexities

• Some ants begin marking on return from discovering food
• Others on their first return trip to food
• Others not at all, or variable behavior
• Probability of trail laying decreases with number of trips
Frequency of Trail Marking

• Ants modulate frequency of trail marking
• May reflect quality of source
  – hence more exploration if source is poor
• May reflect orientation to nest
  – ants keep track of general direction to nest
  – and of general direction to food source
  – trail laying is less intense if the angle to homeward direction is large
Trail Following

• Ants preferentially follow stronger of two trails
  – show no preference for path they used previously
• Ant may double back, because of:
  – decrease of pheromone concentration
  – unattractive orientation
Probability of Choosing One of Two Branches

• Let $C_L$ and $C_R$ be units of pheromone deposited on left & right branches
• Let $P_L$ and $P_R$ be probabilities of choosing them
• Then:

$$P_L = \frac{(C_L + 6)^2}{(C_L + 6)^2 + (C_R + 6)^2}$$

• Nonlinearity amplifies probability
Additional Adaptations

• If a source is crowded, ants may return to nest or explore for other sources
• New food sources are preferred if they are near to existing sources
• Foraging trails may rotate systematically around a nest
Pheromone Evaporation

- Trails can persist from several hours to several months
- Pheromone has mean lifetime of 30–60 min.
- But remains detectable for many times this
- Long persistence of pheromone prevents switching to shorter trail
- Artificial ant colony systems rely more heavily on evaporation
Resnick’s Ants
Environment

• Nest emits *nest-scent*, which
  – diffuses uniformly
  – decays slowly
  – provides general orientation signal
  – by diffusing around barriers, shows possible paths around barriers

• Trail pheromone
  – emitted by ants carrying food
  – diffuses uniformly
  – decays quickly

• Food detected only by contact
Resnick Ant Behavior

1.  Looking for food:
   if trail pheromone weak then wander
   else move toward increasing concentration

2.  Acquiring food:
   if at food then
       pick it up, turn around, & begin depositing pheromone

3.  Returning to nest:
   deposit pheromone & decrease amount available
   move toward increasing nest-scent

4.  Depositing food:
   if at nest then
       deposit food, stop depositing pheromone, & turn around

5.  Repeat forever
Demonstration of Resnick Ants

Run Ants.nlogo
Ant Colony Optimization (ACO)

Developed in 1991 by Dorigo (PhD dissertation) in collaboration with Colorni & Maniezzo
Basis of all Ant-Based Algorithms

• Positive feedback
• Negative feedback
• Cooperation
Positive Feedback

• To reinforce portions of good solutions that contribute to their goodness
• To reinforce good solutions directly
• Accomplished by *pheromone accumulation*
Reinforcement of Solution Components

Parts of good solutions *may* produce better solutions
Negative Reinforcement of Non-solution Components

Parts not in good solutions *tend* to be forgotten
Negative Feedback

• To avoid premature convergence
  \((stagnation)\)

• Accomplished by \textit{pheromone evaporation}
Cooperation

• For simultaneous exploration of different solutions
• Accomplished by:
  – *multiple ants* exploring solution space
  – *pheromone trail* reflecting multiple perspectives on solution space
Traveling Salesman Problem

• Given the travel distances between $N$ cities
  – may be symmetric or not
• Find the shortest route visiting each city exactly once and returning to the starting point
• NP-hard
• Typical combinatorial optimization problem
Ant System for Traveling Salesman Problem (AS-TSP)

• During each iteration, each ant completes a tour

• During each tour, each ant maintains *tabu list* of cities already visited

• Each ant has access to
  – distance of current city to other cities
  – intensity of local pheromone trail

• Probability of next city depends on both
Transition Rule

• Let $\eta_{ij} = 1/d_{ij} = \text{“nearness” of city } j \text{ to current city } i$
• Let $\tau_{ij} = \text{strength of trail from } i \text{ to } j$
• Let $J_i^k = \text{list of cities ant } k \text{ still has to visit after city } i \text{ in current tour}$
• Then transition probability for ant $k$ going from $i$ to $j \in J_i^k$ in tour $t$ is:

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

• Let $T^k(t)$ be tour $t$ of ant $k$
• Let $L^k(t)$ be the length of this tour
• After completion of a tour, each ant $k$ contributes:

$$\Delta \tau^k_{ij} = \begin{cases} 
\frac{Q}{L^k(t)} & \text{if } (i,j) \in T^k(t) \\
0 & \text{if } (i,j) \notin T^k(t)
\end{cases}$$
Pheromone Decay

• Define total pheromone deposition for tour $t$:

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

• Let $\rho$ be decay coefficient

• Define trail intensity for next round of tours:

$$\tau_{ij}(t + 1) = (1 - \rho)\tau_{ij}(t) + \Delta \tau_{ij}(t)$$
Number of Ants is Critical

• Too many:
  – suboptimal trails quickly reinforced
  – \( \therefore \) early convergence to suboptimal solution

• Too few:
  – don’t get cooperation before pheromone decays

• Good tradeoff:
  number of ants = number of cities
  \( m = n \)
Improvement: “Elitist” Ants

• Add a few \( (e \approx 5) \) “elitist” ants to population to reinforce best tour found so far
• Let \( T^+ \) be best tour so far
• Let \( L^+ \) be its length
• Each “elitist” ant reinforces edges in \( T^+ \) by \( Q/L^+ \)
• Add \( e \) more “elitist” ants
• This applies accelerating positive feedback to best tour
Time Complexity

• Let $t$ be number of tours
• Time is $O(tn^2m)$
• If $m = n$ then $O(tn^3)$
  – that is, cubic in number of cities
Convergence

- 30 cities ("Oliver30")
- Best tour length
- Converged to optimum in 300 cycles

fig. < Dorigo et al. (1996)
Evaluation

• Both “very interesting and disappointing”
• For 30-cities:
  – beat genetic algorithm
  – matched or beat tabu search & simulated annealing
• For 50 & 75 cities and 3000 iterations
  – did not achieve optimum
  – but quickly found good solutions
• I.e., does not scale up well
• Like all general-purpose algorithms, it is out-performed by special purpose algorithms
Improving Network Routing

1. Nodes periodically send *forward ants* to some recently recorded destinations
2. Collect information on way
3. Die if reach already visited node
4. When reaches destination, estimates time and turns into *backward ant*
5. Returns by same route, updating routing tables
Application to Other Problems

• Nodes represent necessary subgoals
• Edges represent possible “moves” (parts of solutions)
• Complete trails represent solutions
• Ants reinforce trails based on quality of solutions
Some Applications of ACO

• Routing in telephone networks
• Vehicle routing
• Job-shop scheduling
• Constructing evolutionary trees from nucleotide sequences
• Various classic NP-hard problems
  – shortest common supersequence, graph coloring, quadratic assignment, …
Improvements as Optimizer

• Can be improved in many ways
• E.g., combine local search with ant-based methods
• As method of stochastic combinatorial optimization, performance is promising, comparable with best heuristic methods
• Much ongoing research in ACO
• But optimization is not a principal topic of this course
Nonconvergence

- Standard deviation of tour lengths
- Optimum = 420

fig. < Dorigo et al. (1996)
Average Node Branching Number

- Branching number = number of edges leaving a node with pheromone > threshold
- Branching number = 2 for fully converged solution

fig. < Dorigo et al. (1996)
The Nonconvergence Issue

• ACO often does not converge to single solution
• Population maintains high diversity
• A bug or a feature?
• Potential advantages of nonconvergence:
  – avoids getting trapped in local optima
  – promising for dynamic applications
• Flexibility & robustness are more important than optimality in natural computation
Natural Computation

Natural computation

• is computation that occurs in nature
• or is inspired by computation occurring in nature
Optimization in Natural Computation

• Good, but suboptimal solutions may be preferable to optima if:
  – suboptima can be obtained more quickly
  – suboptima can be adapted more quickly
  – suboptima are more robust
  – an ill-defined suboptimum may be better than a sharp optimum

• “The best is the enemy of the good”
  (*Le mieux est l’ennemi du bien.* – Voltaire)
Robust Optima
Effect of Error/Noise