Part B
Ants (Natural and Artificial)

Langton's Vants
(Virtual Ants)

Vants

- Square grid
- Squares can be black or white
- Vants can face N, S, E, W
- Behavioral rule:
  - take a step forward,
  - **if** on a white square **then**
    paint it black & turn 90° right
  - **if** on a black square **then**
    paint it white & turn 90° left

Example

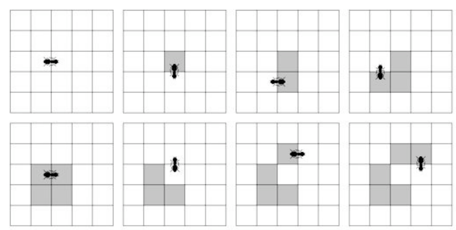


Figure 16.2 Eight steps of Langton's virtual ant, starting from an initially blank grid

Time Reversibility

- Vants are time-reversible
- But time reversibility does not imply global simplicity
- Even a single vant interacts with its own prior history
- But complexity does not always imply random-appearing behavior

Demonstration of Vants
(NetLogo Simulation)

Run Vants-Large-Field.nlogo

Demonstration of Generalized Vants
(NetLogo Simulation)

Run Generalized-Vants.nlogo

Conclusions

- Even simple, reversible local behavior can lead to complex global behavior
- Nevertheless, such complex behavior may create structures as well as apparently random behavior
- Perhaps another example of "edge of chaos" phenomena

Digression: Time-Reversibility and the Physical Limits of Computation

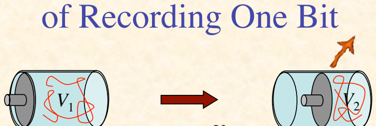
Work done by:

- Rolf Landauer (1961)
- Charles Bennett (1973)
- Richard Feynman (1981–3)

Entropy of Physical Systems

- Recall information content of N equally likely messages: $I_2 = \lg N$ bits.
- Can also use natural logs: $I_e = \ln N$ nats $= I_2 \ln 2$.
- To specify position & momentum of each particle of a physical system: $S = k \ln N = k\, I_2 \ln 2$.
  - k is Boltzmann's constant
- This is the entropy of the system
  - entropies of 10 bits/atom are typical

Thermodynamics of Recording One Bit



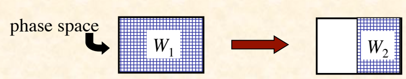
$$\Delta S = k \ln \frac{V_2}{V_1}$$

if $V_2 = V_1/2$, then $\Delta S = -k \ln 2$

also, $\Delta F = kT \ln 2$

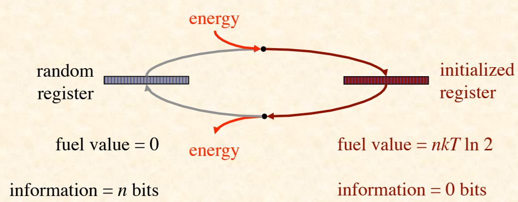
- ΔS derived by gas laws & classical thermodynamics
- Boltzmann constant: $k = 1.381 \times 10^{-23}$ J K^{-1}

Entropy Change in Terms of Phase Space



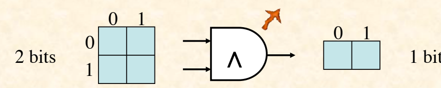
- Let W = number of microstates corresponding to a macrostate
- Entropy $S = k \ln W$
- Then $\Delta S = k \ln W_2 - k \ln W_1 = k \ln (W_2 / W_1)$
- If $W_2 = W_1 / 2$, then $\Delta S = -k \ln 2$

Information and Energy



- initialization equivalent to storing energy
- information and energy are complementary

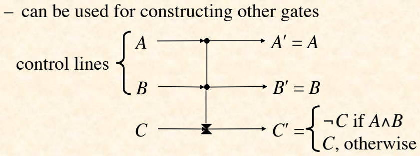
Minimum Energy for Irreversible Computation



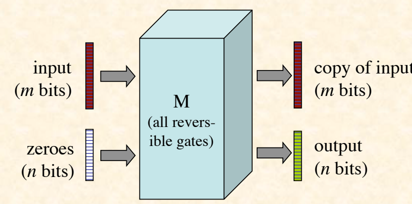
- Loss of one bit of information
  - an irreversible operation (many to one)
- $\Delta S = -k \ln 2$
  - entropy decrease must be compensated by heat dissipation
- Minimum energy required: $\Delta F = kT \ln 2$
  - transistors: ~$10^8\,kT$; RNA polymerase: ~100 kT

Reversible Gates

- Can make dissipation arbitrarily small by using reversible gates
- All outputs must go somewhere
- Cannot *ever* throw information away
- The Fredkin CCN gate ("Controlled Controlled Not") is reversible
  - can be used for constructing other gates



Reversible Computer

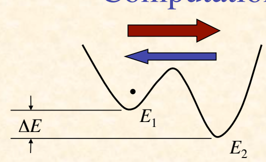


- Reversible because get input back
- Only loss is resetting machine for next job
  - energy is proportional to n, number of output bits

Summary: Energy Required for Reversible Computing

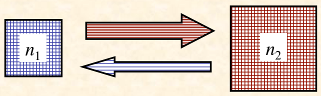
- There is no lower limit on the energy required for basic operations (gates, bit copying, etc.) provided:
  - it is done reversibly
  - it is done sufficiently slowly
- What is the fundamental relation between speed and energy dissipation?

Energy and the Speed of Computation



- Let r be ratio of forward to backward rate
- Statistical mechanics shows: $kT \ln r = \Delta E$
- Greater "driving energy" ⇒ greater rate

Entropy and the Speed of Computation



- Consider number of accessible microstates, n_1 and n_2
- Can show: $r = n_2 / n_1$
- Hence, $kT \ln r = kT (\ln n_2 - \ln n_1)$ $= (S_2 - S_1)T \;=\; T\Delta S$

Conclusions

- Entropy increase and energy dissipation can be made arbitrarily small by doing reversible computation
- However, the speed of computation is an exponential function of the driving energy or entropy increase

Additional Information

1. Feynman, R. P. *Feynman Lectures on Computation*, ed. by A.J.G Hey & R.W. Allen. Perseus, 1996.
2. Hey, A.J.G. (ed.) *Feynman and Computation: Exploring the Limits of Computation*. Perseus, 1999.

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 recruitor 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

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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

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Resnick's Ants

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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

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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

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Demonstration of Resnick Ants

Run Ants.nlogo

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Exploitation of Multiple Food Sources

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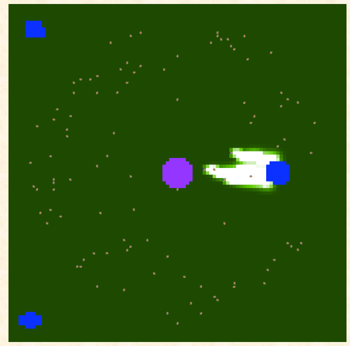

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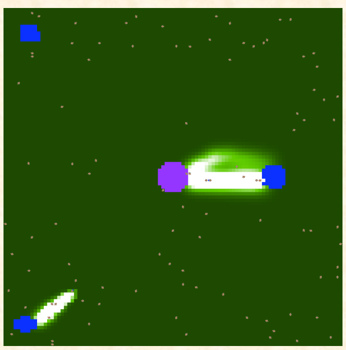

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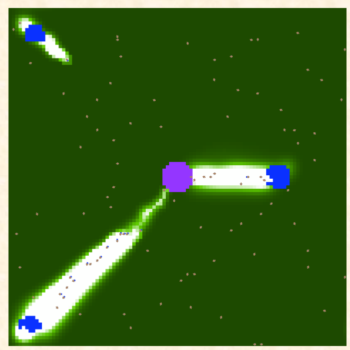

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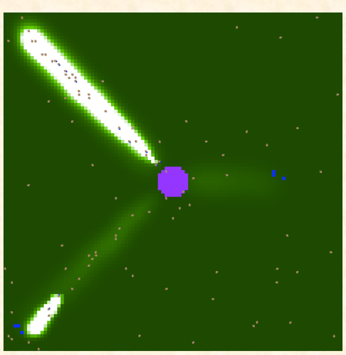

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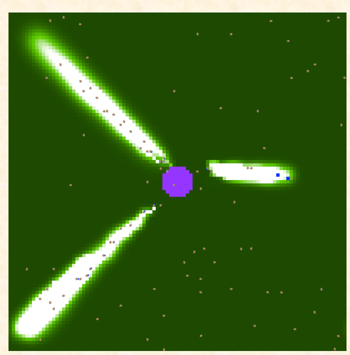

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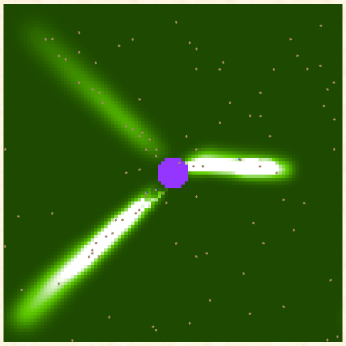

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Insertion of Barrier

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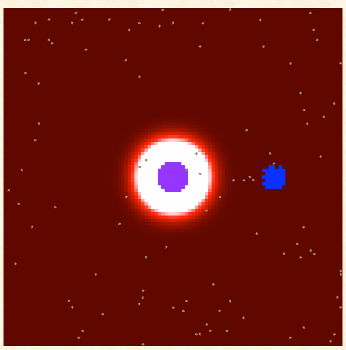

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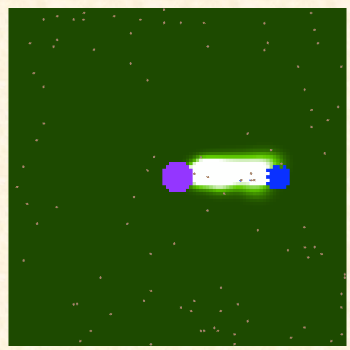

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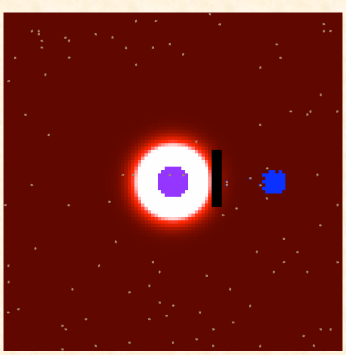

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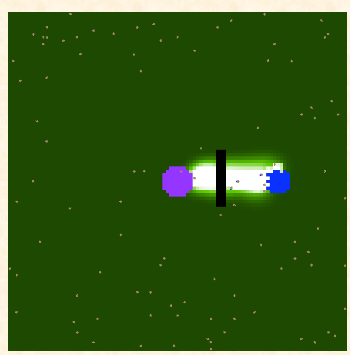

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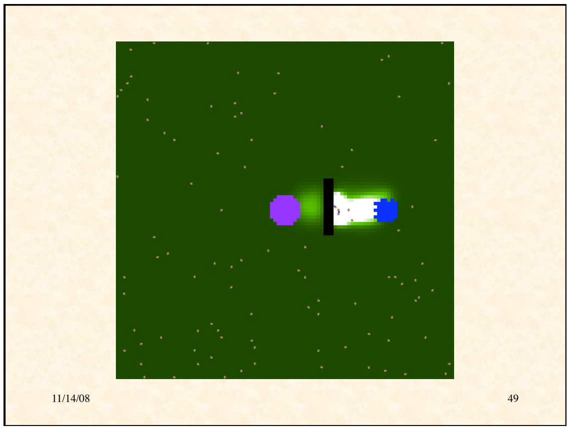
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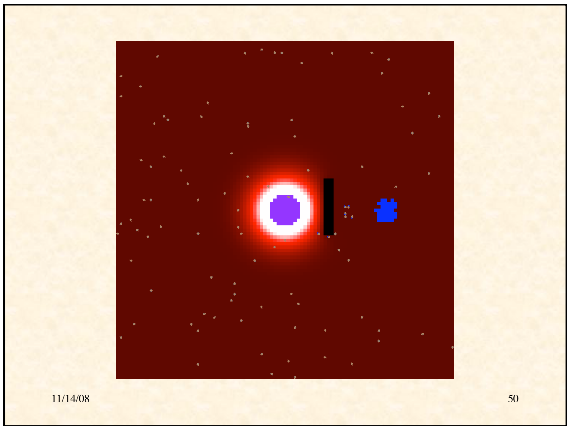
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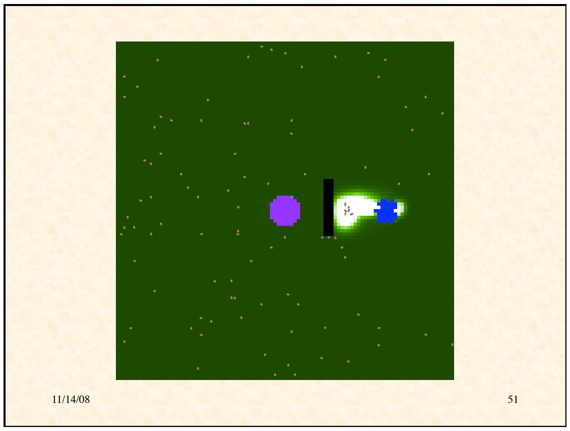
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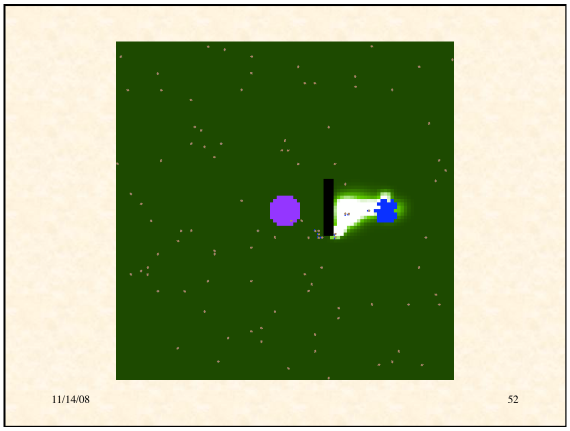
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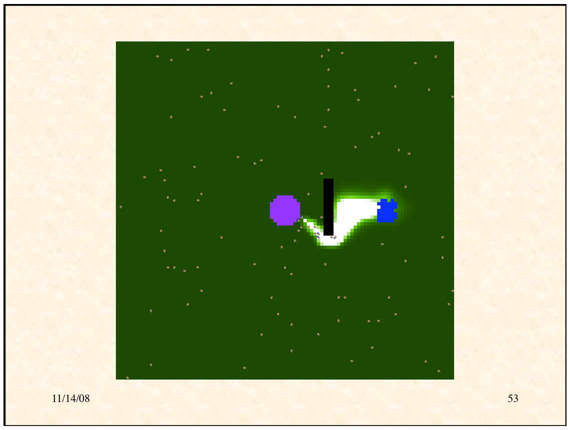
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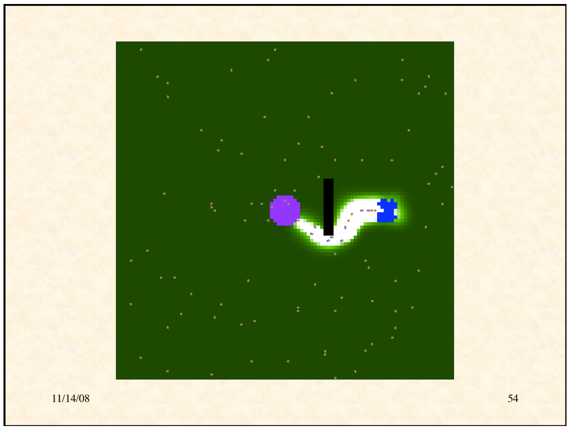
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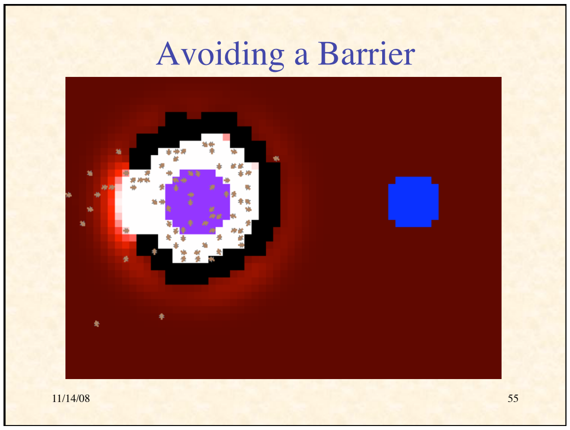
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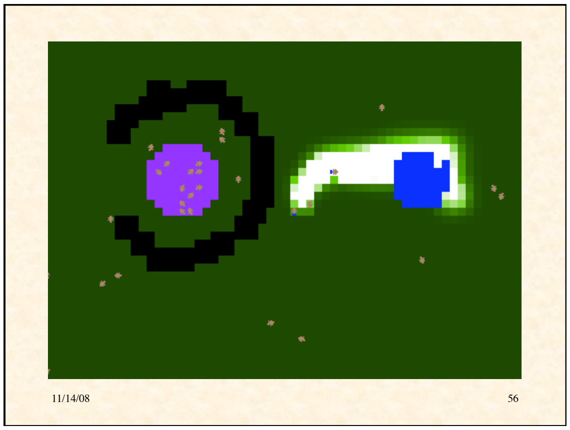
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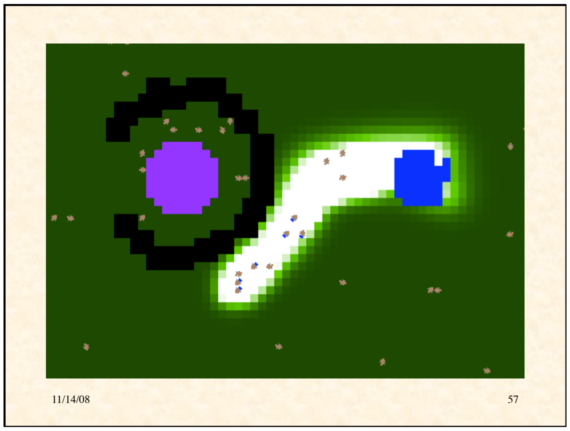
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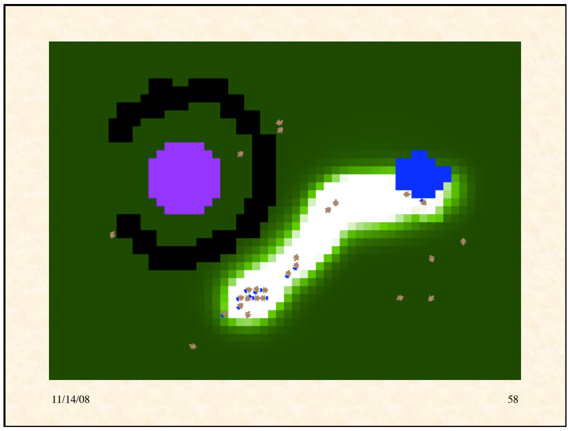
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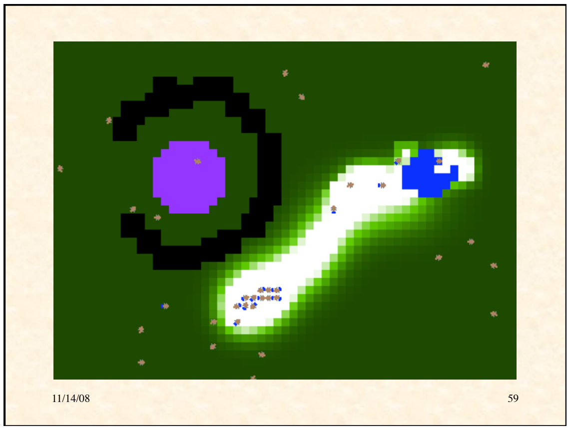
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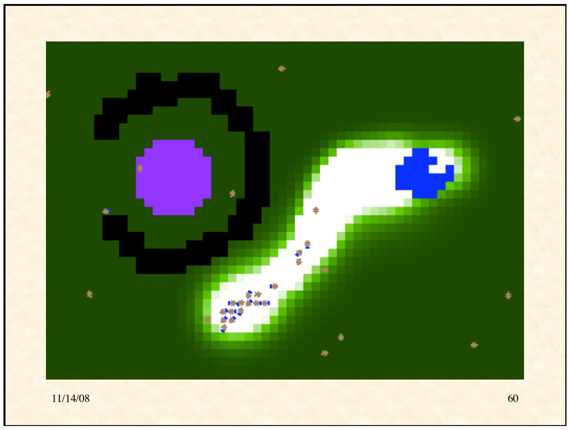
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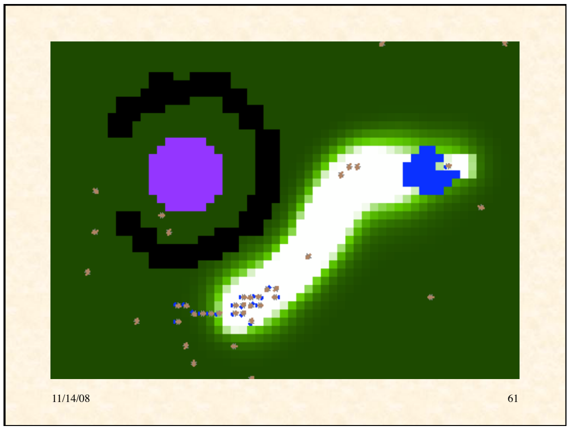
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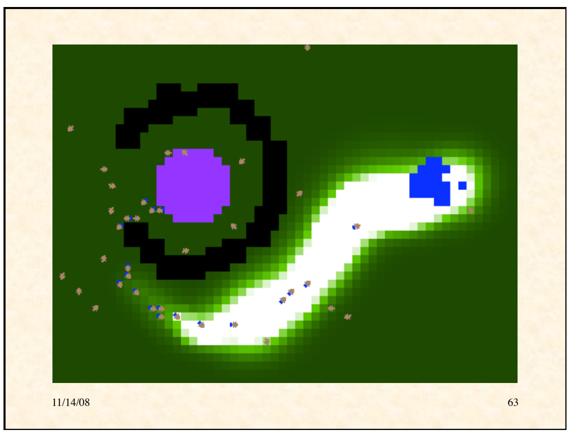
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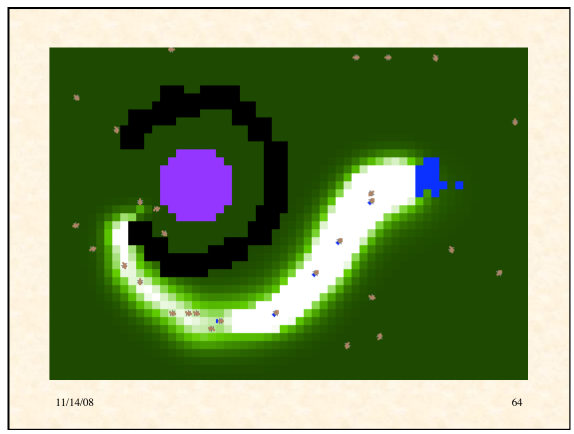
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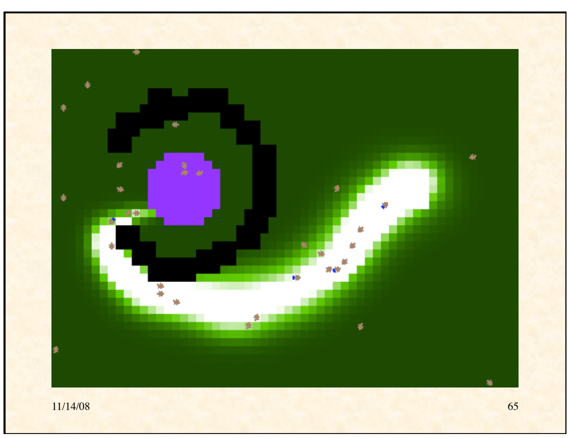
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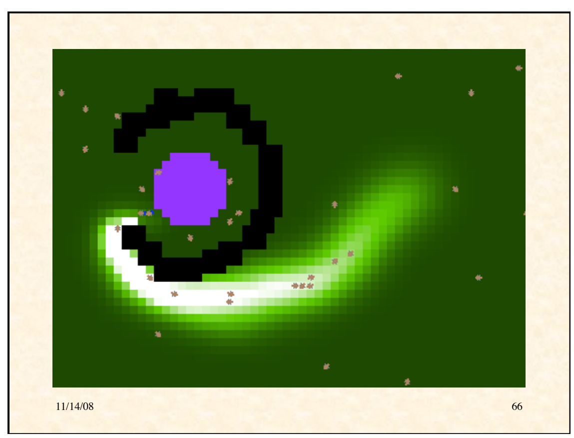
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Ant Colony Optimization (ACO)

Developed in 1991 by Dorigo (PhD dissertation) in collaboration with Colorni & Maniezzo

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Basis of all Ant-Based Algorithms

- Positive feedback
- Negative feedback
- Cooperation

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Positive Feedback

- To reinforce portions of good solutions that contribute to their goodness
- To reinforce good solutions directly
- Accomplished by *pheromone accumulation*

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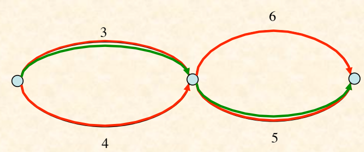
Reinforcement of Solution Components



Parts of good solutions *may* produce better solutions

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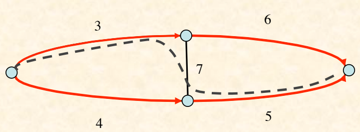
Negative Reinforcement of Non-solution Components



Parts not in good solutions *tend* to be forgotten

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Negative Feedback

- To avoid premature convergence (*stagnation*)
- Accomplished by *pheromone evaporation*

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

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

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:

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

Pheromone Decay

- Define total pheromone deposition for tour *t*:

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

- Let ρ 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
  - ∴ early convergence to suboptimal solution
- Too few:
  - don't get cooperation before pheromone decays
- Good tradeoff:
  number of ants = number of cities
  ($m = n$)

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Improvement: "Elitist" Ants

- Add a few (e≈5) "elitist" ants to population
- 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

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Time Complexity

- Let t be number of tours
- Time is $\mathcal{O}(tn^2m)$
- If $m = n$ then $\mathcal{O}(tn^3)$
  - that is, cubic in number of cities

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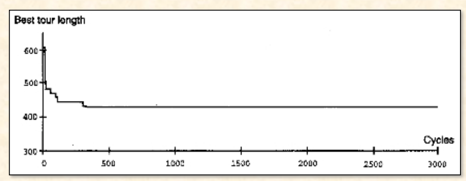
Convergence



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

11/14/08 fig. < Dorigo et al. (1996) 82

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

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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

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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, …

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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

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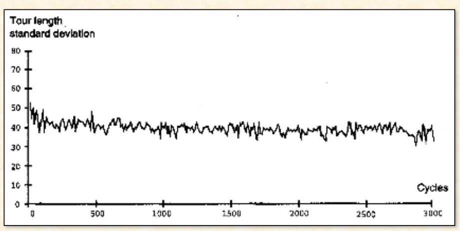
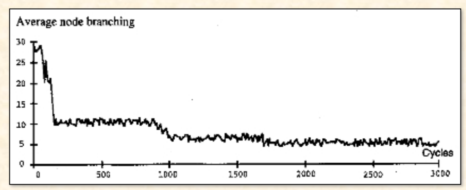
Nonconvergence



- Standard deviation of tour lengths
- Optimum = 420

11/14/08 fig. < Dorigo et al. (1996) 87

Average Node Branching Number



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

11/14/08 fig. < Dorigo et al. (1996) 88

The Nonconvergence Issue

- AS 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

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Natural Computation

Natural computation is computation that occurs in nature or is inspired by computation occurring in nature

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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 often the enemy of the good"

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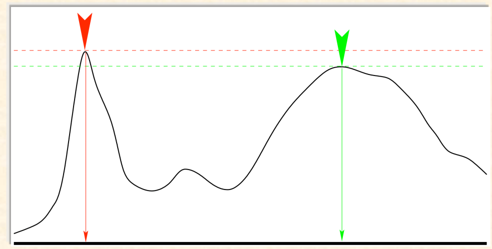
Robust Optima



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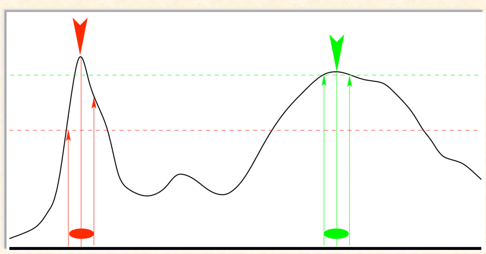
Effect of Error/Noise



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