

presenting

Evolution of Self-Organized Systems

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Introduction

- “Biological systems are, in general, global patterns produced by local interactions” that self-organize
 - A bold example: DNA is not a central pattern generator
 - Protein shape not simply encoded in DNA
 - Nor is DNA a “linear” developmental map
- Insect colonies are self-organizing systems of “intermediate” integration
 - Single organism < social insect colony < group of unconnected agents
- Inheritance sets biological self-organization apart from non-biological self-organized systems
 - BZ-reaction diffusion / propagation (for example) may be modified only by changing external conditions or container / volume
 - Biological inheritance allows for a kind of persistence of memory w/ (occasionally or possibly) modified rules

An appeal to evolutionary biologists

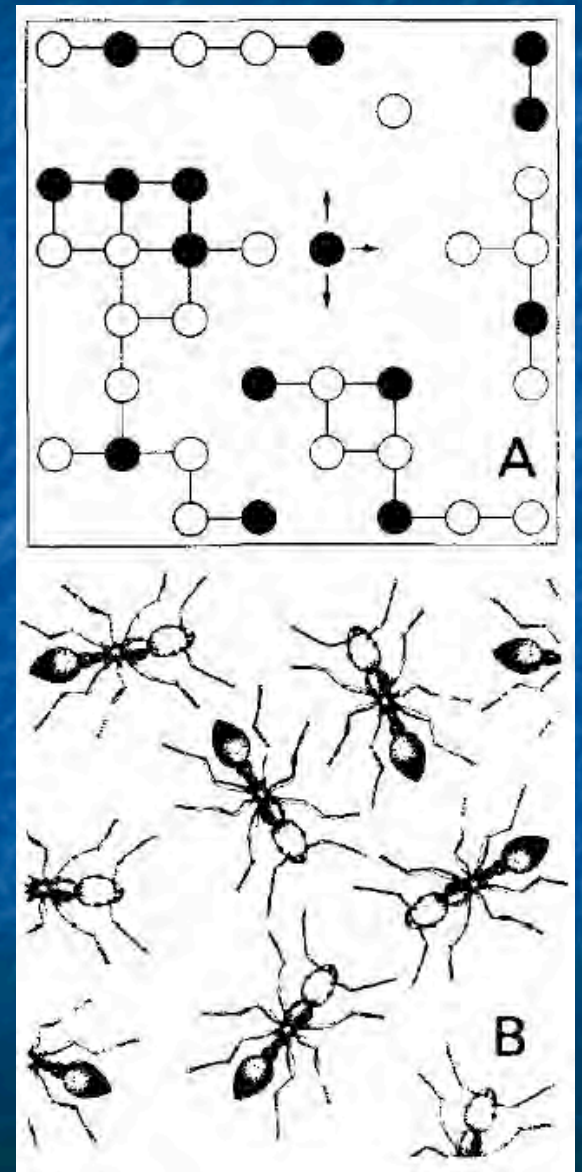
- Inherited self-organized structures are significant biological phenomena
 - Self-organizing systems “produce phenotypes subject to selection or other evolutionary processes”
 - Evolution operates on the inherited elements of self-organized systems. Moreover, it operates on the interactions of said elements
 - Small changes in components-> drastic phase changes
 - Of course, phase change and criticality are not unique to biology; Cole means to describe evolution as what it is: a source for small changes (unique to biology in the natural world)
- Purpose: “To look at an example of selection operating on colony functions to change interactions among workers in such a way as to alter the self-organized activity patterns of the colony”

The system studied

- Dynamics of activity in *Leptothorax* ant colonies
- Two Solé et al papers (1993, 1995) [previously read for homework 2] present a model for the activity dynamics of *Leptothorax* ants, modeling actual ants described experimentally by Cole in 1991!
 - Cole observed (and others' in the field) ant colonies exhibiting irregular but periodic cycles of activity, yet individual ants behaved randomly and low-density populations had no synchrony
- In the present study, Cole introduces a genetic algorithm (GA) to a Solé-like model to explore evolution and adaptation in this self-organized system

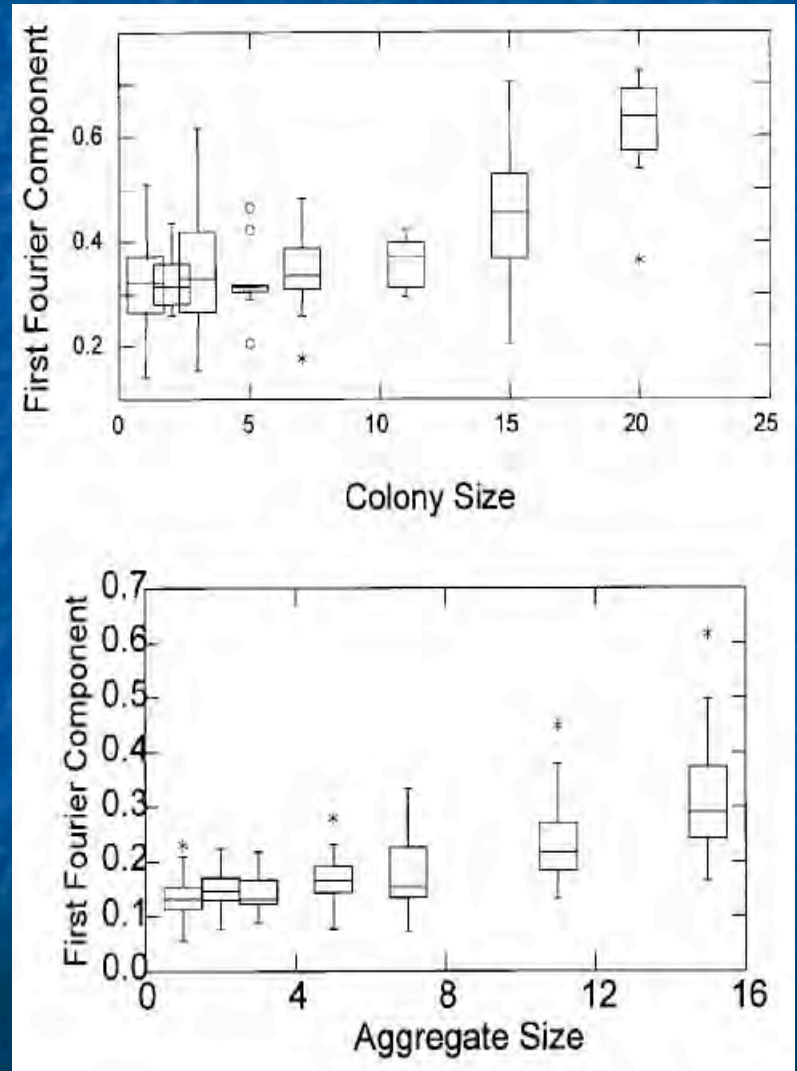
Modeling oscillating activity patterns

- Using a *Fluid Neural Network (FNN)*, also called *Mobile Cellular Automata or MCA* model
 - Inactive ants can spontaneously self-activate and thus move (both probabilistic and chaotic functions work) to an adjacent empty node at random
 - The state function (for which an ant is active above a specified value) of an active ant undergoes exponential decay towards inactivity (a refractory period)
 - Active ants wander their 2D lattice 1 node / time increment...
 - Interacting with ants they make neighbors of
 - By rules specified in a 2x2 interaction matrix, J , that determines allowed interactions between and among neighboring active and inactive ants



Leptothorax allardycei & model activity vs. colony size

- A) actual ants
- B) some of Cole's FNN
 - Note: size ~ density for fixed lattice size.
 - Fourier transformed activity measures appear to trend similarly



The rule matrix, J

- Active ants may activate (or do nothing), inactive ants can in/deactivate (or do nothing) by these rules
- Each J_i is either $\{0,1\}$
 - If $J_1=1$, active ants can be activated by active ants
 - If $J_4=0$, inactive ants cannot further deactivate inactive ants (or themselves)
- 16 combinations of J
 - $J_1=1$ rules are necessary and sufficient to generate periodic activity and can be regarded as self-interacting

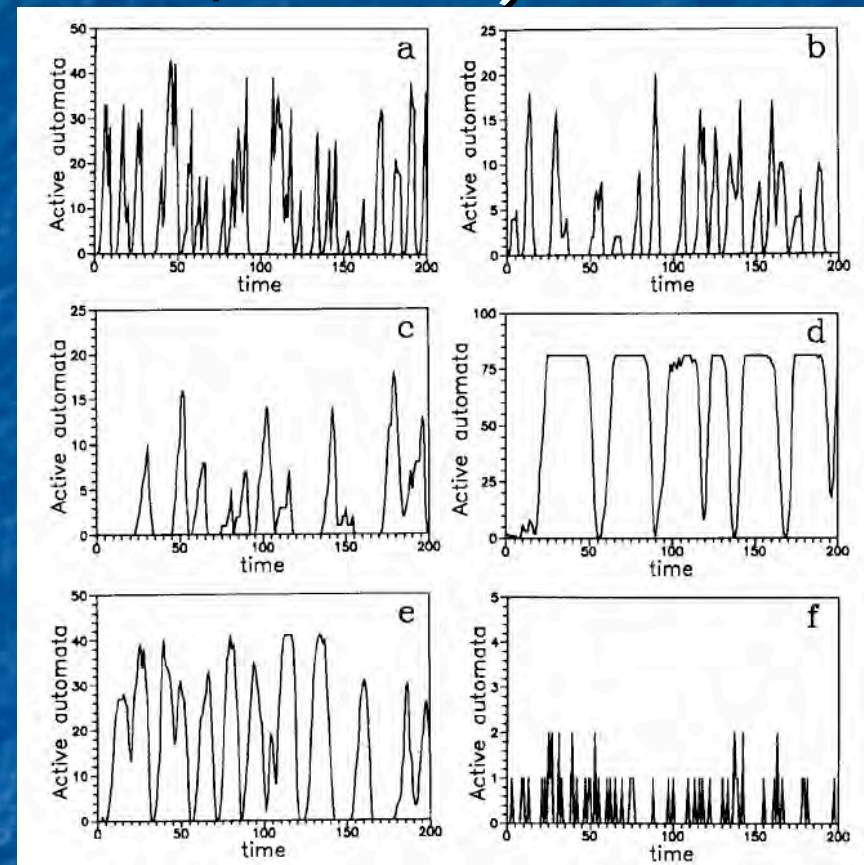
	Active	Inactive
Active	$J_1=1$	J_2
Inactive	J_3	$J_4=0$

$J_1=1$ rules and emergent periodicity (Solé 1993, 1995)

- High density ($D > 0.5$) systems converge to a regular(!) period of activity (Solé 1993)
- Irregular oscillations emerge

Ant
Density

- Low density systems: # of active elements changes chaotically



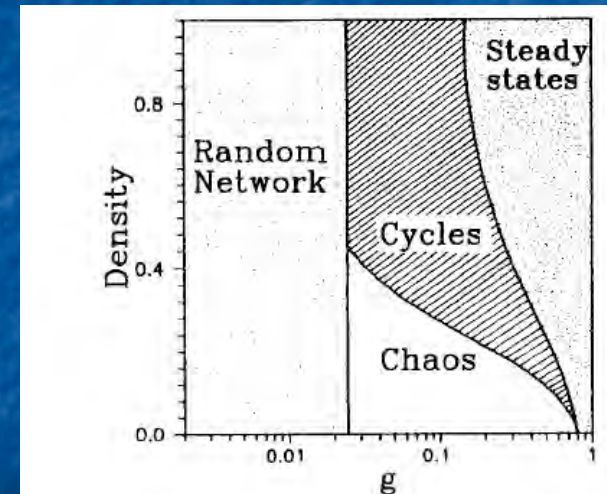
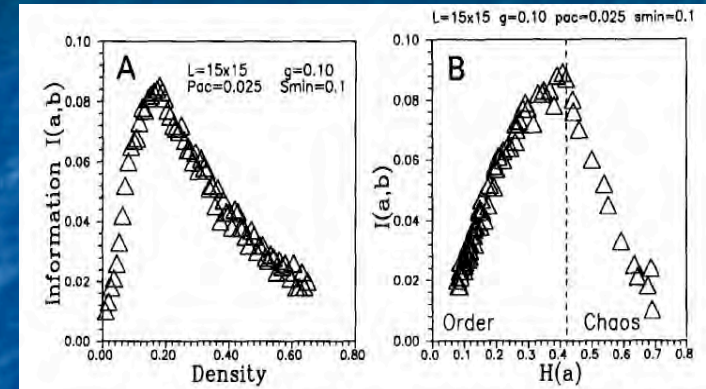
Dynamic patterns of activity for various densities (and gains, a value for ease of activation). In c,d,e: $g=0.1$ and $p=0.2, 0.8,$ and $0.4,$ respectively. Solé et al 1995

The Genetic Algorithm

- Fitness : Let fitness be dependent upon the rate of information (or food) propagation in the colony
 - Colonies where information and ants can move quickly are more fit
 - Thus, length of transit time of ants seems to specify $1/\text{fitness}$
- Set-up *seems a bit unclear but I read it as:* @ t_0 , all $J=0$ for exactly three workers
 - At each increment of t , fitness is assessed as a function of the "transit time of workers within colonies that use particular" rules
 - 10 simulations sampled for ea. rule-set and population
 - (*how this part fits, I can't figure out*) 15 different population sizes from 3 to 65 ants tested as well?
 - Fixed colony space means increasing density
- Mutation rules:
 - ± 1 worker or
 - single rule shift in one J (i.e. $[1,0,0,1] \rightarrow [1,1,0,1]$)
 - Rate = $0.01/(\text{colony} \times \text{generation})$ or 10 mutants / generation
- Repopulation:
 - A set of 1000 colonies is repopulated for 500 generations based on relative fitness-weighted random replication of colonies

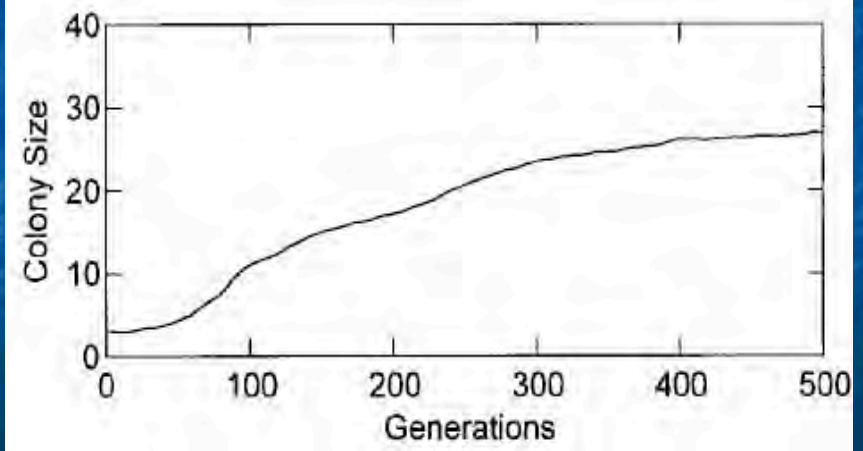
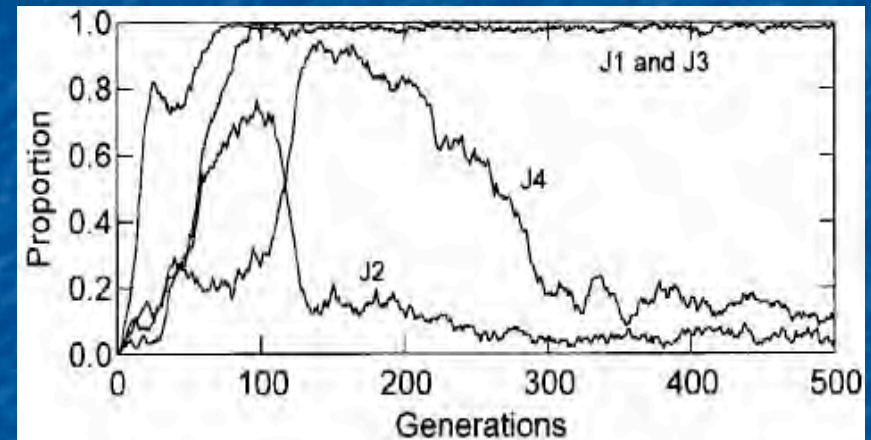
Again, to contrast w/ Solé et al studies

- Solé et al define FNN models for ant colonies, and simulate models spanning all densities and gains (gain reduces “resistance” to activation)
 - Defining phase boundaries
 - Discovering that entropy and information maximizing critical densities that demark phase changes between order and chaos
 - Explicitly describing only 2 (maybe 4) J matrices
- While Cole aims to evolve said FNN, letting density and J mutate, interrogating for adaptations



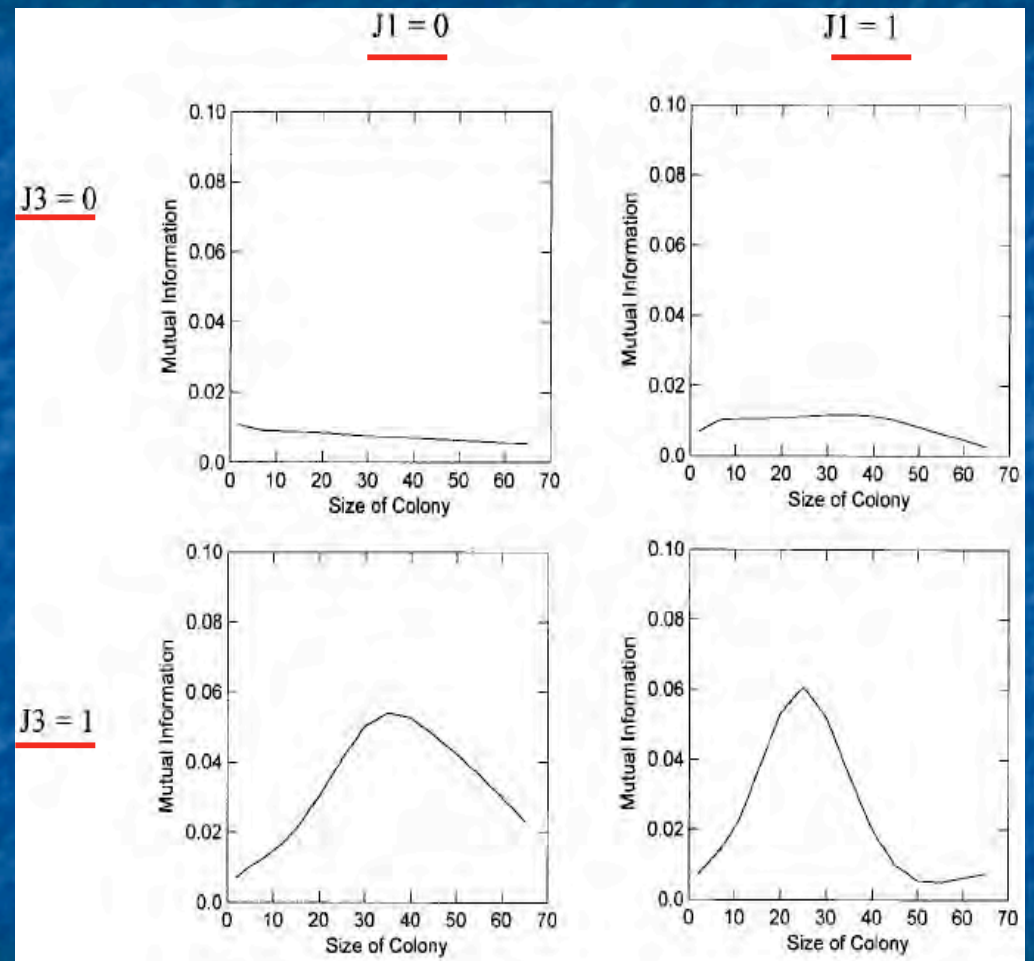
GA results

- A) Proportions for ea. : $J_i=1$ among successive generations
 - J_1, J_3 fix rapidly and do not “unfix”
- B) Colony population (density) through generations
 - Converges to ~ 28 (Why no units?!)
 - As size increases (from gen_0 : 3 ants) density can help ants co-activate ?
 - While increasing colony sizes(density) increasingly stifles diffusion
 - Size selection in early generations accounts for transient J_2, J_4 selection
- “selection on transit time produced a rule set that generates self-organized activity cycles. These self-organized patterns are themselves not the outcome of selection; they have no effect on function or fitness.”



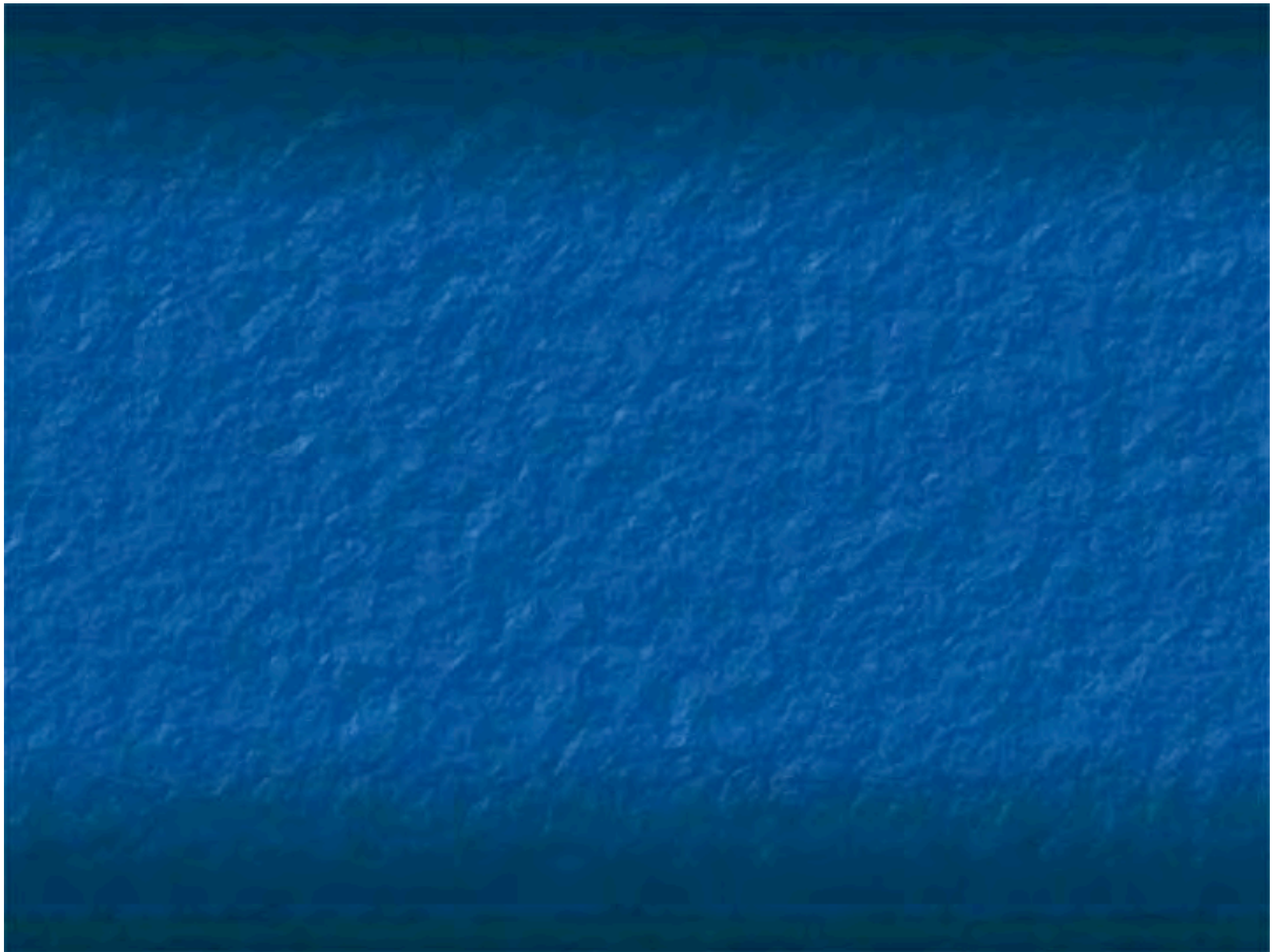
J1 & J3 pairs and Information

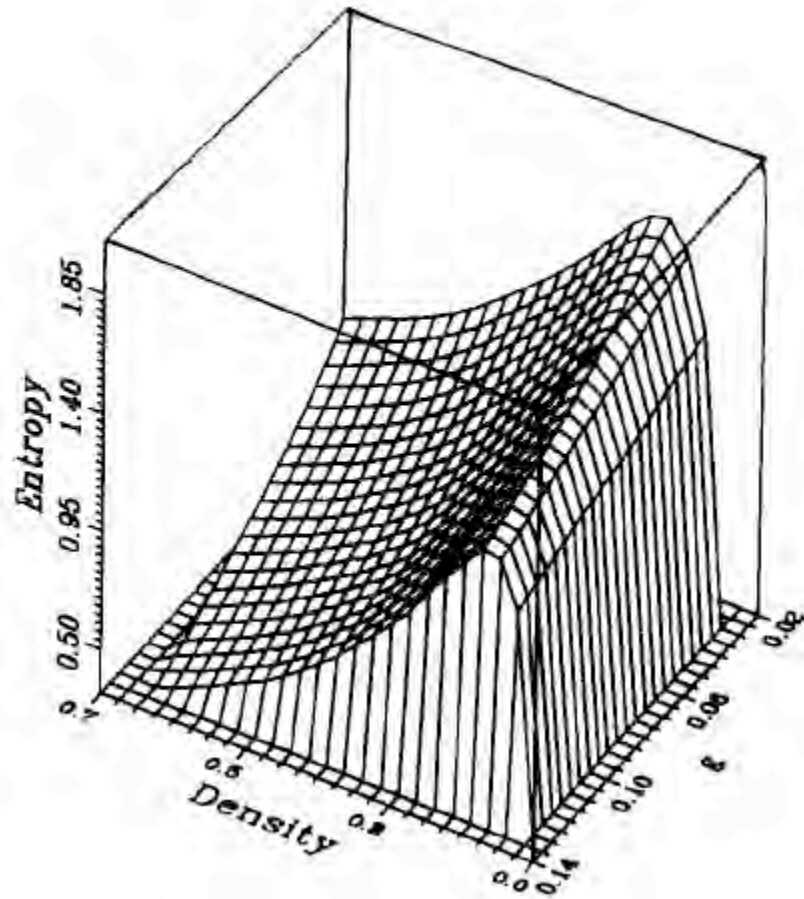
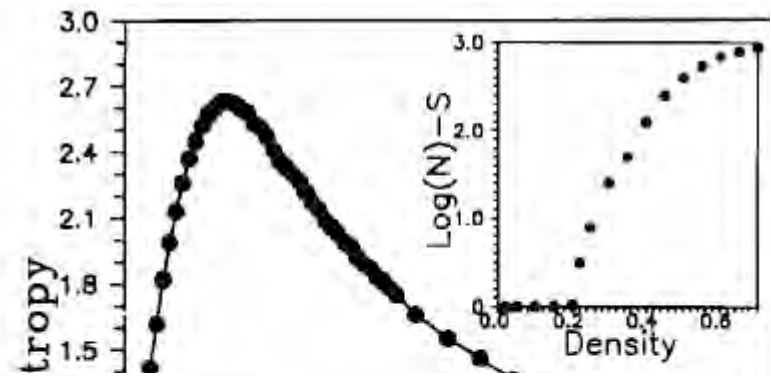
- An entropic measure of information transfer among pairs of CA is given for J1 and J3 values for a range of densities
- When $I = 0$, ants behave independently and when ants maintain state over long t , I is low.
- “When selection operates on the speed of movement through the nexs, the correlated effect is to increase the complexity of activity patterns.”



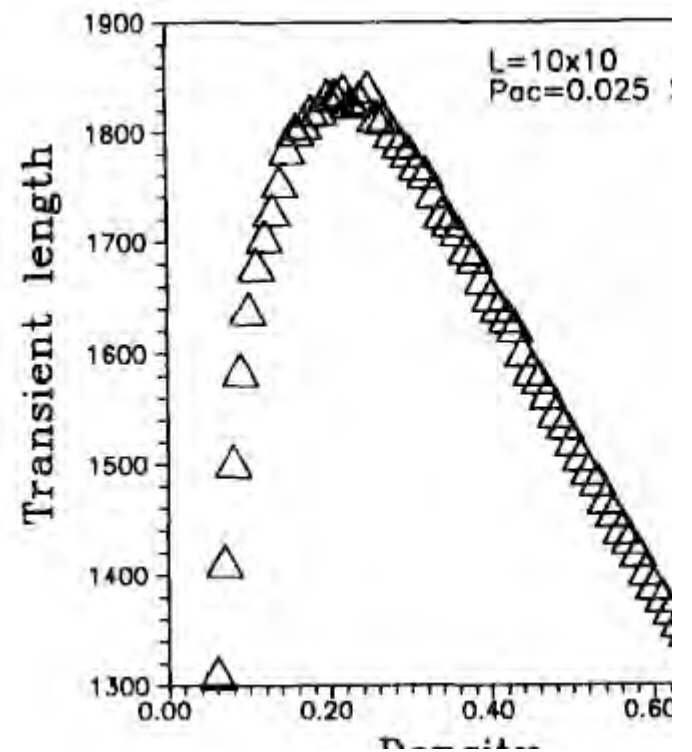
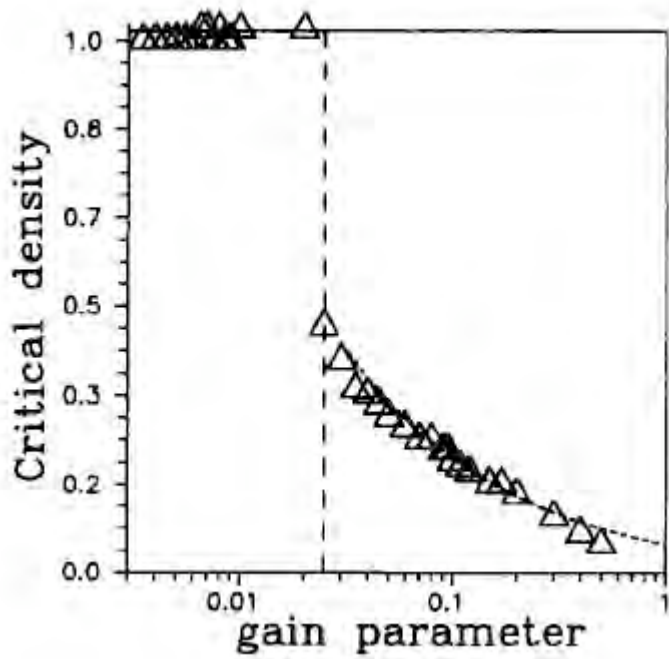
Conclusions

- Observed self-organized patterns are not necessarily adaptations in systems subject to selection
- Periodicity occurs simply as a side-effect of rule adaptations that favor activity (which obviously favors travel rate)
- An interesting extension: nothing rules out some future environment wherein periodicity directly confers some advantage: an exaption.





0.9 1.



Information at the edge of chaos (Solé)

- “[Order] appears to be a compromise between two antagonists: the nonlinear process where fluctuations are strongly but coherently amplified; and the communication[...] process, which captures relays and stabilizes the signals” (Solé 1995)
- An entropic measure of information transfer between pairs of CA has a maximum value at the phase transition point of entropy and at a critical density

