


Lecture 2

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How Do They Do It?

- Communication in Red Harvester Ants
- Good source: Deborah Gordon: *Ants at Work* (1999)



8/28/07 (video from *Stanford Report*, April 2003) 2


How do they do it?

- Semiochemically: deposit pheromones
 - 10-20 signs, many signal tasks
 - ants detect pheromone gradients and frequency of encounter
- Follow trails imperfectly
 - ⇒ exploration
- Feedback reinforces successful trails
 - ⇒ biased randomness

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Ant foraging

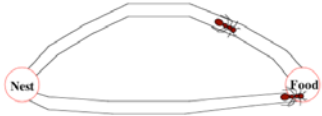
Cooperative search by pheromone trails



8/28/07 slides from EVALife 4

Ant foraging

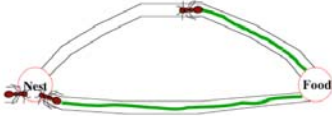
Cooperative search by pheromone trails



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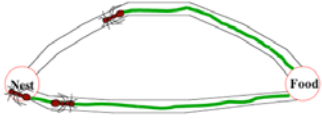
Ant foraging

Cooperative search by pheromone trails



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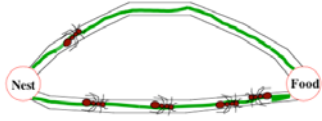
Ant foraging
Cooperative search by pheromone trails



8/28/07 slides from EVALife 7

This diagram illustrates cooperative search by pheromone trails on a closed loop. A path is shown between a 'Nest' and a 'Food' source, forming a closed loop. The path is highlighted in green, indicating the presence of pheromone trails. Several ants are shown on the path, moving in both directions between the nest and the food source.

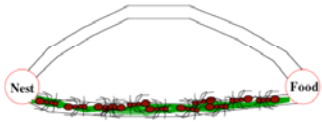
Ant foraging
Cooperative search by pheromone trails



8/28/07 slides from EVALife 8

This diagram shows the same closed loop path as slide 7, but with a higher density of ants. The green pheromone trails are more prominent, suggesting a more established and reinforced path.


Ant foraging
Cooperative search by pheromone trails



8/28/07 slides from EVALife 9

This diagram shows an open path between a 'Nest' and a 'Food' source. The path is highlighted in green, and many ants are shown moving along it, illustrating cooperative search by pheromone trails in an open environment.

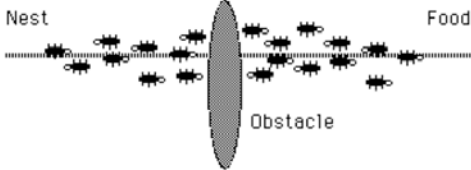
Adaptive Path Optimization



8/28/07 slides from iridia.ulb.ac.be/~mdorigo 10

This diagram illustrates adaptive path optimization on a straight path between a 'Nest' and a 'Food' source. The path is shown as a series of small black squares, with ants moving along it. The path is slightly curved, suggesting an optimization process.

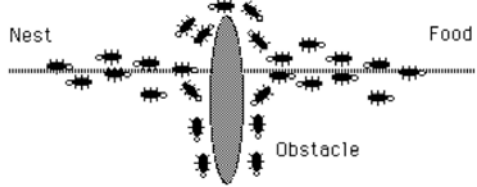
Adaptive Path Optimization



8/28/07 slides from iridia.ulb.ac.be/~mdorigo 11

This diagram shows adaptive path optimization in the presence of an obstacle. A 'Nest' is on the left, 'Food' is on the right, and a grey oval obstacle is in the center. The path is shown as a series of small black squares, with ants moving along it. The path is curved around the obstacle, illustrating an optimization process.

Adaptive Path Optimization



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This diagram shows the same setup as slide 11, but with a higher density of ants. The path is more clearly defined and curved around the obstacle, illustrating the result of adaptive path optimization.

Adaptive Path Optimization

Nest Food

Obstacle

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Circular Causality

Global Chemical Field

- Global pattern emergent from total system
- Individuals respond to local field

8/28/07 fig. from Solé & Goodwin 14

Stigmergy

- From $\sigma\tau\iota\gamma\mu\acute{o}\varsigma$ = pricking + $\acute{\epsilon}\rho\gamma\omicron\nu$ = work
- The project (work) in the environment is an instigation
- Agent interactions may be:
 - direct
 - indirect (time-delayed through environment)
- Mediates individual and colony levels

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Stigmergy in termite nest building

(Individual S_1)
(Individual S_2)
(Individual S_3)
(Individual S_4)
(Individual S_i)

Fig. from EVALife 16

Stigmergy in spider webs

Stage 1 Stage 2
Stage 3 Stage 4


8/28/07 Fig. from EVALife 17

Rules Behaviour Patterns Sensors and Motors

8/28/07 Fig. from EVALife 18

Advantages of Stigmergy

- Permits simpler agents
- Decreases direct communication between agents
- Incremental improvement
- Flexible, since when environment changes, agents respond appropriately



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Emergence

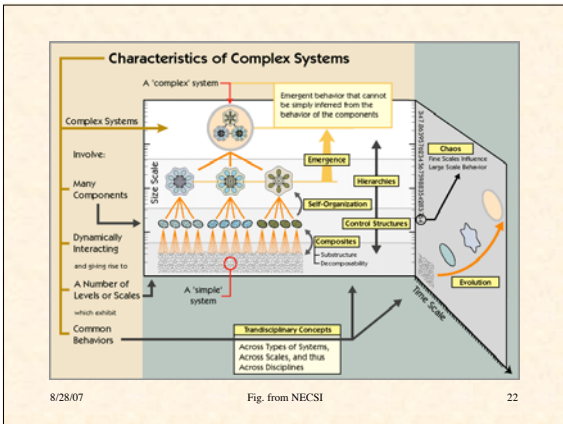
- The appearance of *macroscopic* patterns, properties, or behaviors
- that are not simply the “sum” of the *microscopic* properties or behaviors of the components
 - non-linear but not chaotic
- Macroscopic order often described by fewer & different variables than microscopic order
 - e.g. ant trails vs. individual ants
 - *order parameters*

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Self-Organization

- Order may be imposed from outside a system
 - to understand, look at the external source of organization
- In *self-organization*, the order emerges from the system itself
 - must look at interactions within system
- In biological systems, the emergent order often has some adaptive purpose
 - e.g., efficient operation of ant colony

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Why Are Complex Systems & Self-Organization Important for CS?

- Fundamental to theory & implementation of massively parallel, distributed computation systems
- How can millions of independent computational (or robotic) agents cooperate to process information & achieve goals, in a way that is:
 - efficient
 - self-optimizing
 - adaptive
 - robust in the face of damage or attack

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Some Principles Underlying Emergent Systems

- “More is different”
- “Ignorance is useful”
- “Encourage random encounters”
- “Look for patterns in signals”
- “Pay attention to your neighbor” (“Local information leads to global wisdom”)

– Johnson, *Emergence*, pp. 77-9.

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Similar Principles of SO

- Ant colonies
- Development of embryo
- Molecular interactions within cell
- Neural networks

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Comparison of Ant Colonies and Neural Networks

	<i>Ant Colonies</i>	<i>Neural Nets</i>
No. of units	high	high
Robustness	high	high
Connectivity	local	local
Memory	short-term	short/long term
Connect. stability	weak	high
Global patterns	trails	brain waves
Complex dynamics	observed	common

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from Solé & Goodwin: *Signs of Life*, p. 149

Self-Organization

- Concept originated in physics and chemistry
 - emergence of macroscopic patterns
 - out of microscopic processes & interactions
- “Self-organization is a set of dynamical mechanisms whereby structures appear at the global level of a system from interactions among its lower-level components.” — Bonabeau, Dorigo & Theraulaz, p. 9

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Four Ingredients of Self-Organization

- Activity amplification by positive feedback
- Activity balancing by negative feedback
- Amplification of random fluctuations
- Multiple Interactions

— Bonabeau, Dorigo & Theraulaz, pp. 9-11

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Characteristics of Self-Organized System

- Creation of spatiotemporal structures in initially homogeneous medium
- Multistability
- Bifurcations when parameters are varied

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— Bonabeau, Dorigo & Theraulaz, *Swarm Intelligence*, pp. 12-14

Additional Bibliography

1. Solé, Ricard, & Goodwin, Brian. *Signs of Life: How Complexity Pervades Biology*. Basic Books, 2000.
2. Bonabeau, Eric, Dorigo, Marco, & Theraulaz, Guy. *Swarm Intelligence: From Natural to Artificial Systems*. Oxford, 1999.
3. Gordon, Deborah. *Ants at Work: How an Insect Society Is Organized*. Free Press, 1999.
4. Johnson, Steven. *Emergence: The Connected Lives of Ants, Brains, Cities, and Software*. Scribner, 2001. A popular book, but with many good insights.

Part II

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II. Cellular Automata

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Cellular Automata (CAs)

- Invented by von Neumann in 1940s to study reproduction
- He succeeded in constructing a self-reproducing CA
- Have been used as:
 - massively parallel computer architecture
 - model of physical phenomena (Fredkin, Wolfram)
- Currently being investigated as model of quantum computation (QCs)

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Structure

- Discrete space (lattice) of regular *cells*
 - 1D, 2D, 3D, ...
 - rectangular, hexagonal, ...
- At each unit of time a cell changes state in response to:
 - its own previous state
 - states of neighbors (within some “radius”)
- All cells obey same state update rule
 - an FSA
- Synchronous updating

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Example: Conway’s Game of Life

- Invented by Conway in late 1960s
- A simple CA capable of universal computation
- Structure:
 - 2D space
 - rectangular lattice of cells
 - binary states (alive/dead)
 - neighborhood of 8 surrounding cells (& self)
 - simple population-oriented rule

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State Transition Rule

- Live cell has 2 or 3 live neighbors
⇒ stays as is (stasis)
- Live cell has < 2 live neighbors
⇒ dies (loneliness)
- Live cell has > 3 live neighbors
⇒ dies (overcrowding)
- Empty cell has 3 live neighbors
⇒ comes to life (reproduction)

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Demonstration of Life

[Run NetLogo Life](#)

or

www.cs.utk.edu/~mclennan/Courses/420/NetLogo/Life.html

[Go to CBN](#)

[Online Experimentation Center](#)

mitpress.mit.edu/books/FLA0H/cbnhtml/java.html

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Some Observations About Life

1. Long, chaotic-looking initial transient
 - unless initial density too low or high
2. Intermediate phase
 - isolated islands of complex behavior
 - matrix of static structures & “blinkers”
 - gliders creating long-range interactions
3. Cyclic attractor
 - typically short period


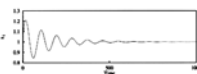

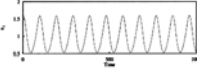

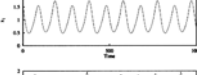

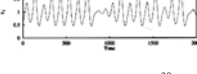
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From Life to CAs in General

- What gives Life this very rich behavior?
- Is there some simple, general way of characterizing CAs with rich behavior?
- It belongs to Wolfram’s Class IV

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The four classes of feedback behaviour

(a) Fixed points		
(b) Simple periodic orbits		
(c) Period-n orbit		
(d) Chaos		

8/28/07 fig. from Flake via EVALife 39

Wolfram’s Classification

- Class I: evolve to fixed, homogeneous state
~ limit point
- Class II: evolve to simple separated periodic structures
~ limit cycle
- Class III: yield chaotic aperiodic patterns
~ strange attractor (chaotic behavior)
- Class IV: complex patterns of localized structure
~ long transients, no analog in dynamical systems

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Langton’s Investigation

Under what conditions can we expect a complex dynamics of information to emerge spontaneously and come to dominate the behavior of a CA?

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Approach

- Investigate 1D CAs with:
 - random transition rules
 - starting in random initial states
- Systematically vary a simple parameter characterizing the rule
- Evaluate qualitative behavior (Wolfram class)

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Why a Random Initial State?

- How can we characterize typical behavior of CA?
- Special initial conditions may lead to special (atypical) behavior
- Random initial condition effectively runs CA in parallel on a sample of initial states
- Addresses emergence of order from randomness

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Assumptions

- Periodic boundary conditions
 - no special place
- Strong quiescence:
 - if all the states in the neighborhood are the same, then the new state will be the same
 - persistence of uniformity
- Spatial isotropy:
 - all rotations of neighborhood state result in same new state
 - no special direction
- Totalistic [not used by Langton]:
 - depend only on sum of states in neighborhood
 - implies spatial isotropy

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Demonstration of 1D Totalistic CA

Run [NetLogo 1D CA General Totalistic](#)

or

www.cs.utk.edu/~mclennan/Courses/420/NetLogo/CA-1D-General-Totalistic.html

[Go to CBN](#)
[Online Experimentation Center](#)

mitpress.mit.edu/books/FLA0H/cbnhtml/java.html

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Langton’s Lambda

- Designate one state to be quiescent state
- Let K = number of states
- Let $N = 2r + 1$ = size of neighborhood
- Let $T = K^N$ = number of entries in table
- Let n_q = number mapping to quiescent state
- Then

$$\lambda = \frac{T - n_q}{T}$$

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Range of Lambda Parameter

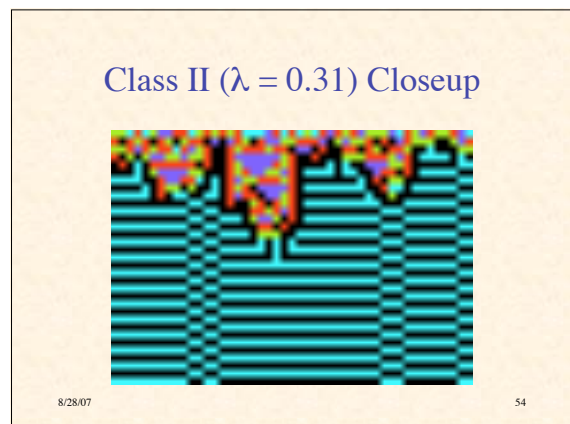
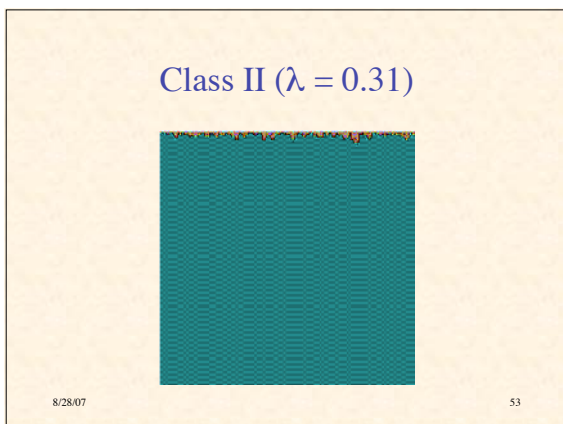
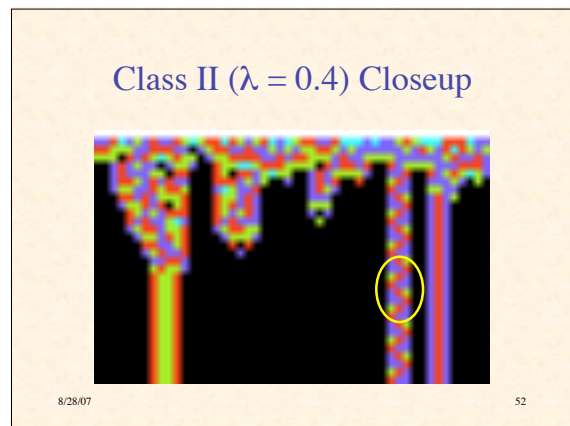
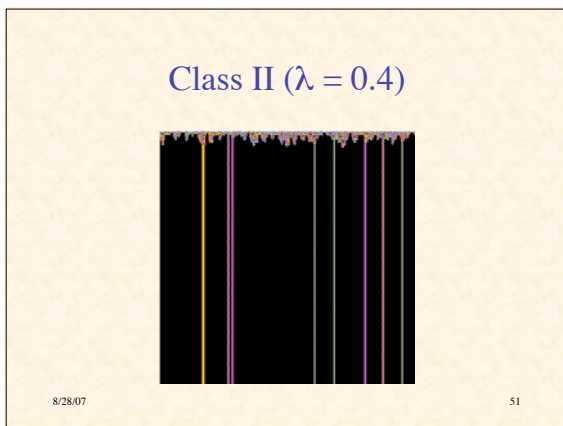
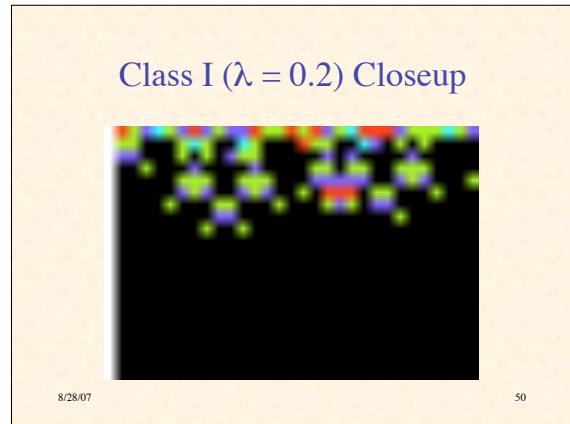
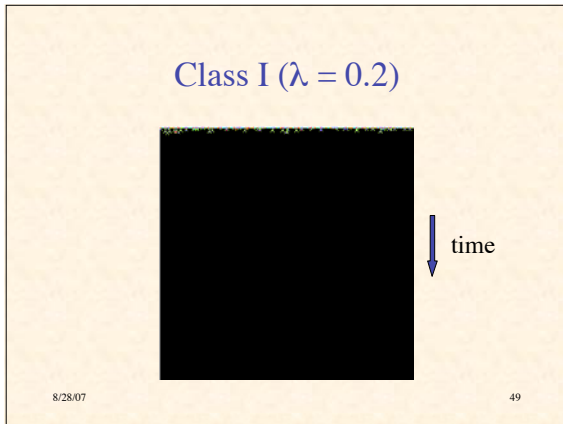
- If *all* configurations map to quiescent state:
 $\lambda = 0$
- If *no* configurations map to quiescent state:
 $\lambda = 1$
 - If every state is represented *equally*:
 $\lambda = 1 - 1/K$
 - A sort of measure of “excitability”

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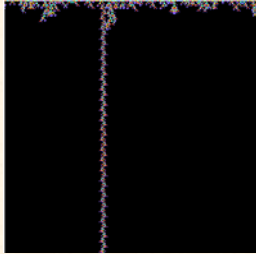
Example

- States: $K = 5$
- Radius: $r = 1$
- Initial state: random
- Transition function: random (given λ)

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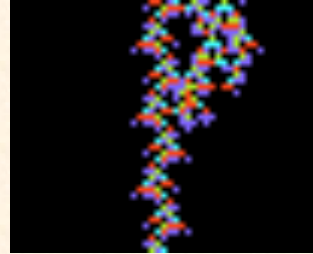
Class II ($\lambda = 0.37$)



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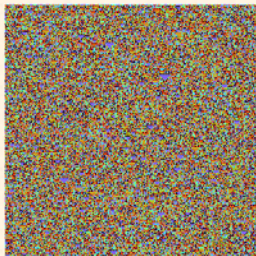
Class II ($\lambda = 0.37$) Closeup



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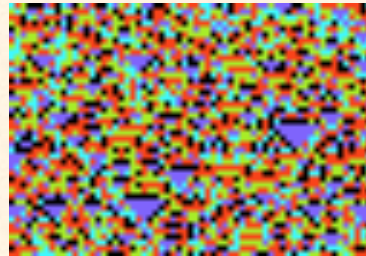
Class III ($\lambda = 0.5$)



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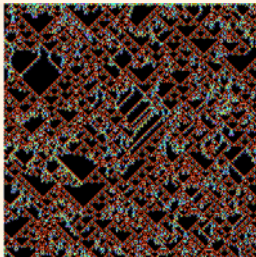
Class III ($\lambda = 0.5$) Closeup



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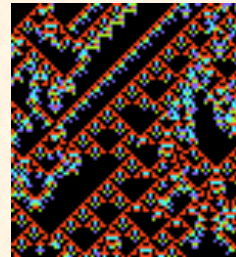
Class IV ($\lambda = 0.35$)



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Class IV ($\lambda = 0.35$) Closeup



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Class IV ($\lambda = 0.34$)

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Class IV Shows Some of the Characteristics of Computation

- Persistent, but not perpetual storage
- Terminating cyclic activity
- Global transfer of control/information

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λ of Life

- For Life, $\lambda \approx 0.273$
- which is near the critical region for CAs with:
 - $K = 2$
 - $N = 9$

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