

Evolving Intelligence

Lecture 13 I400/I590

Artificial Life as an approach to Artificial Intelligence

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Evolution is a Tautology

- That which survives, persists.
- That which reproduces, increases its numbers.
- Things change.
- Any little niche...
- "The cheapest, least intensively designed system will be 'discovered' first by Mother Nature, and myopically selected." — Dennett (*Kinds of Minds*)

Evolutionary Algorithms

- Genetic Algorithms are powerful optimizers
 - Good for common engineering tasks, ranging from airfoil design to plant layout
 - Good for management tasks, such as timetables, resource scheduling, and packet routing
 - Even good for evolving learning algorithms and simulated organisms and behaviors

Evolutionary Algorithms

- Making them open-ended is a challenge
 - Many niches and niche creation
 - GAs are good at exploring multiple, simultaneous solutions
 - Self-interpreting digital DNA, artificial chemistries
 - Development processes, responsive to environment
 - Neutral mutations

Evolutionary Constraints

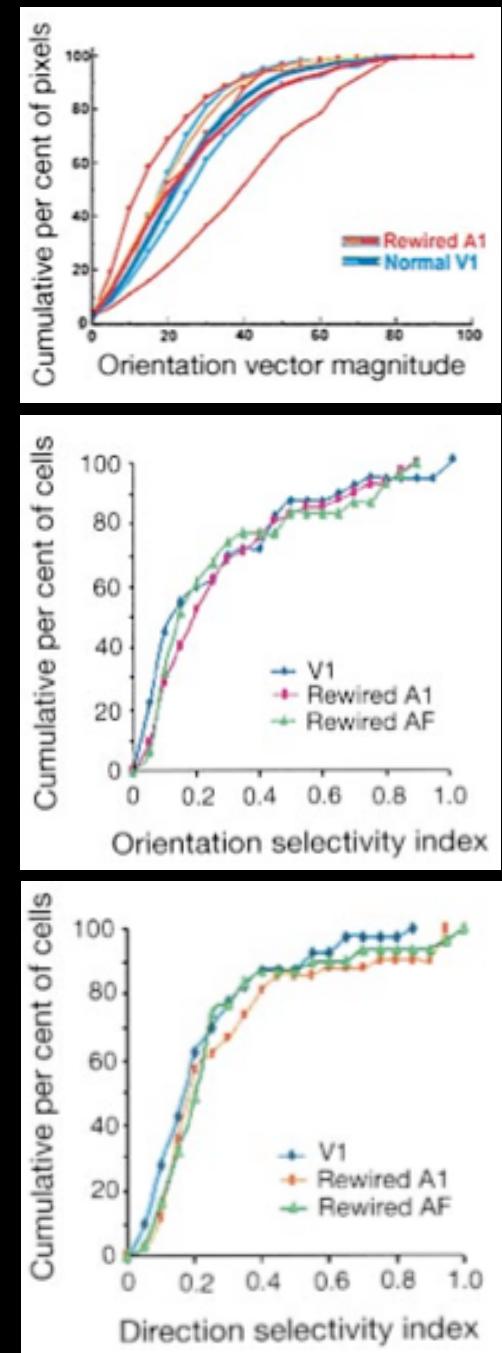
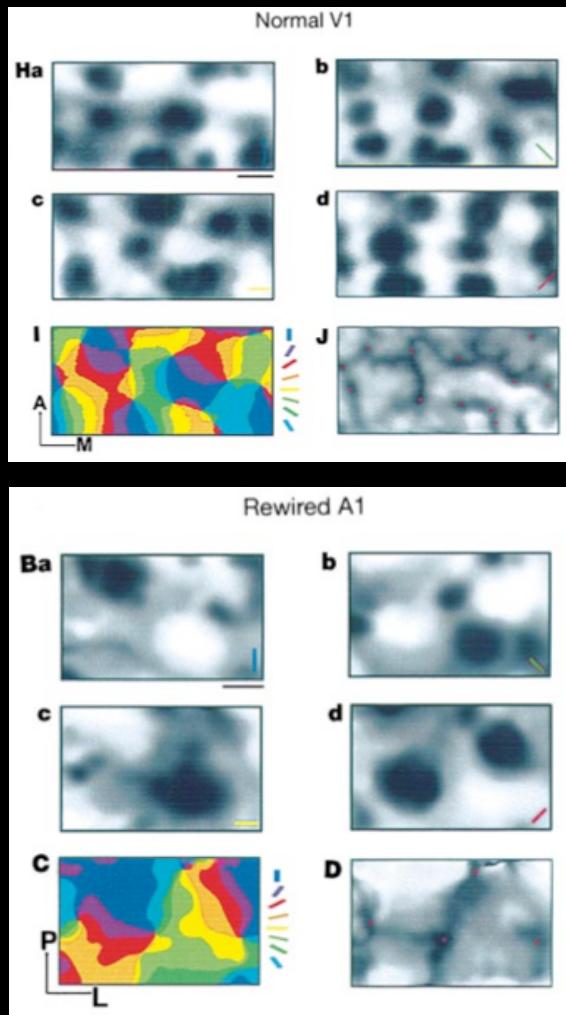
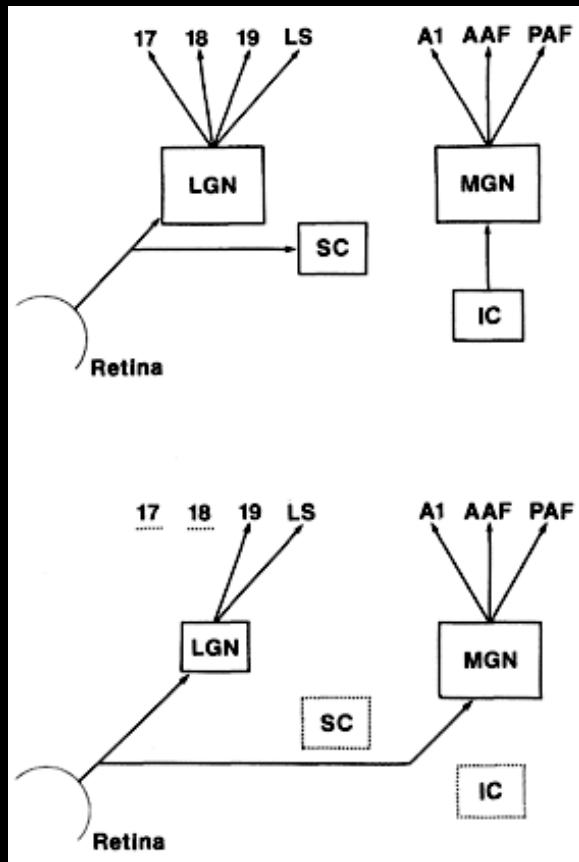
- Evolution is often constrained by its previous successes
 - Can't afford to lose fitness, even in order to gain it
 - Unable to start from scratch and compete with existing successes
 - Disrupting any existing function may reduce fitness
 - Disrupting metabolic pathways may be fatal

Nervous Systems

- Evolution found and stuck with nervous systems for controlling behavior at all levels of complexity
 - Networks of neurons and synaptic connections
 - Provide all behaviors—including anything that might be considered intelligence—in all organisms more complex than plants, *c. elegans* to *homo sapiens*
 - Some behaviors are innate, so the wiring diagram must matter
 - Some behaviors are learned, so learning—phenotypic plasticity—must also matter

Plasticity in Function

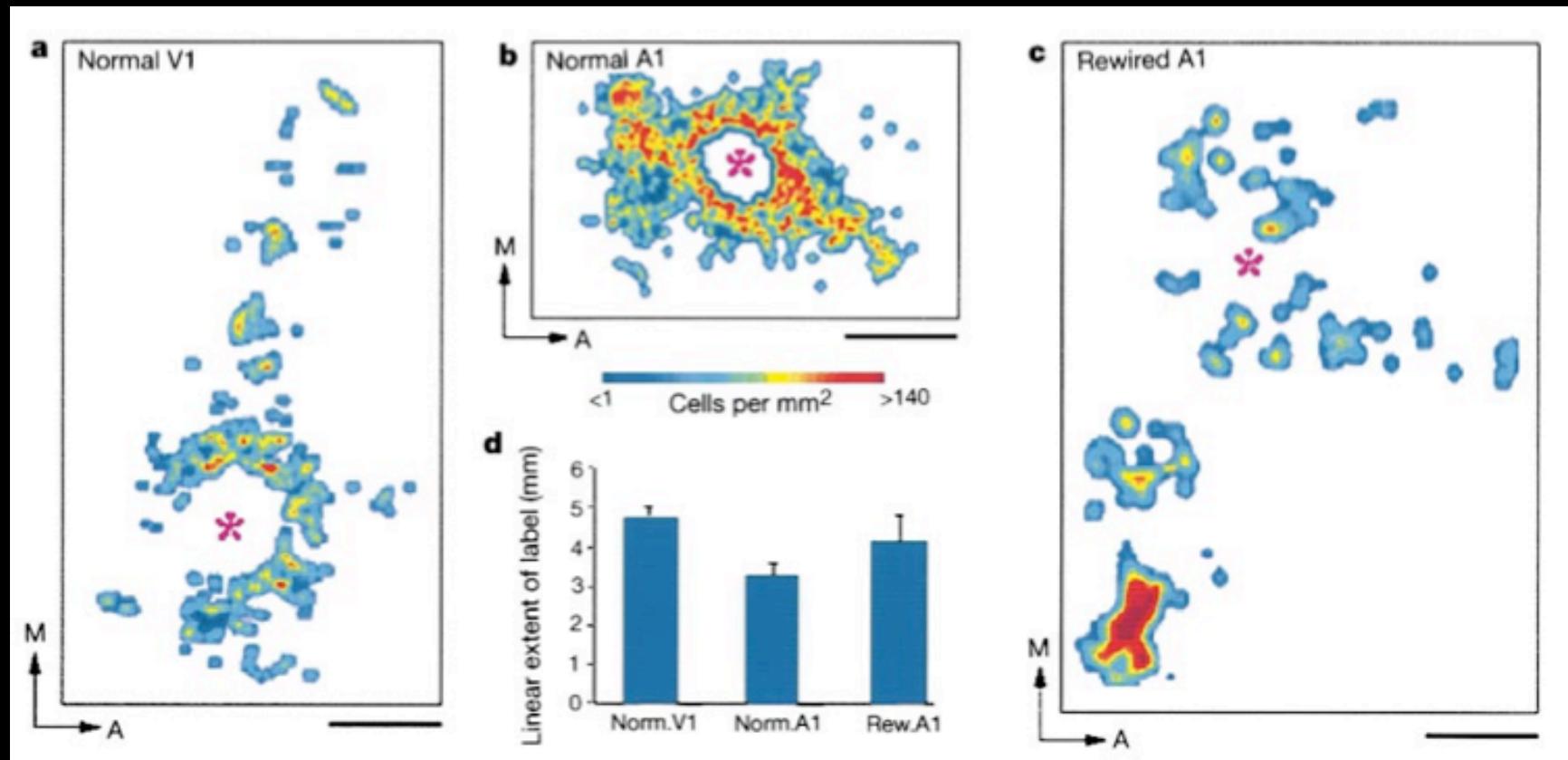
Orientation maps:



Mriganka Sur, et al
Science 1988, Nature 2000

Plasticity in Wiring

Patterns of long-range horizontal connections in V1, normal A1, and rewired A1:

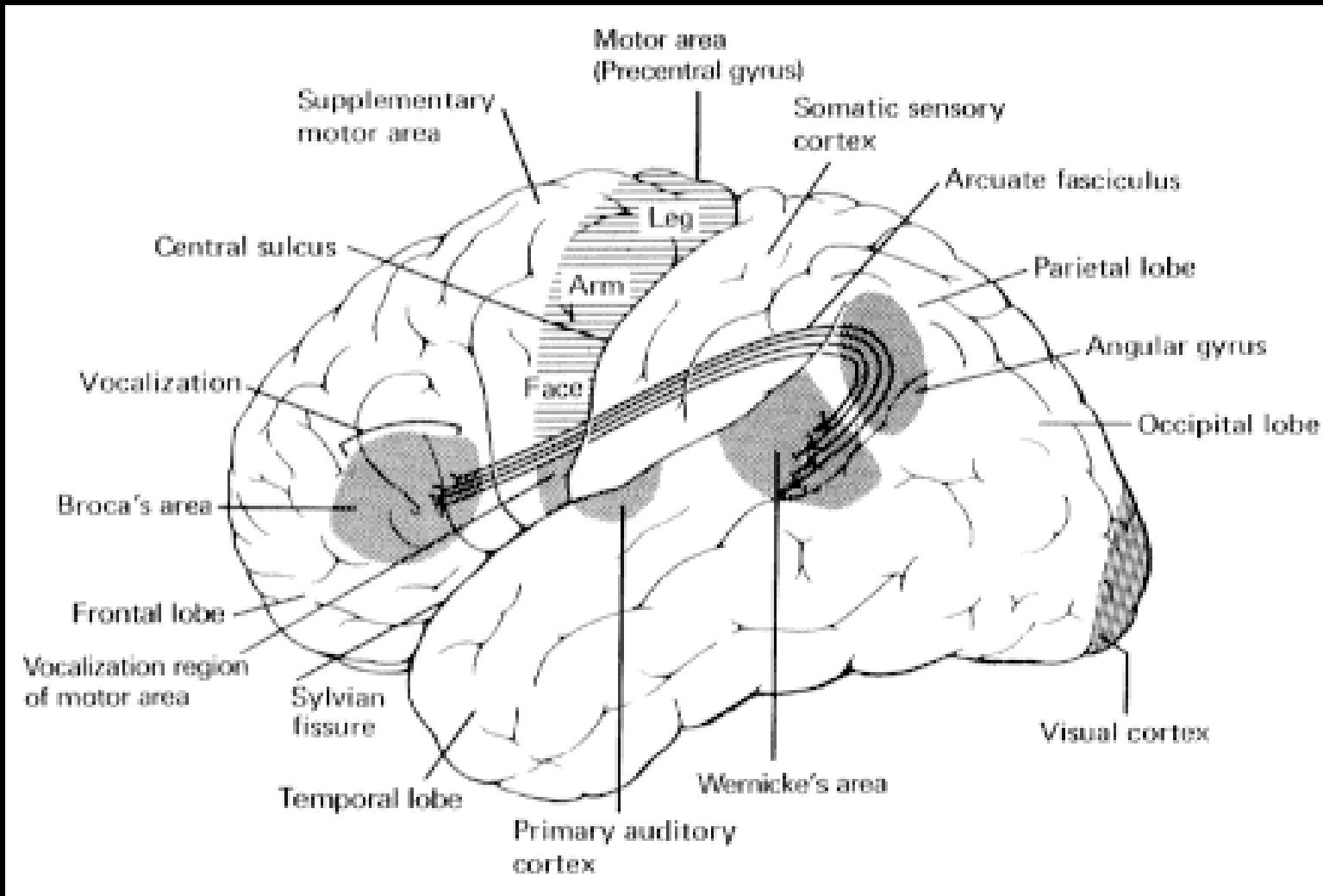


Mriganka Sur, et al / Nature 2000

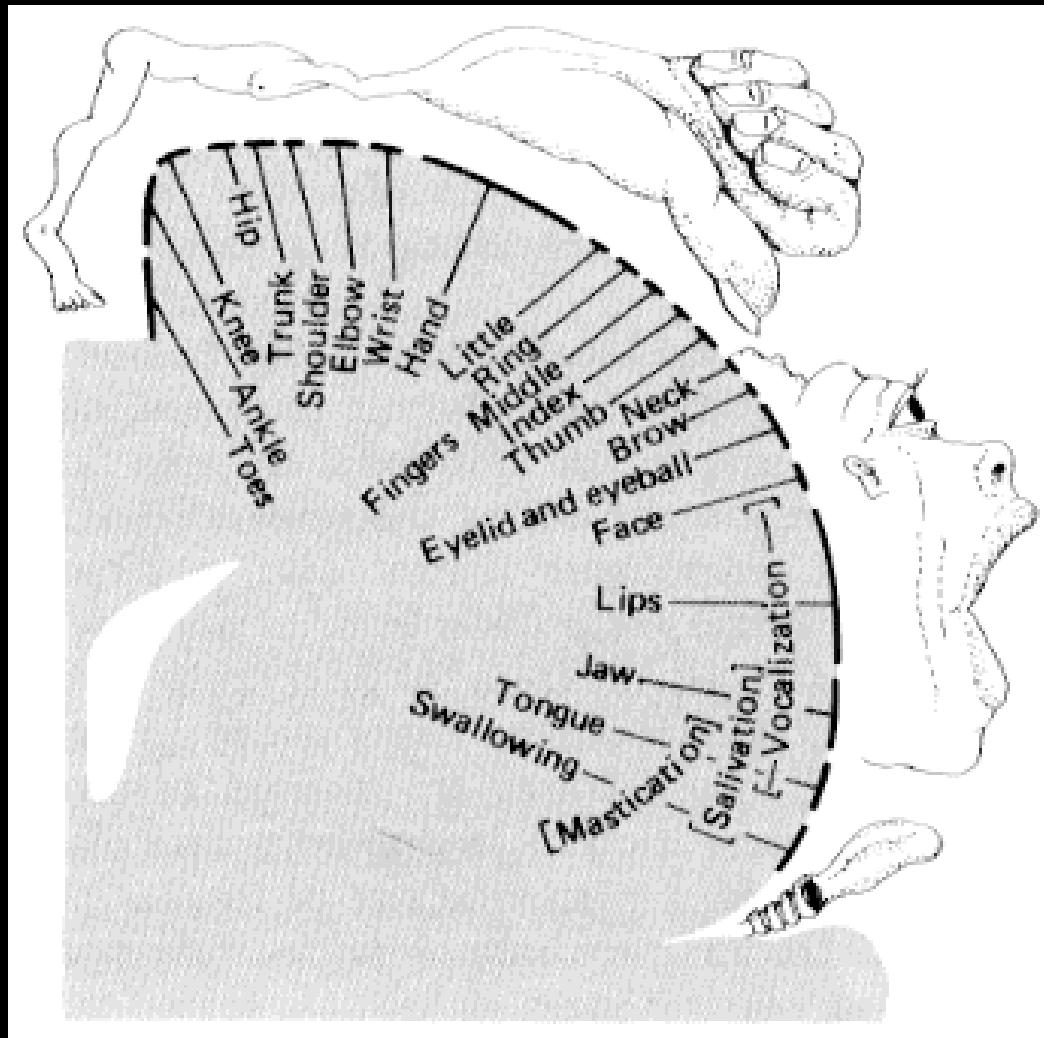
Wiring Diagram Matters

- Relative consistency of brain maps across large populations
- Infants predisposed to focus on two dark spots separated by a lighter space between them (face priming)
- Lesion/aphasia studies illustrate specific, limited effects
 - Injury to hippocampus can cause a loss of ability to store new memories
 - Lesions of prefrontal cortex can eliminate ability to plan for the future, make rational decisions, and process emotion
 - Moderate stroke damage to occipital lobe can induce rare Charcot-Wilbrand syndrome (loss of dreams)
- Scarcity of tissue in localized portion of visual system is method of action for gene disorder, Williams Syndrome (lack of depth perception, inability to assemble parts into wholes)

Wiring Diagram + Learning = Brain Maps



Motor Cortex Map

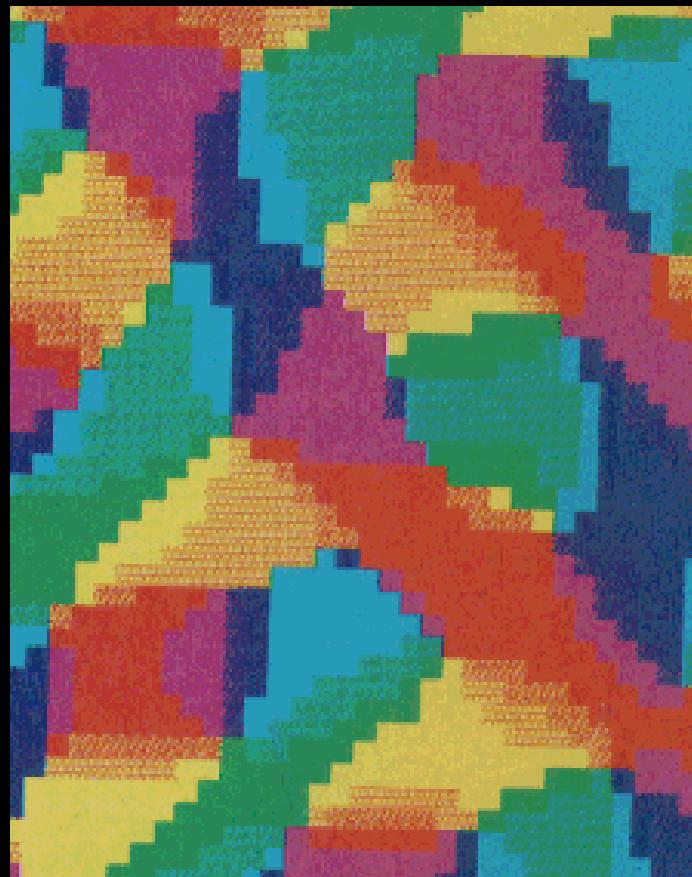


Real & Artificial Brain Maps

Distribution of orientation-selective cells in visual cortex

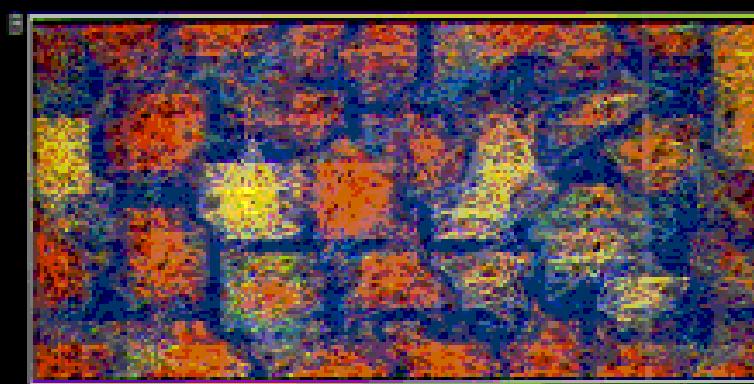
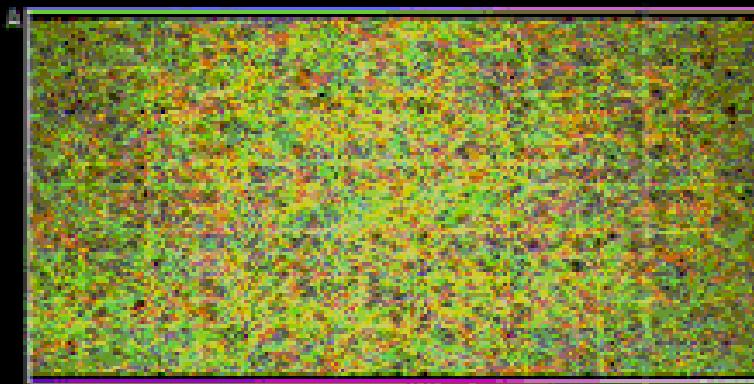


Monkey Cortex, Blasdel and Salama



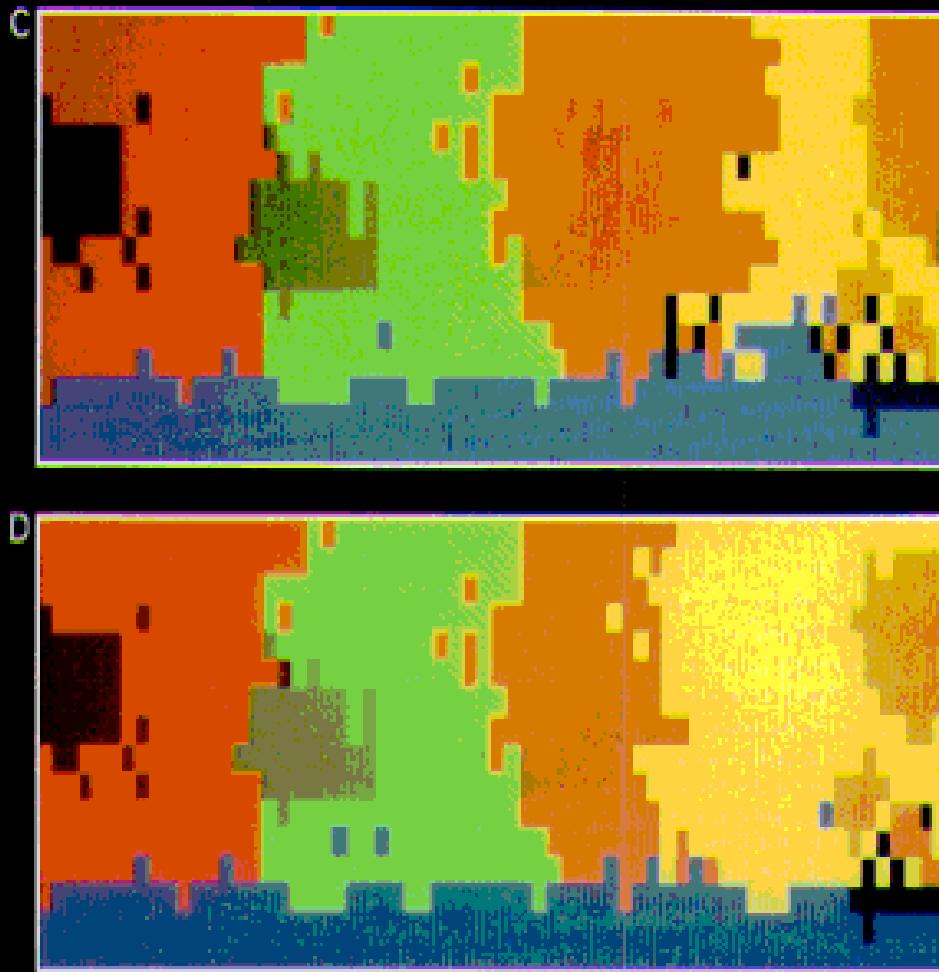
Simulated Cortex, Ralph Linsker

Neuronal Cooperation



John Pearson, Gerald Edelman

Neuronal Competition



John Pearson, Gerald Edelman

The Brain Story So Far...

- Brain maps are good
- Brain maps are derived from
 - General purpose learning mechanism
 - Suitable wiring diagram
- Artificial neural networks capture key features of biological neural networks using
 - Hebbian learning
 - Suitable wiring diagram

How to Proceed?

- Design a suitable neural architecture
 - Simple architectures are easy, but are limited to simple (but robust) behaviors
 - W. Grey Walter's Turtles
 - First few Valentino Braatenberg Vehicles (#1-5, of 14)
 - Complex architectures are much more difficult
 - We know a lot about neural anatomy
 - There's a lot more we don't know
 - It is being tried - Steve Grand's Lucy

How to Proceed?

- Evolve a suitable neural architecture
 - It ought to work
 - Valentino Braitenberg's Vehicles (#6 and higher)
 - We know it works
 - Genetic Algorithms (computational realm)
 - Natural Selection (biological realm)

Is There Really Any Hope?

- Danny Hillis ("Intelligence as an Emergent Behavior", *Daedalus* 1988) observes

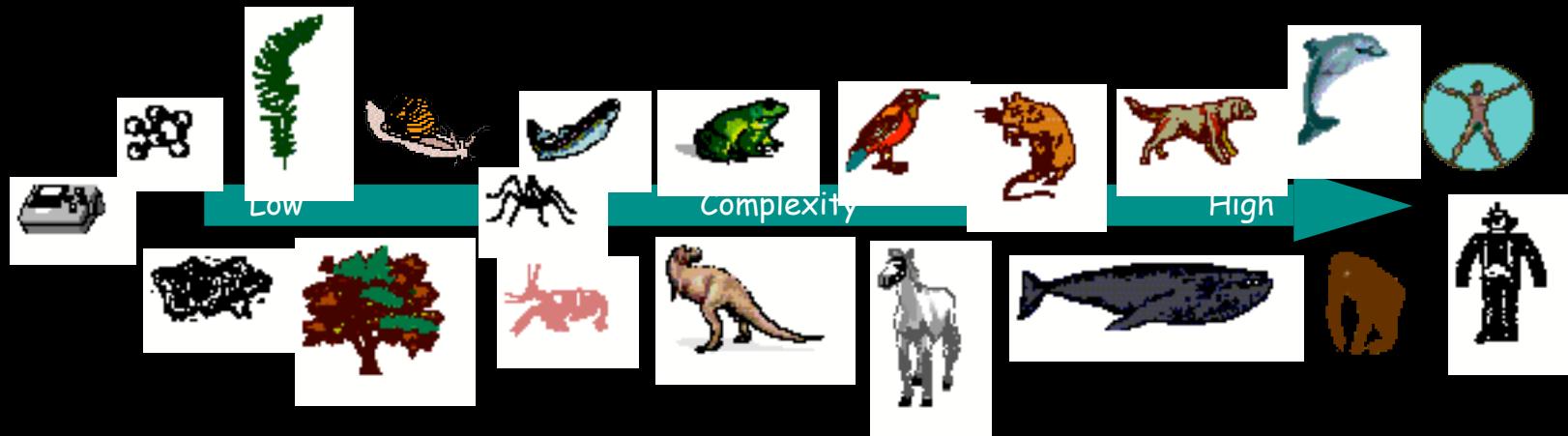
"It would be convenient if intelligence were an emergent behavior of randomly connected neurons in the same sense that snowflakes and whirlpools are emergent behaviors of water molecules."
- From Cog Sci/Psychology experiments he estimates that a model brain would need 10^9 bits and 10^{11} bits/sec memory access to support human-level thought ("plus or minus two orders of magnitude")

Progress with Limited Understanding

- Hillis points to successes with emergent systems developed with limited knowledge (either deliberately or unavoidably):
 - Cellular automata models of fluid flow
 - Unit mass, unit speed particles on a hexagonal lattice, behaving as billiard balls, produce laminar, vortical, and turbulent flows "indistinguishable from the behavior of real fluids"
 - Computational models of evolutionary biology
 - Evolved sorting algorithms that compete with the best human-designed algorithms

to show how "Even a little understanding could go a long way toward the construction of an emergent system."

Measuring Progress



Spectrum of Life and Intelligence

Graduated Intelligence

- Darwin wrote (*The Descent of Man, and Selection in Relation to Sex* 1871, 1927, 1936)

"If no organic being excepting man had possessed any mental power, or if his powers had been of a wholly different nature from those of the lower animals, then we should never have been able to convince ourselves that our high faculties had been gradually developed. But it can be shewn that there is no fundamental difference of this kind. We must also admit that there is a much wider interval in mental power between one of the lowest fishes, as a lamprey or lancelet, and one of the higher apes, than between an ape and a man; yet this interval is filled up by numberless gradations."

Graduated Intelligence

- "A conservative hypothesis: 'Sentience' comes in every imaginable grade or intensity, from the simplest and most 'robotic', to the most exquisitely sensitive, hyper-reactive 'human'." — Dennett (*Kinds of Minds*)
- Tononi (BMC Neuroscience 2004) discussing a quantitative theory of consciousness based on his information-theoretic Phi:
 - "It also follows that consciousness is not an all-or-none property, but it is graded: to varying degrees, it should exist in most natural (and artificial) systems."

Measuring Intelligence

- Seth, Izhikevich, Rekke, Edelman in *Theories and measures of consciousness: An extended framework* (PNAS 2006)

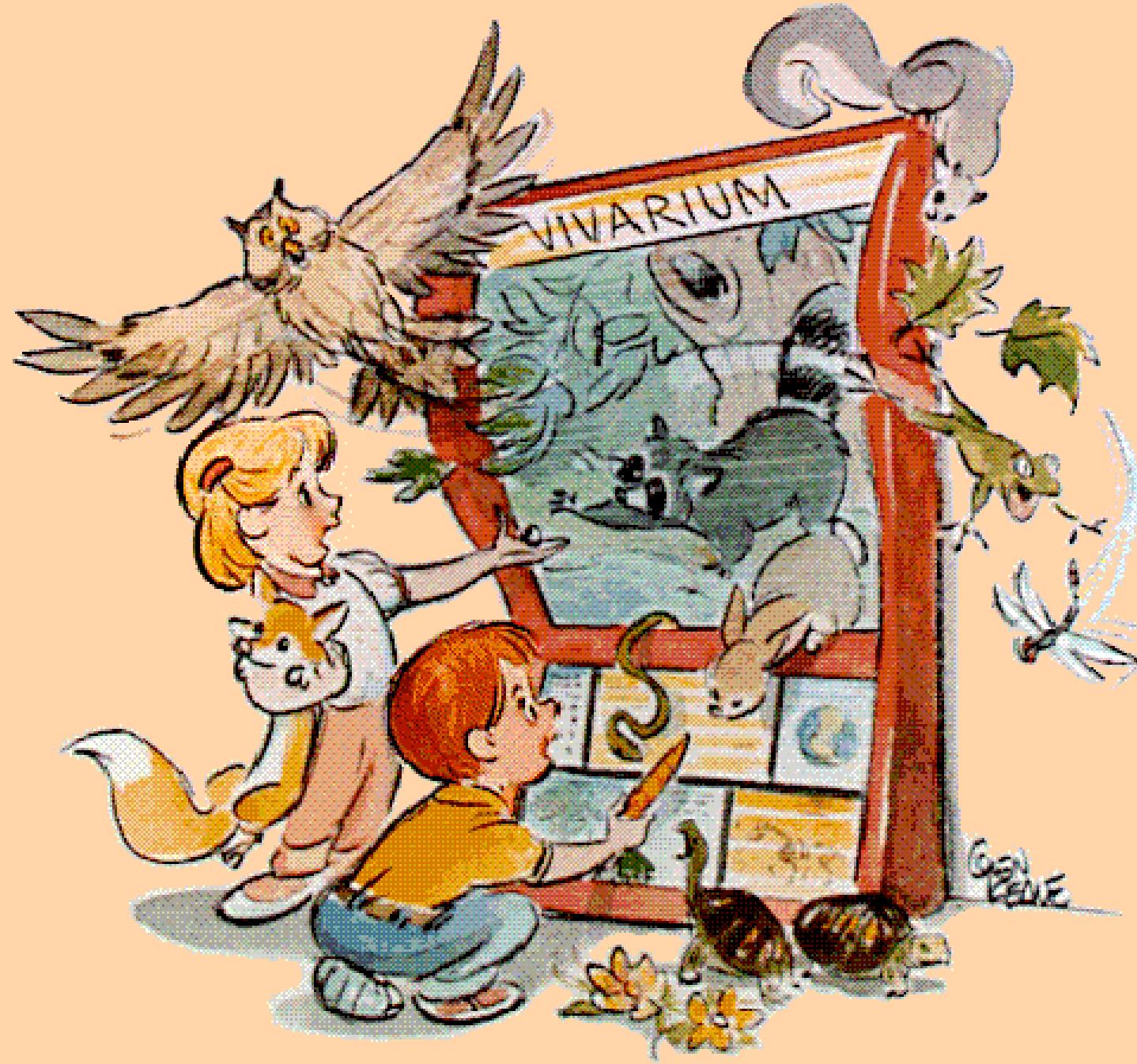
"The existence of quantitative measures of relevant complexity, however preliminary they may be, raises the important issue of identifying the ranges of values that would be consistent with consciousness. ... it may then become possible to define a measurement scale for a proposed measure of relevant complexity by establishing a value for a known conscious system (for example, an awake human) and a value for a known nonconscious system (for example, the same human during dreamless sleep)."

Spectrum of Intelligence

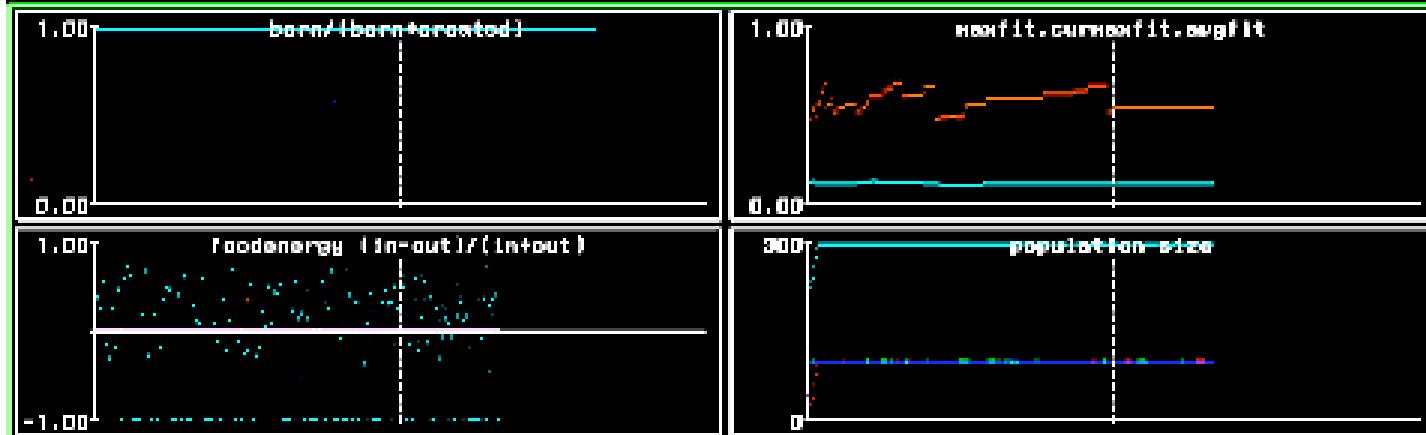
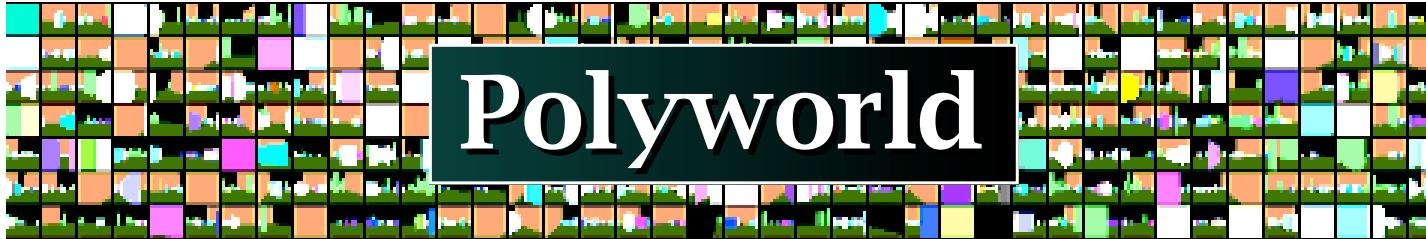
- Laboratory evidence exists for self-awareness in humans, chimpanzees, orangutans, and elephants
- Koko the gorilla, Washoe the chimp, and Kanzi the bonobo ape all demonstrate language skills comprehensible to humans
- Alex the parrot demonstrates language skills comprehensible to humans
- Betty the crow demonstrates tool creation
- Various simians and birds in the wild demonstrate tool use and creation
- Scrub-jays project their own behaviors onto that of conspecifics (exhibit a "theory of mind") and demonstrate planning for the future

Spectrum of Intelligence

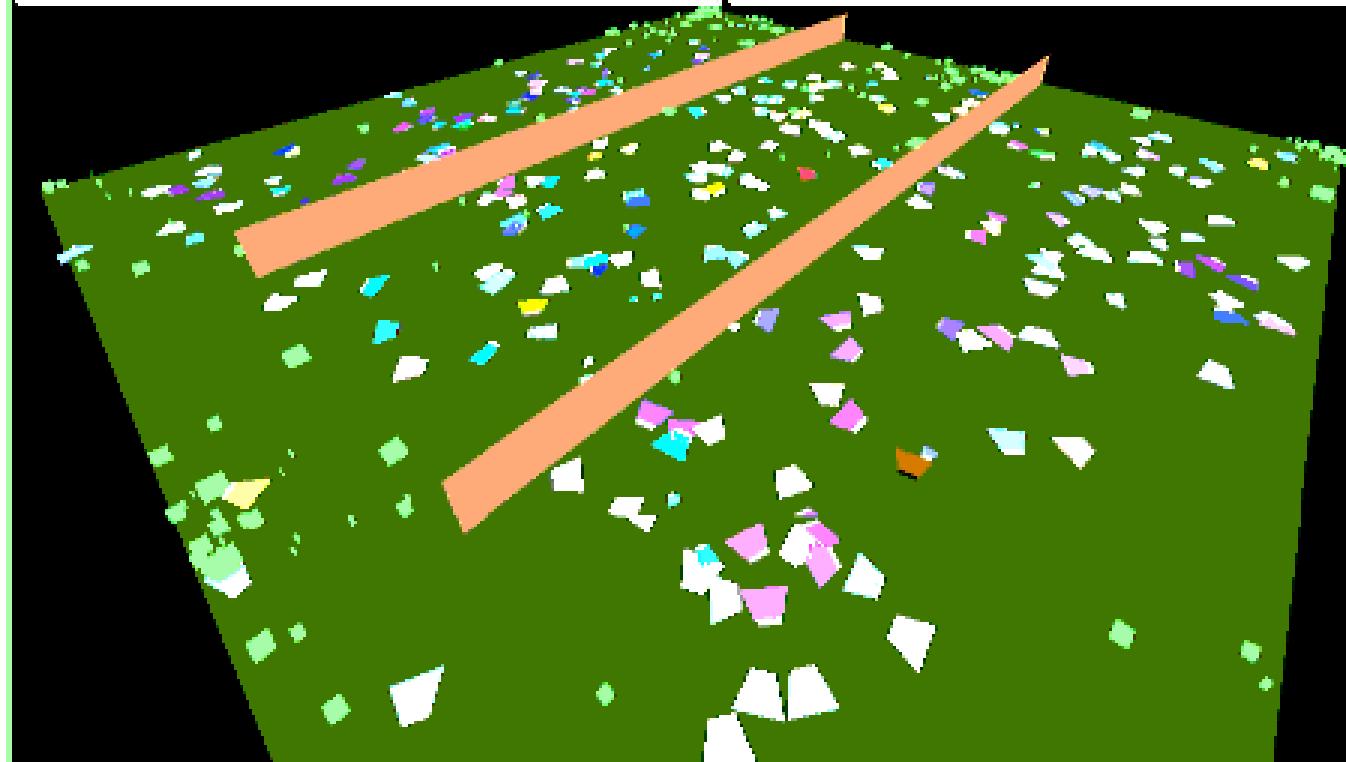
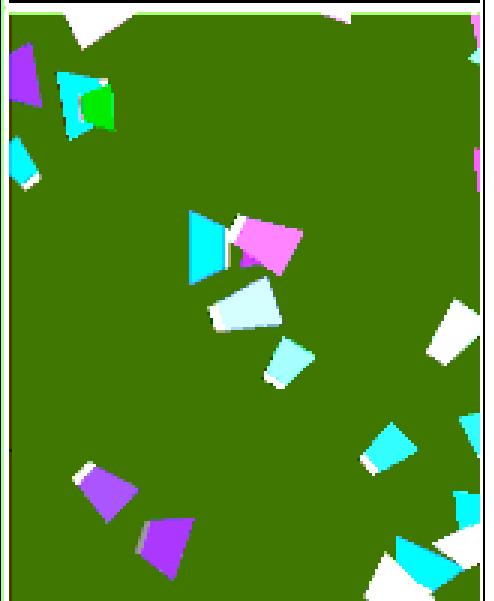
- Honeybees, with 1M neurons, interpolate visual information, exhibit associative recall, categorize visual information, learn contextual information, and demonstrate the ability to learn the abstract concepts *same* and *different*
- Fruit flies, with 250K neurons, learn by association, have short-term, medium-term, and long-term memories, with a short-term working memory of about 5 seconds (comparable to pigeons and other bird species), respond to anesthesia at comparable doses and with progressive loss of brain function like humans, and exhibit a *salience* mechanism with much in common with the human attention mechanism
- Even with only about 10K neurons, *Aplysia californica* demonstrates sensitization, habituation, classical, and operant conditioning



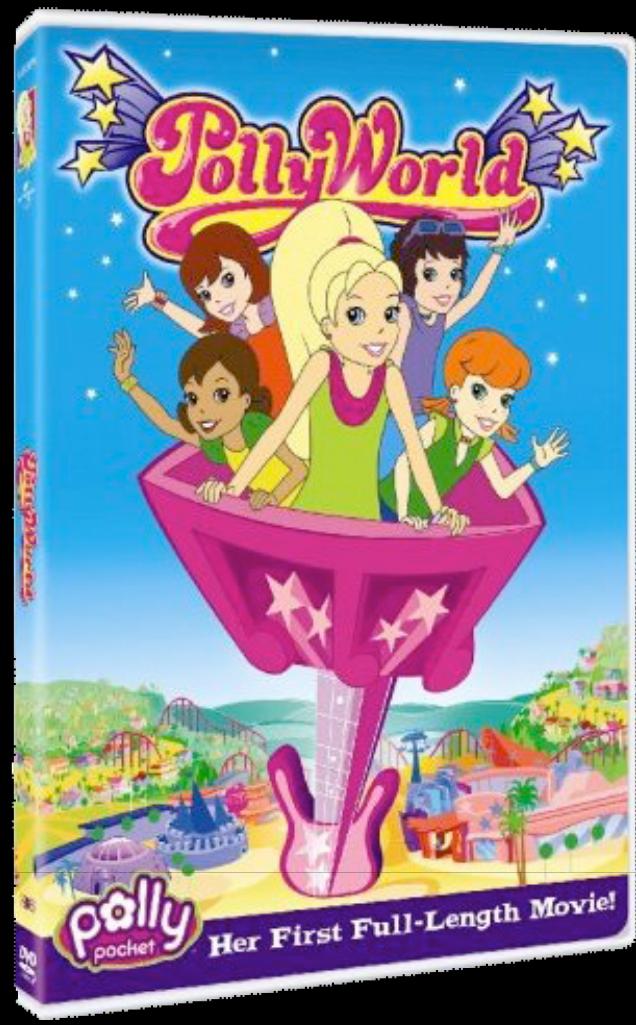
Polyworld



```
46, sf
age = 80458
critters = 300 (100, 100, 100)
created = 786 (1577, 52, 86)
-random = 458
-two = 331
-one = 6
born = 48811 (4112, 15776, 28824)
died = 48306 (4935, 15581, 28780)
-age = 5070
-emerged = 12818
-right = 18055
-edge = 13383
food = 288 (88, 89, 89)
misdaden = 18911
agreement = 48085 (48085, 3588, 1850)
misdaperr = 4805 (4805, 48888, 49105)
born/total = 0.98
meanfitN = 1.11
currentfitN = 0.54
avgfitN = 0.12
maxfit = 139, 097
meanfit = 88, 2303
avgfit = 14, 5185
netenergy = 0.04
totenergy = 0.04
```



Not affiliated with...



What Polyworld Is

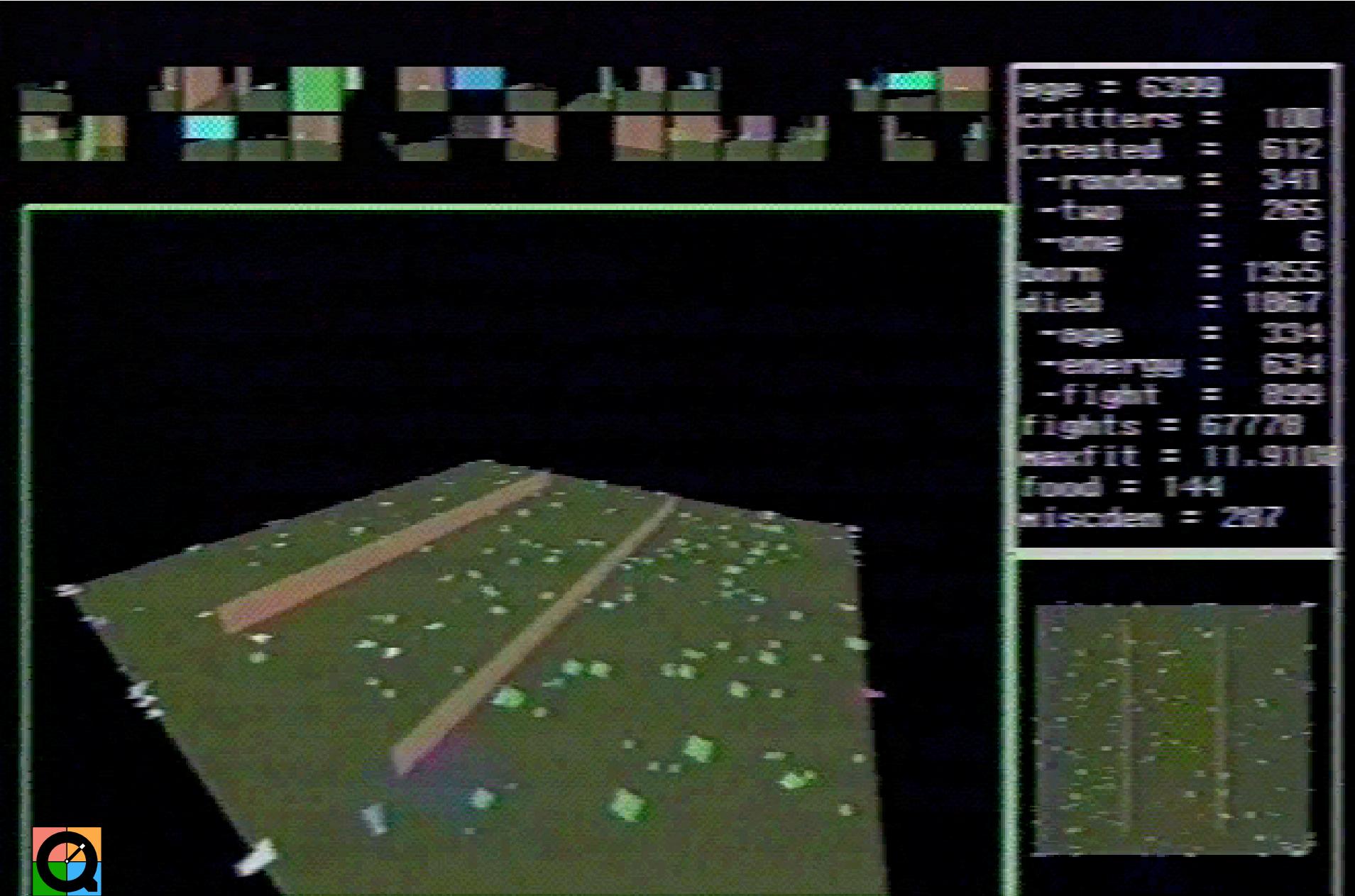
- An *electronic primordial soup* experiment
 - Why do we get science, instead of ratatouille?
 - Right ingredients in the right pot under the right conditions
- An attempt to approach artificial intelligence the way natural intelligence emerged:
 - Through the *evolution of nervous systems* in an *ecology*
- An opportunity to work our way up through the intelligence spectrum
- Tool for evolutionary biology, behavioral ecology, cognitive science

What Polyworld Is Not

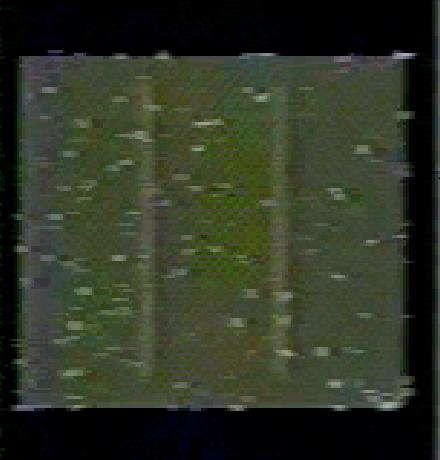
- Fully open ended
 - Even natural evolution is limited by physics (and previous successes)
- Accurate model of microbiology
- Accurate model of any particular ecology
 - Though it is possible to model specific ecologies
- Accurate model of any particular organism's brain
 - Though many neural models are possible
- A strong model of ontogeny

Polyworld Overview

- Computational ecology
- Organisms have genetic structure and evolve over time
- Organisms have simulated physiologies and metabolisms
- Organisms have neural network “brains”
 - Control all behaviors
 - Arbitrary, evolved neural architectures
 - Hebbian learning at synapses
- Organisms perceive their environment through vision
- Fitness is determined by Natural Selection alone
 - Bootstrap “online GA” if required



age = 6399
critters = 188
created = 612
creations = 341
-base = 265
-one = 6
born = 1355
died = 1887
-age = 304
-energy = 634
-fight = 899
fights = 5778
maxfit = 11.9102
food = 144
missions = 267



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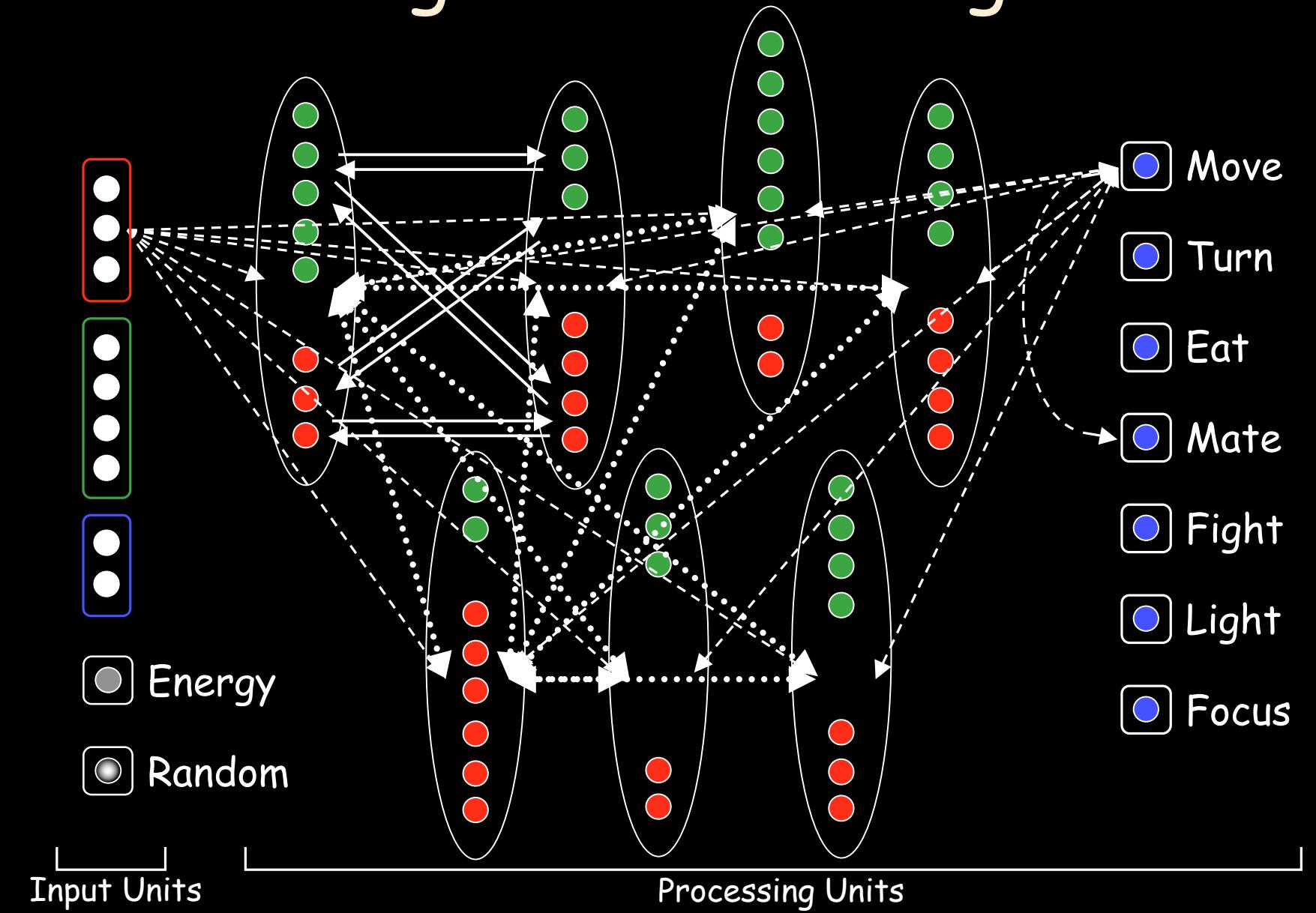
Genetics: Physiology Genes

- Size
- Strength
- Maximum speed
- Mutation rate
- Number of crossover points
- Lifespan
- Fraction of energy to offspring
- ID (mapped to body's green color component)

Genetics: Neurophysiology Genes

- # of neurons for red component of vision
- # of neurons for green component of vision
- # of neurons for blue component of vision
- # of internal neuronal groups
- # of excitatory neurons per group
- # of inhibitory neurons per group
- Initial bias of neurons per group
- Bias learning rate per group
- Connection density per pair of groups & types
- Topological distortion per pair of groups & types
- Learning rate per pair of groups & types

Neural Architectures for Controlling Behavior using Vision



Neural Development

- Generative statistical model may be thought of as capturing the end result of a development process
- Same genetic code may produce multiple distinct phenotypes
- Synaptic weights initialized randomly
- 25 time steps of random noise provided as input to vision system to allow some self-organization (before being placed into the world)

Physiology and Metabolism

- Energy is expended by behavior & neural activity
- Size and strength affect behavioral energy costs (and energy costs to opponent when attacking)
- Neural complexity affects mental energy costs
- Size affects maximum energy capacity
- Energy is replenished by eating food (or other organisms)
- Health energy is distinct from Food-Value energy
- Body is scaled by size and maximum speed

Perception: Neural System Inputs

- Vision
- Internal energy store
- Random noise

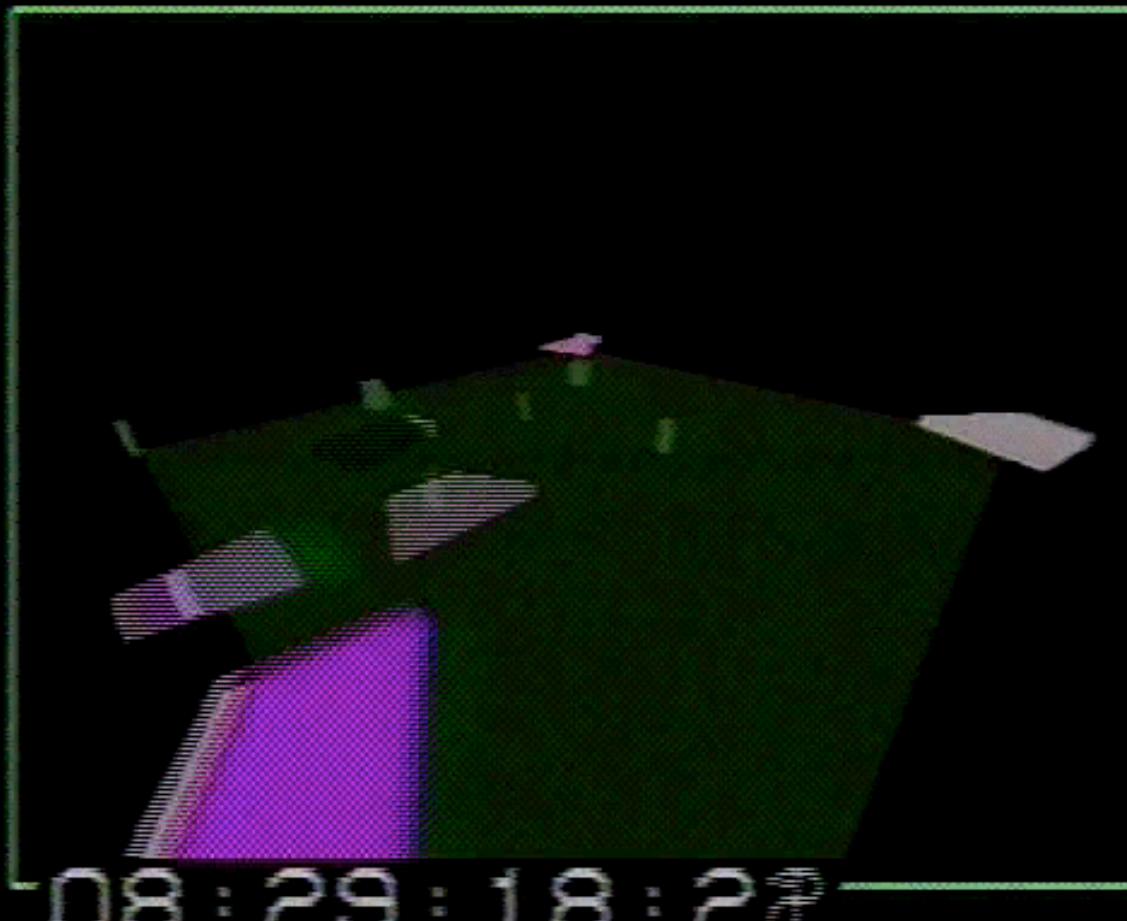
Behavior: Neural System Outputs

- Primitive behaviors controlled by single neuron
 - “Volition” is level of activation of relevant neuron
- Move
- Turn
- Eat
- Mate (mapped to body's blue color component)
- Fight (mapped to body's red color component)
- Light
- Focus

Behavior Sample: Eating

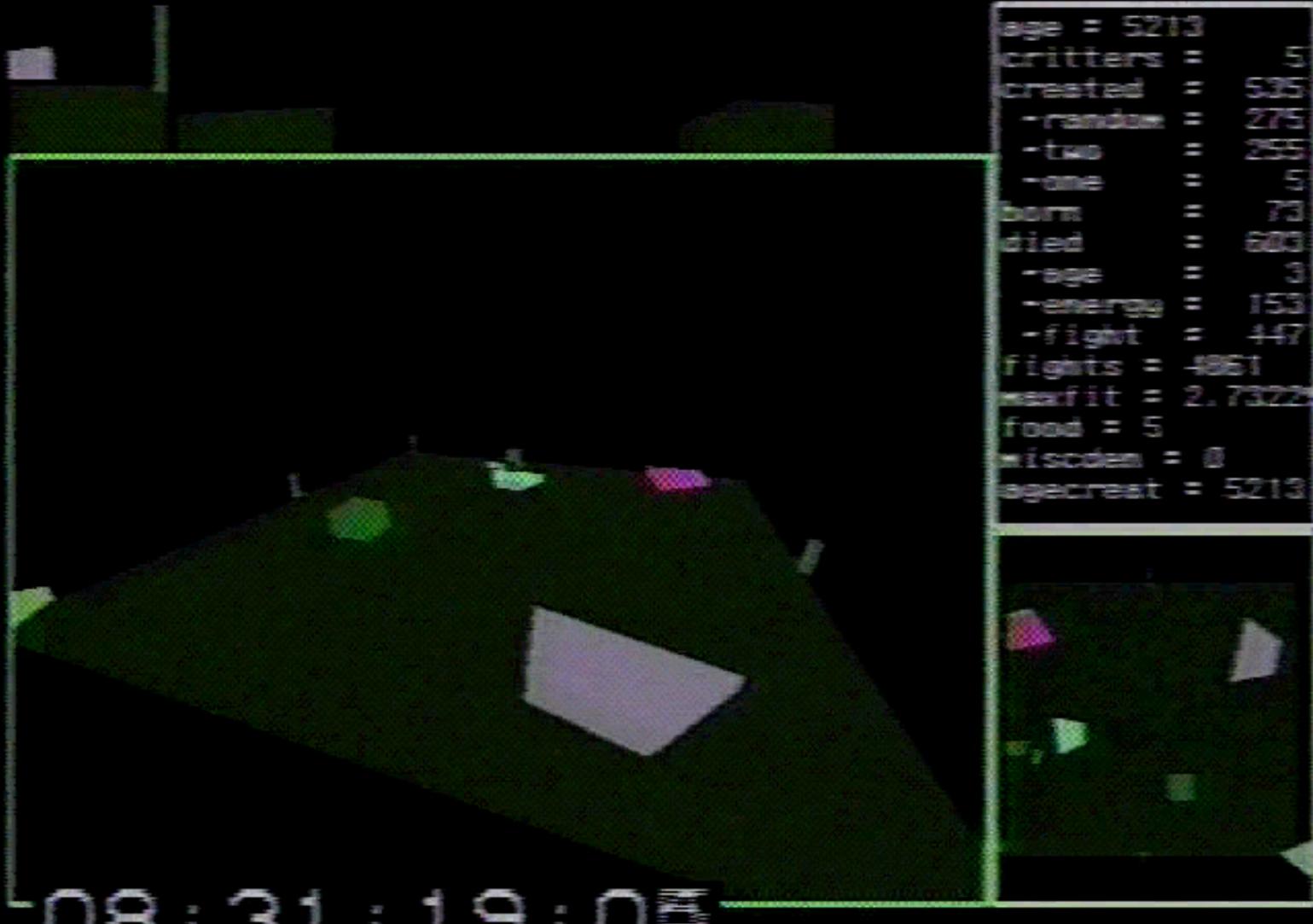


Behavior Sample: Killing & Eating

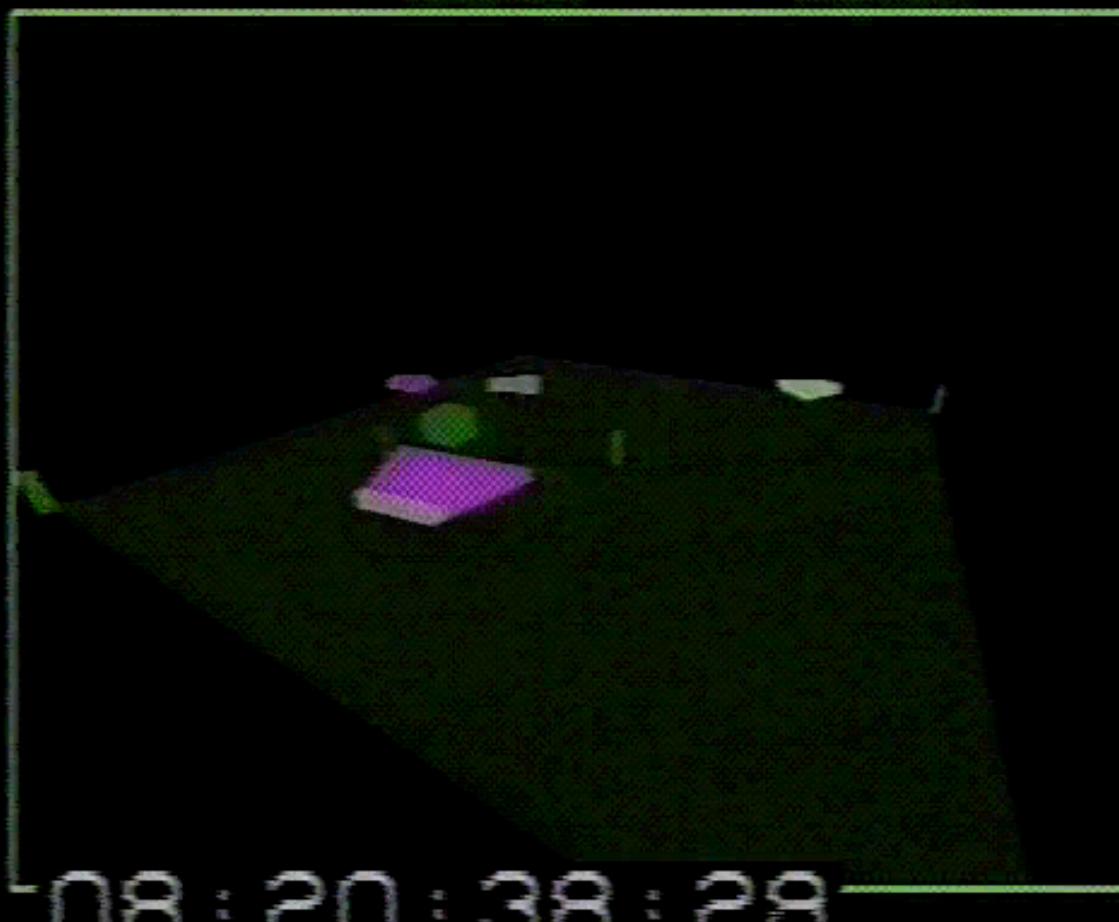


```
age = 164  
critters = 5  
created = 452  
-random = 233  
-two = 215  
-one = 4  
born = 61  
died = 508  
-age = 21  
-energy = 131  
-fight = 375  
fights = 4056  
maxfit = 2.7322  
food = 5  
incidence = 0  
agecreat = 164
```

Behavior Sample: Mating



Behavior Sample: Lighting

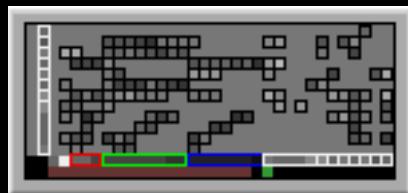
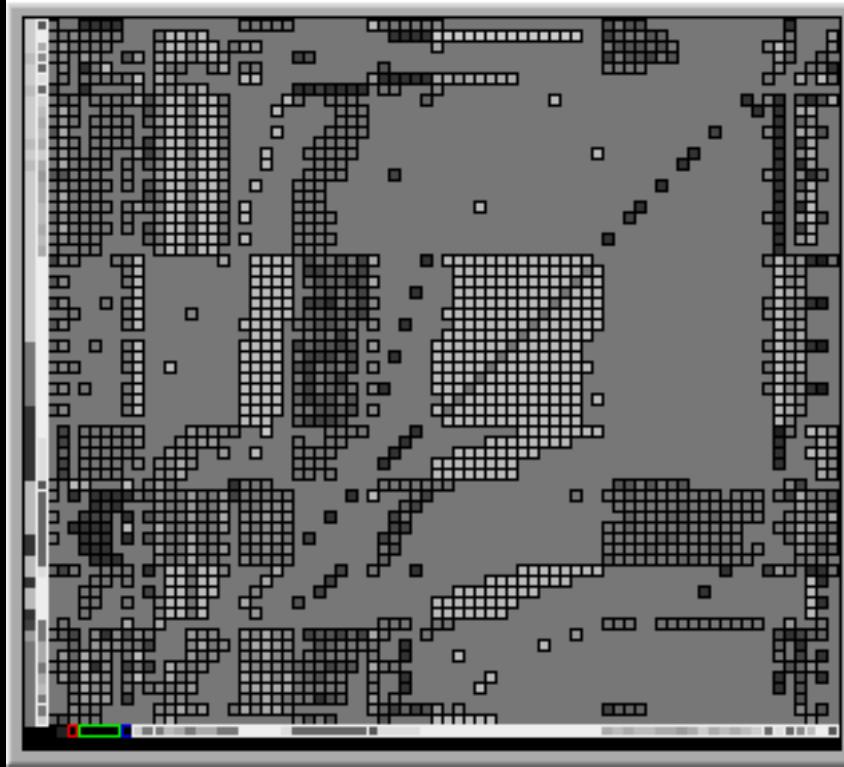
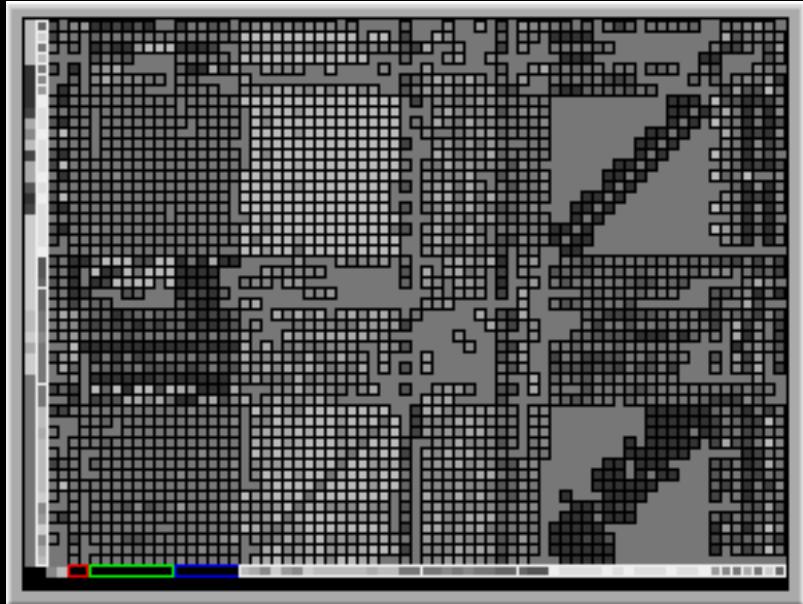


```
age = 1334  
critters = 5  
created = 114  
-random = 64  
-two = 49  
-none = 1  
dans = 2  
died = 116  
-age = 1  
-energy = 39  
-fight = 76  
fights = 953  
maxfit = 2.3054  
food = 6  
missed = 0  
agecreat = 1333
```

Neural System: Internal Units

- No prescribed function
 - Neurons
 - Synaptic connections

Evolving Neural Architectures



Neural System: Learning and Dynamics

- Firing-rate / summing-and-squashing neuron model
 - $x_i = \sum_j a_j^t s_{ij}^t$
 - $a_i^{t+1} = 1 / (1 + e^{-x_i})$
- Hebbian learning
 - $s_{ij}^{t+1} = s_{ij}^t + \eta c_{kl} (a_i^{t+1} - 0.5) (a_j^t - 0.5)$

s_{ij}^t = synaptic efficacy from neuron j to neuron i at time t

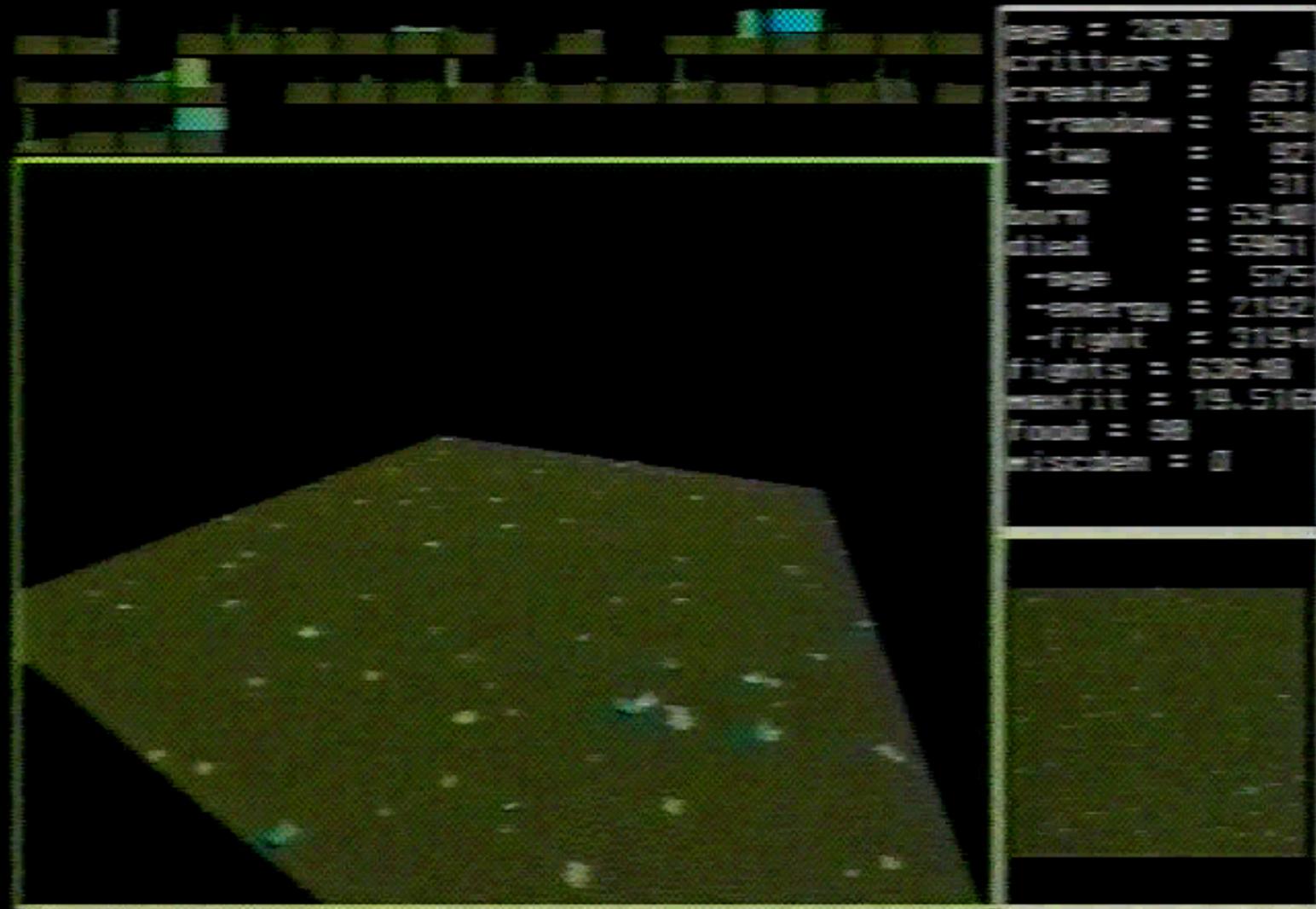
a_i^t = neuronal activation of neuron i at time t

ηc_{kl} = learning rate for connection of type c (e-e, e-i, i-e, or i-i) from cluster l to cluster k

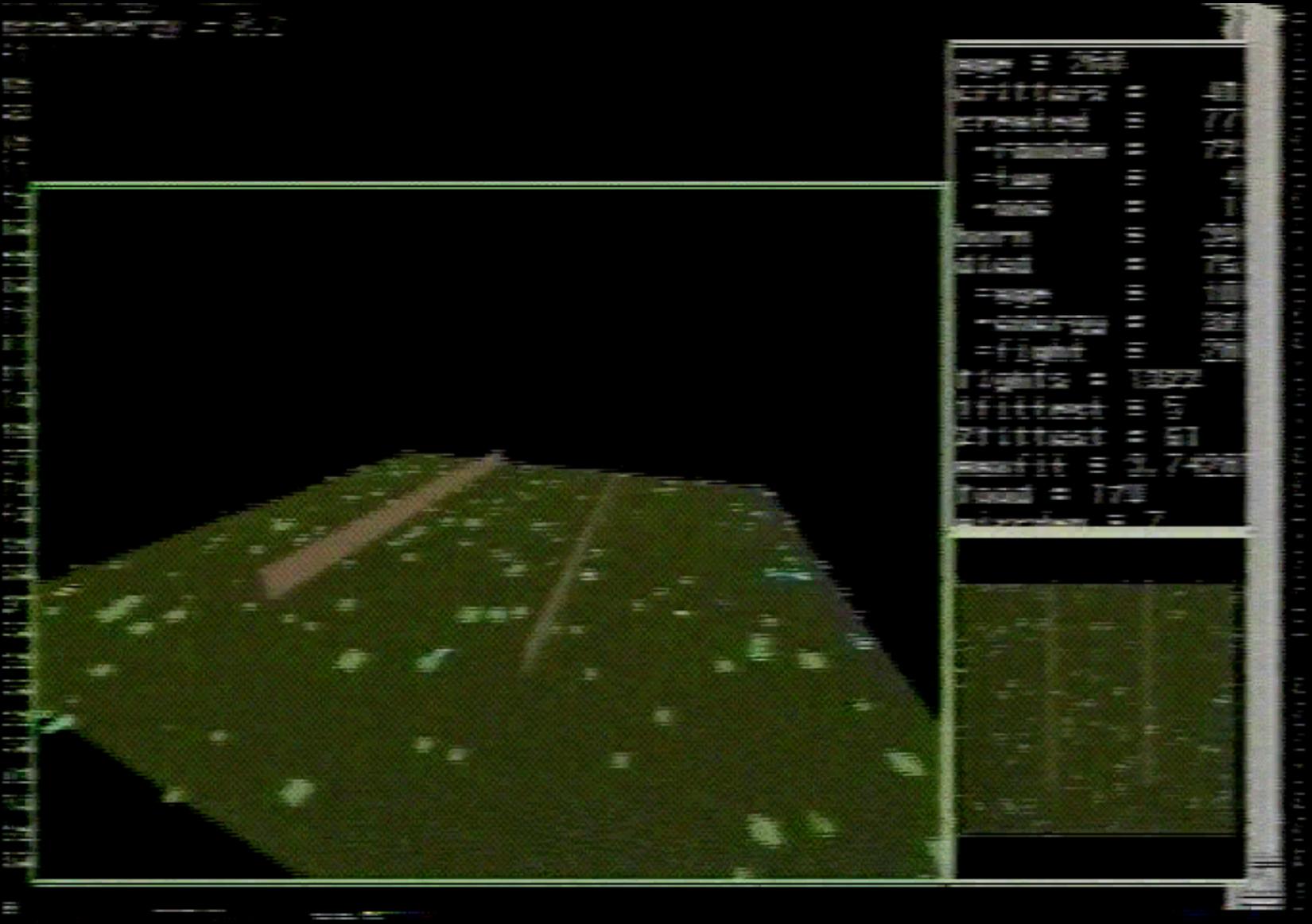
Neural Dynamics



Emergent Species: "Joggers"



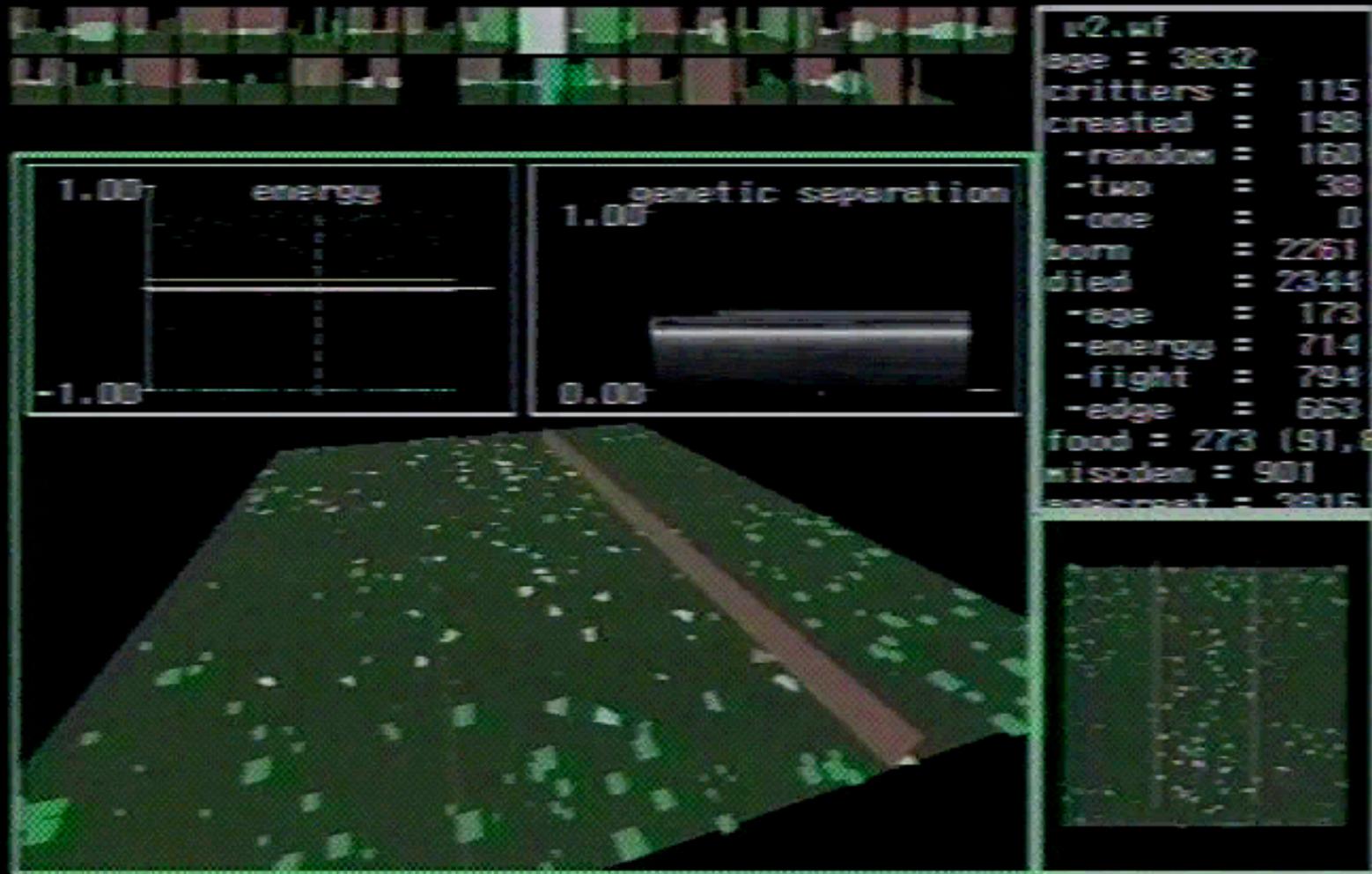
Emergent Species: "Indolent Cannibals"



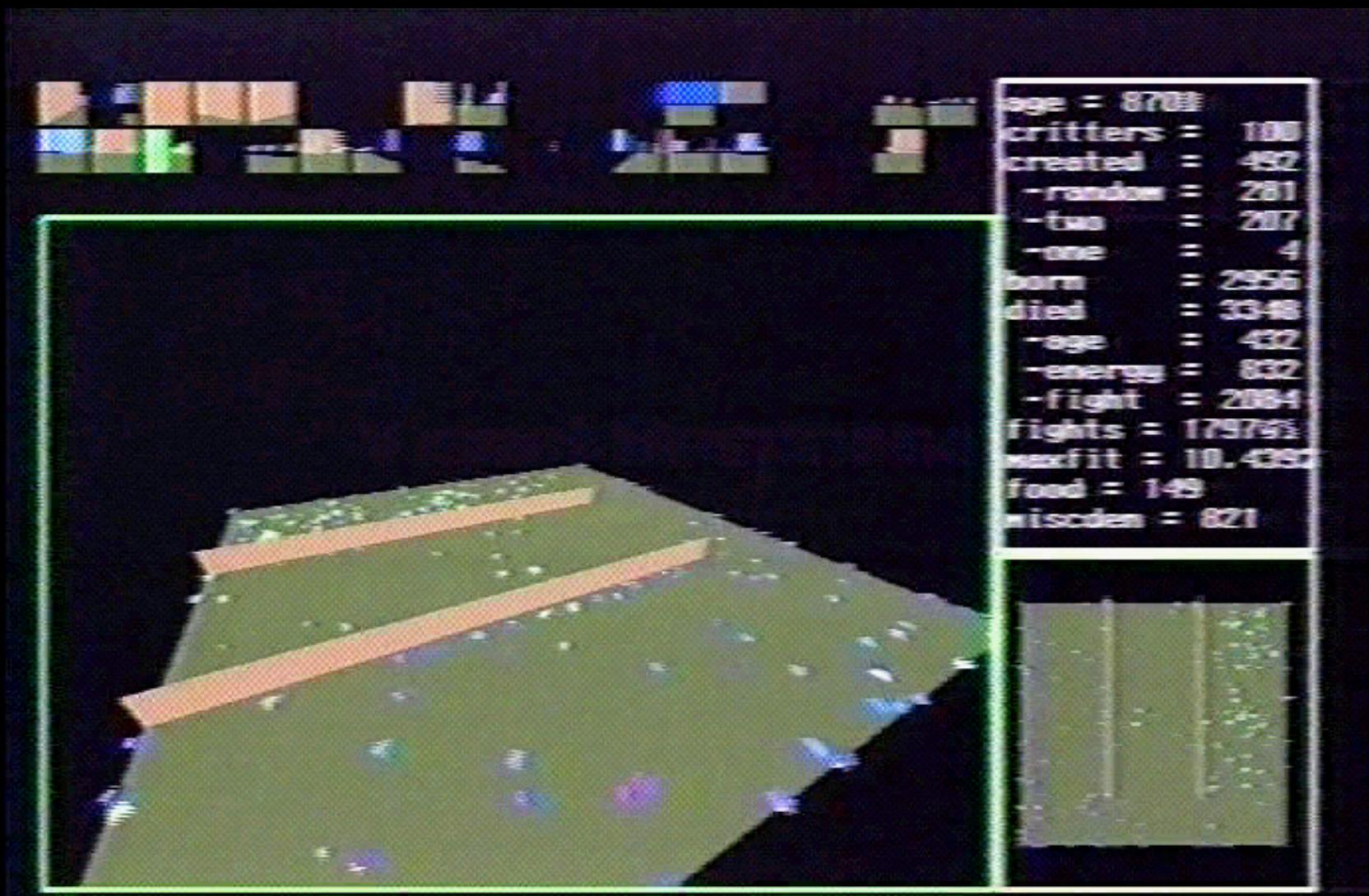
Emergent Species: “Edge-runners”



Emergent Species: "Dervishes"

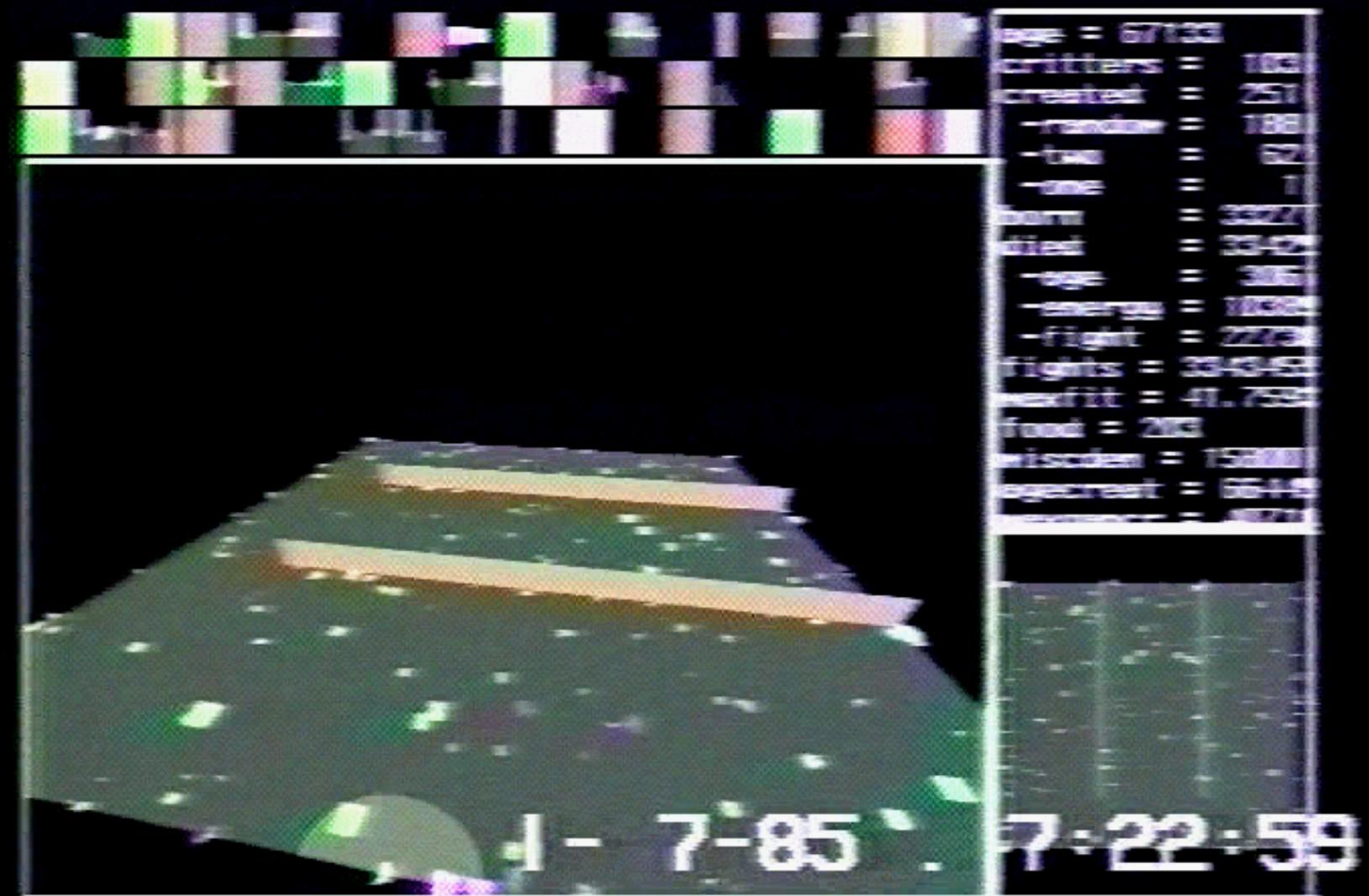


Emergent Behavior: Visual Response

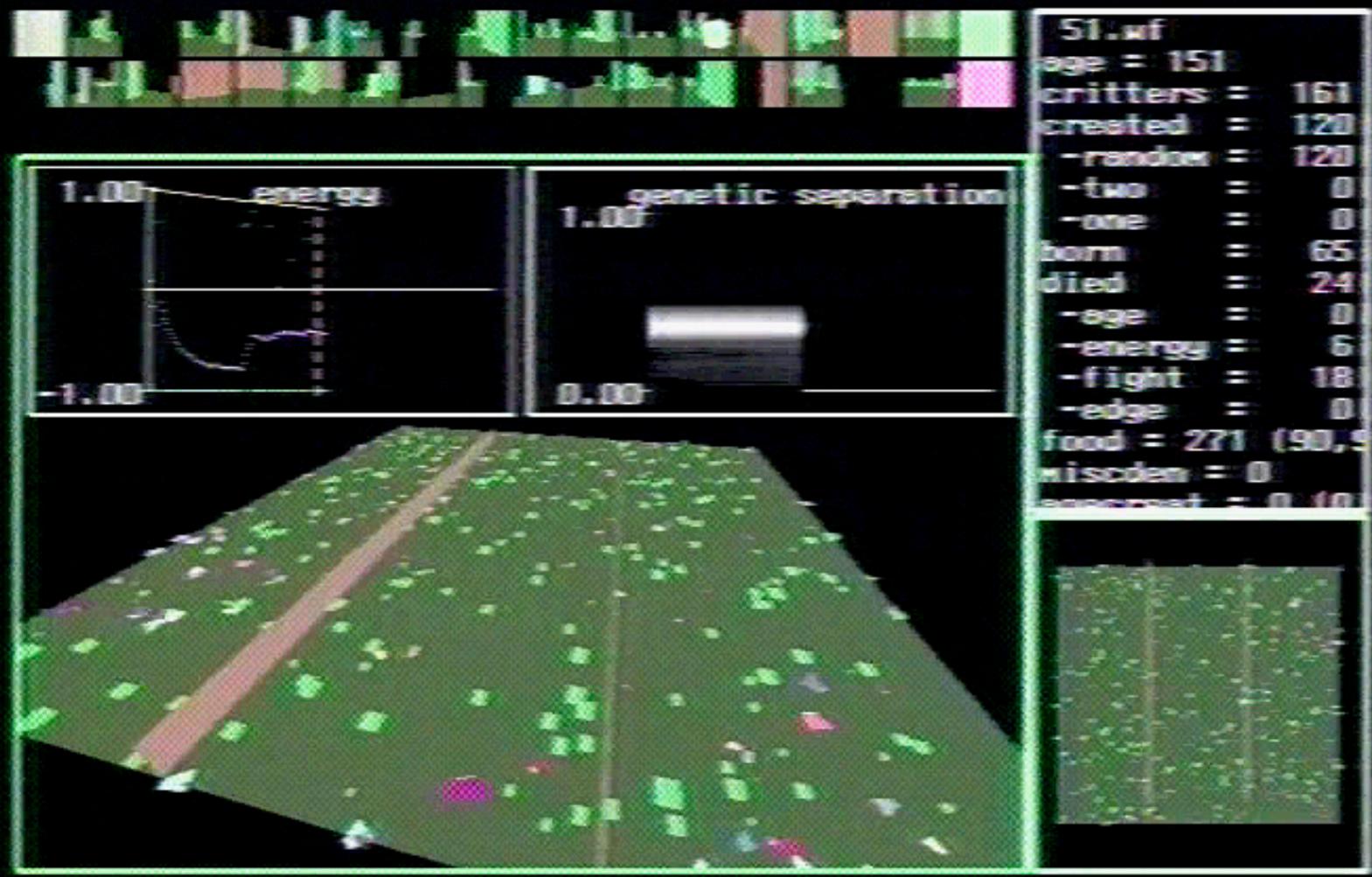


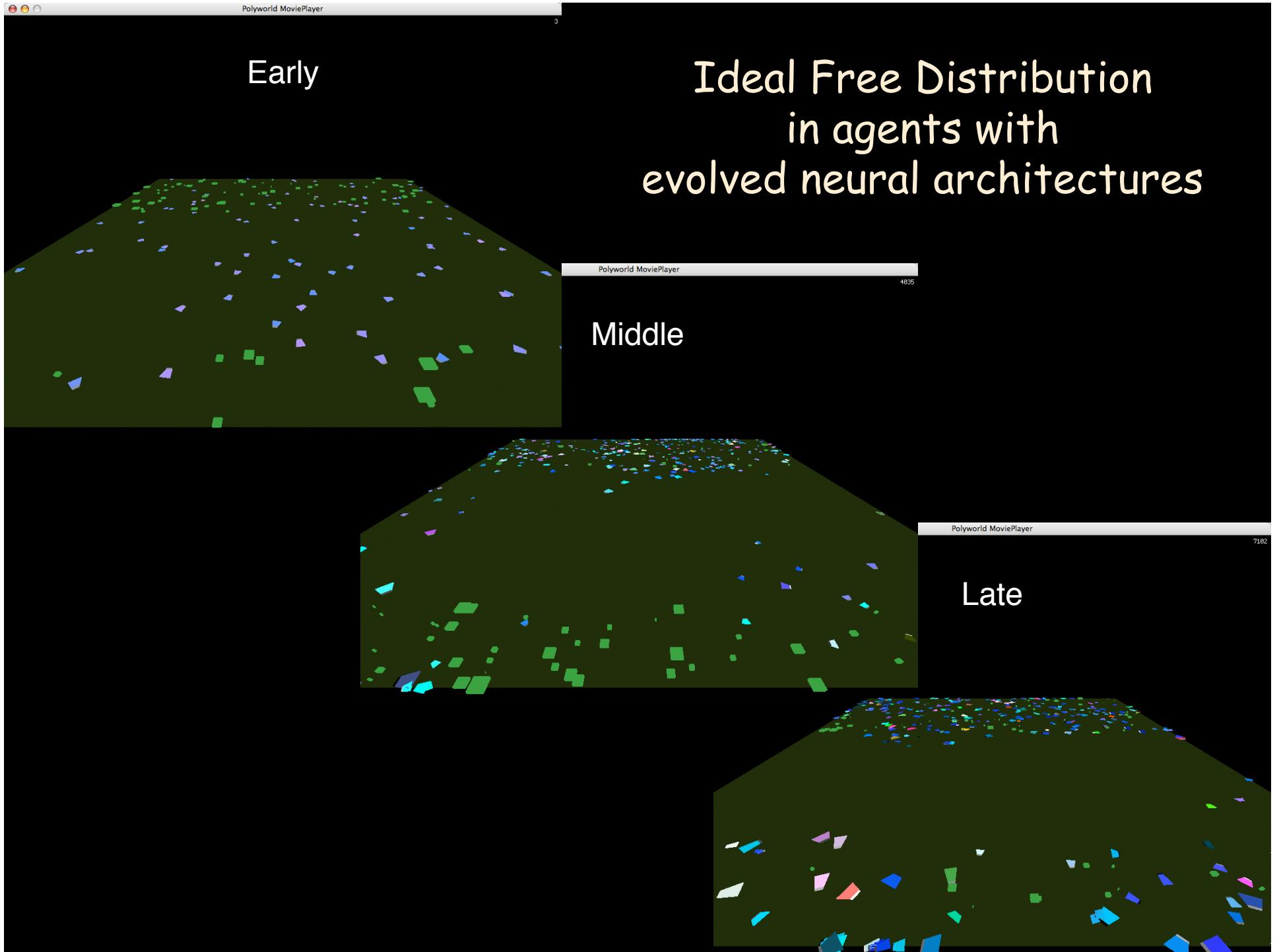
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Emergent Behavior: Fleeing Attack

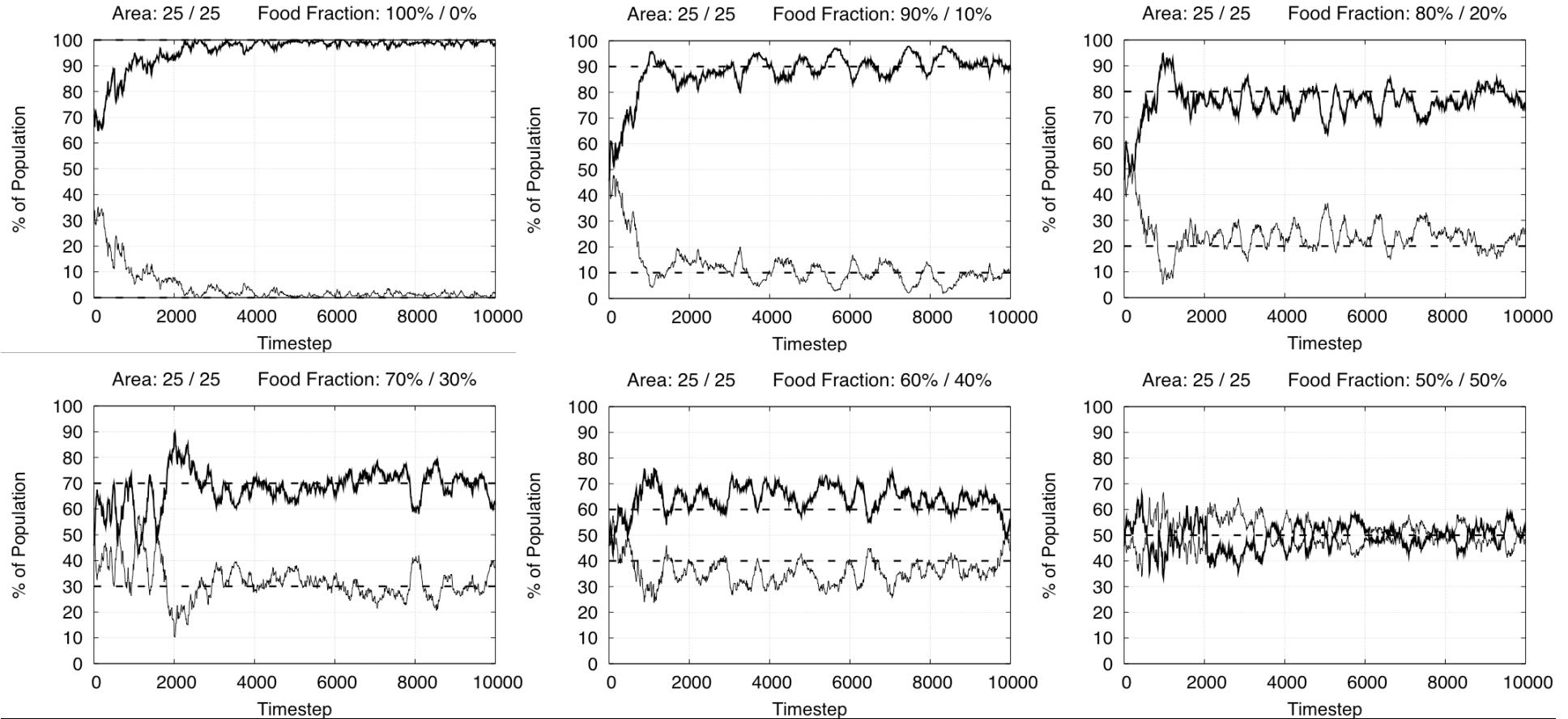


Emergent Behaviors: Foraging, Grazing, Swarming





Ideal Free Distribution in agents with evolved neural architectures



Is It Alive? Ask Farmer & Belin...

- "Life is a pattern in spacetime, rather than a specific material object."
- "Self-reproduction."
- "Information storage of a self-representation."
- "A metabolism."
- "Functional interactions with the environment."
- "Interdependence of parts."
- "Stability under perturbations."
- "The ability to evolve."

Information Is What Matters

- "Life is a pattern in spacetime, rather than a specific material object." - Farmer & Belin (*ALife II*, 1990)
- Schrödinger speaks of life being characterized by and feeding on "negative entropy" (*What Is Life?* 1944)
- Von Neumann describes brain activity in terms of information flow (*The Computer and the Brain, Silliman Lectures*, 1958)
- Physicist Edwin T. Jaynes identifies a direct connection between Shannon entropy and physical entropy in 1957
- James Avery's *Information Theory and Evolution* (2003): Information storage transiently and locally defeats 2nd law of thermodynamics, and is typical of life
- *Informational functionalism*
 - It's the process, not the substrate
 - What can information theory tell us about living, intelligent processes...

Energy -> Information -> Life

- In 1957 physicist Edwin T. Jaynes pointed out the direct connection between Shannon entropy and physical entropy
- Ludwig Boltzmann's grave is embossed with his equation:

$$S = k \log W$$

Entropy = Boltzmann's-constant

* log(function of # of possible micro-states)

- Claude E. Shannon's famous measure of information (or uncertainty or entropy) can be written:

$$I = K \log \Omega$$

Entropy = constant (usually dropped)

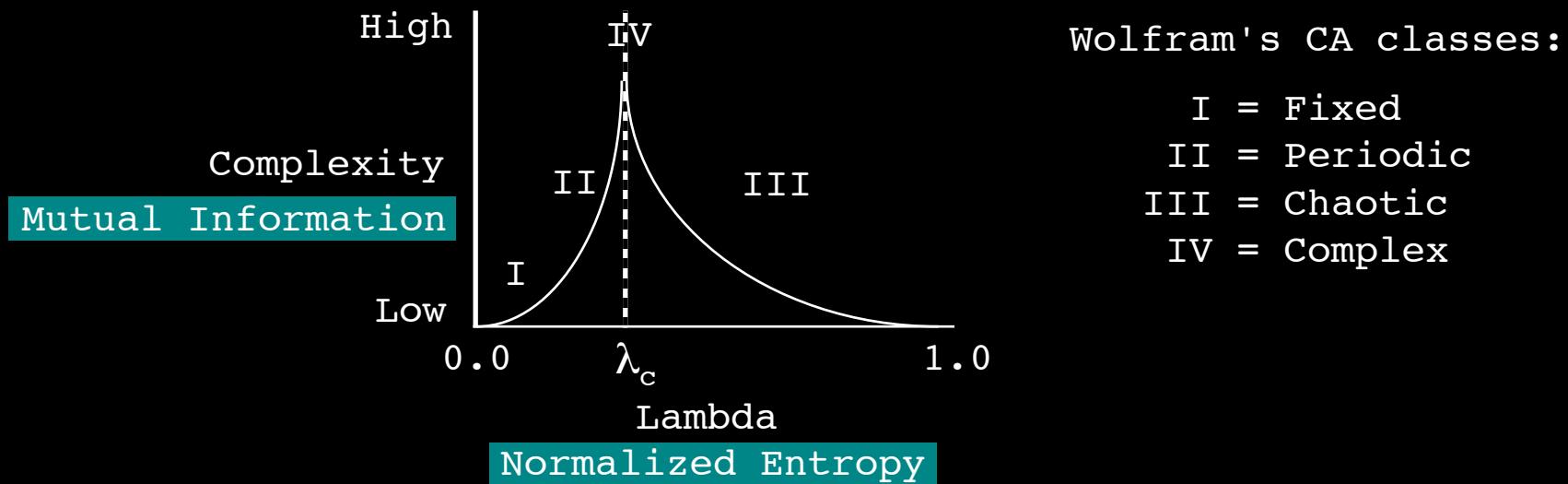
* log(function of # of possible micro-states)

Energy -> Information -> Life

- John Avery (*Information Theory and Evolution*) related physical entropy to informational entropy as
 $1 \text{ electron volt / kelvin} = 16,743 \text{ bits}$
- So converting one electron-volt of energy into heat, at room temperature will produce an entropy change of
 $1 \text{ electron volt / } 298.15 \text{ kelvin} = 56.157 \text{ bits}$
- Thus energy, such as that which washes over the Earth from the Sun, can be seen as providing a constant flow of not just "free energy", but free information
- Living systems take advantage of, and encode this information, temporarily and locally reducing the conversion of energy into entropy

Information and Complexity

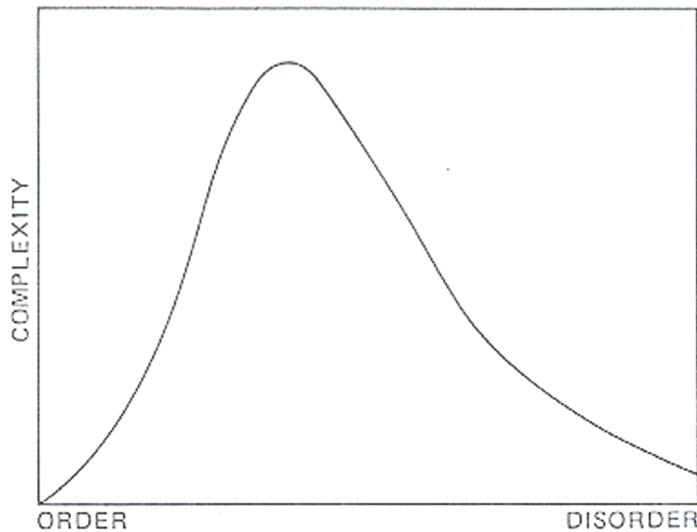
- Chris Langton's "lambda" parameter (ALife II)
 - Complexity = length of transients
 - $\lambda = \# \text{ rules leading to nonquiescent state} / \# \text{ rules}$



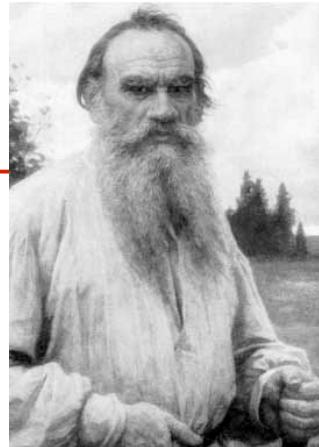
- Crutchfield: Similar results measuring complexity of finite state machines needed to recognize binary strings
- Tononi, Sporns, Edelman: Similar results measuring complexity of dynamics in artificial neural networks



“What clashes here of wills gen wonts,
oystrygods gaggin fishygods! Brékkek Kékkek
Kékkek Kékkek! Kóax Kóax Kóax! Ualu
Ualu Ualu! Quáouauh!”



Reference:
B.A. Huberman and T.Hogg (1986) Physica 22D, 376.



DM

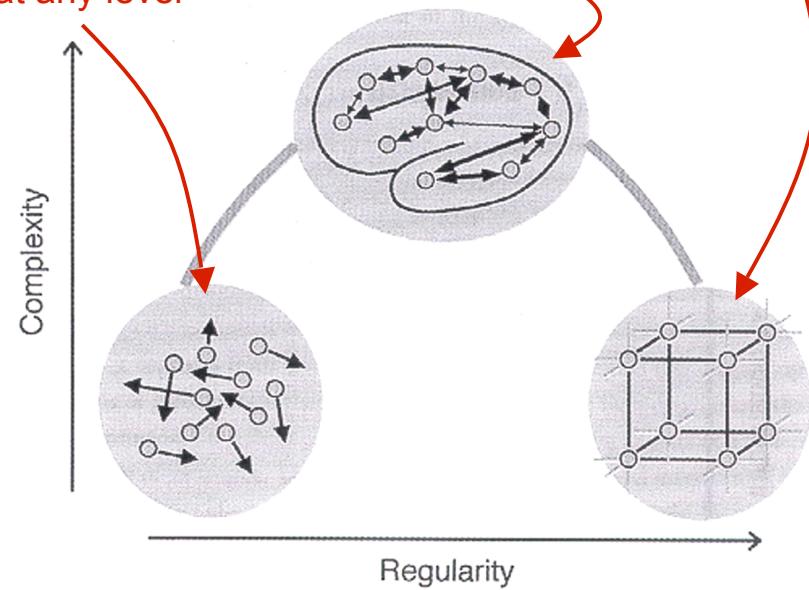


“All work and no play makes Jack a dull boy.
All work and no play makes Jack a dull boy.
All work and no play makes Jack a dull boy.”

randomness,
no structure at any level

non-repeating structure
at multiple levels

identical structure
at all levels



Reference:
G. Tononi, G.M. Edelman, O. Sporns (1998) TICS 2, 474.

Integration

Integration measures the statistical dependence among all elements $\{x_i\}$ of a system X.

$$I(X) = \sum_{i=1}^n H\{x_i\} - H(X) \quad MI(x_1, x_2) = H(x_1) + H(x_2) - H(x_1x_2)$$

$H\{x_i\}$ is the entropy of the i^{th} individual element x_i
 $H(X)$ is the joint entropy of the entire system X

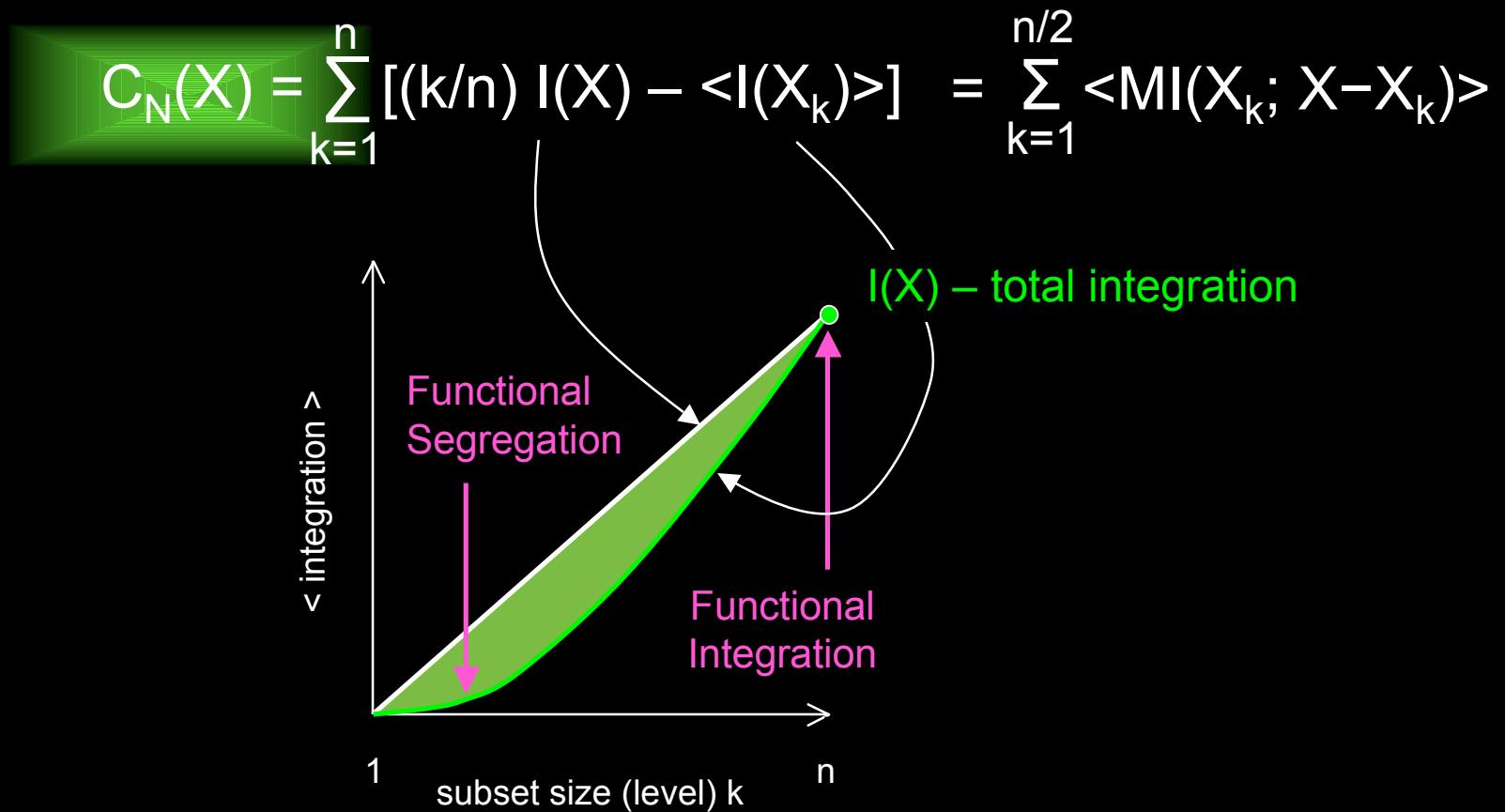
Note, $I(X) \geq 0$.

Note, $I(X) = 0$ if all elements are statistically independent

Any amount of structure (i.e. connections) within the system will reduce the joint entropy $H(X)$ and thus yield positive integration.

Information and Complexity

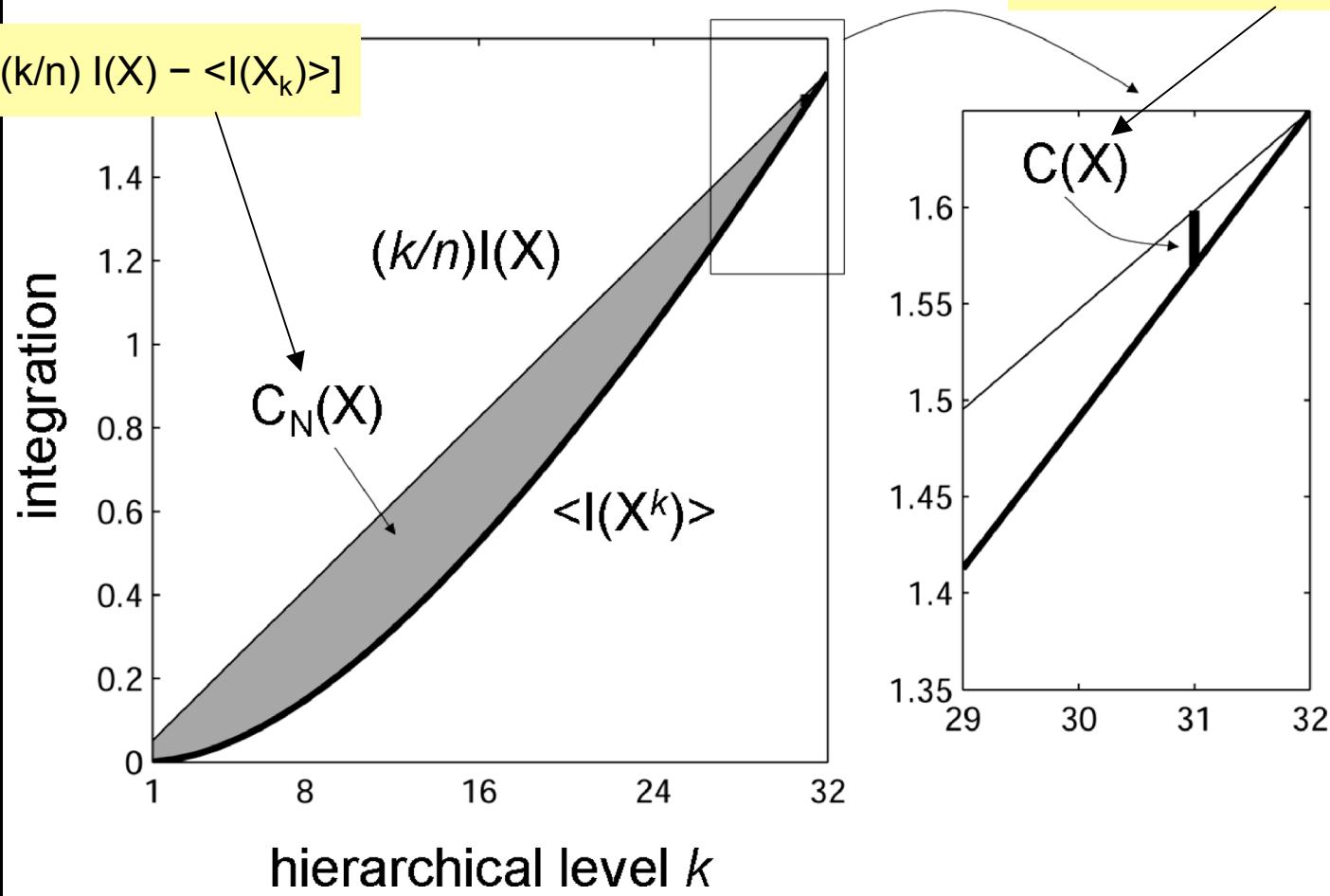
- **Complexity**, as expressed in terms of the ensemble average of integration (structure) at all levels:



Simpler Complexity

$$\begin{aligned} C(X) &= H(X) - \sum_i H(x_i | X - x_i) \\ &= \sum_i MI(x_i, X - x_i) - I(X) \\ &= (n-1)I(X) - n\langle I(X - x_i) \rangle \end{aligned}$$

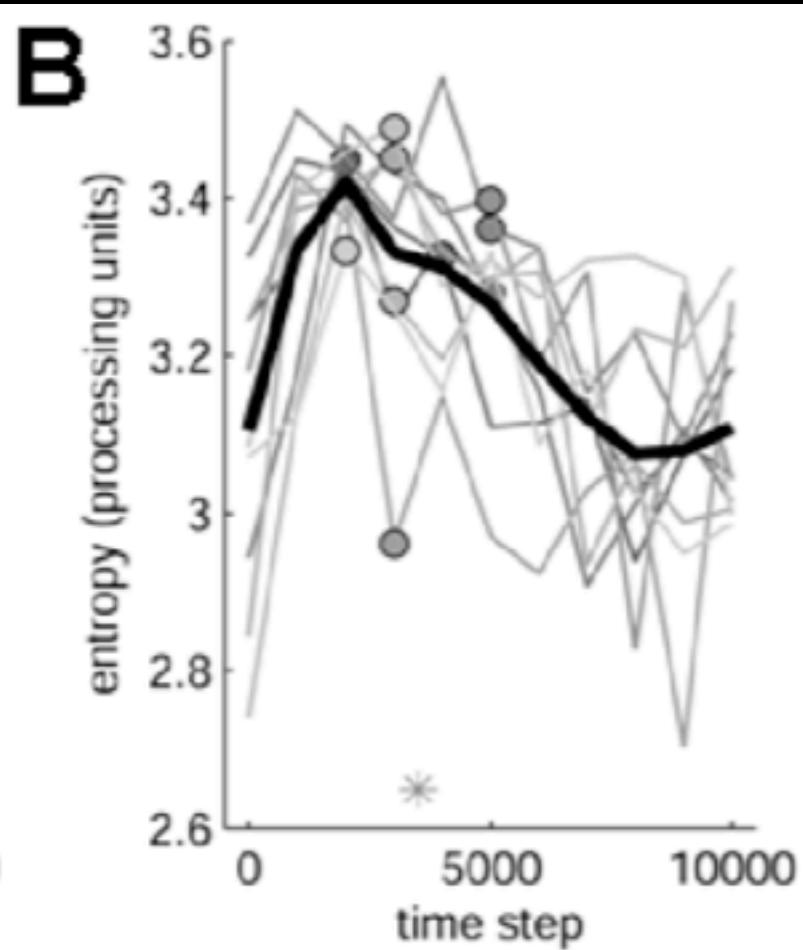
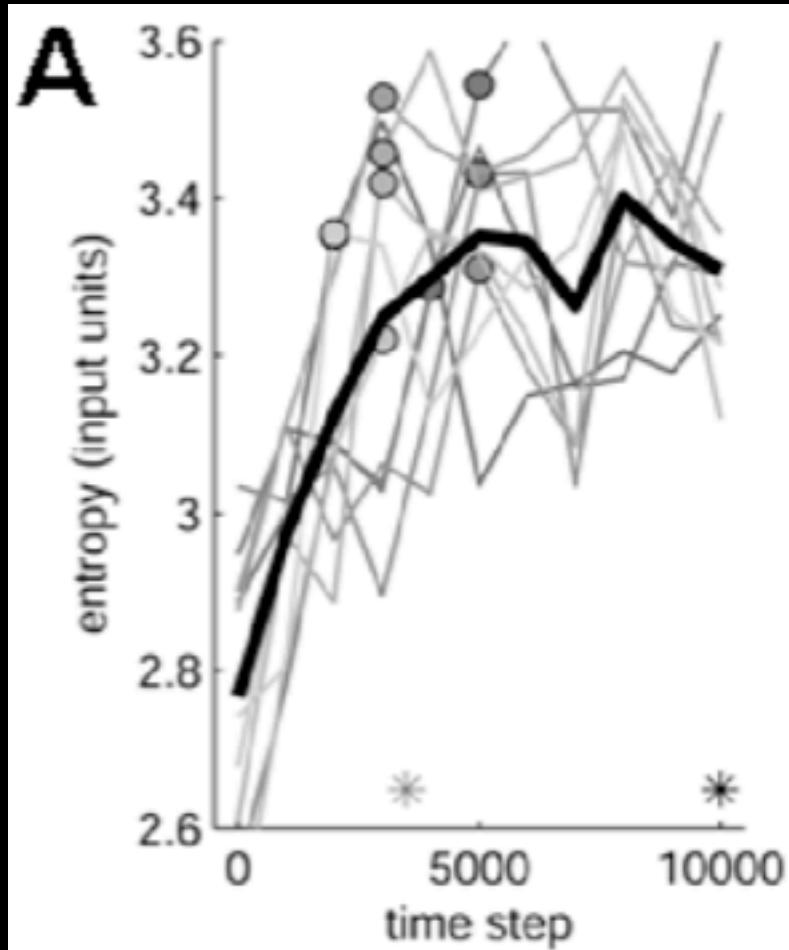
$$C_N(X) = \sum_{k=1}^n [(k/n) I(X) - \langle I(X_k) \rangle]$$



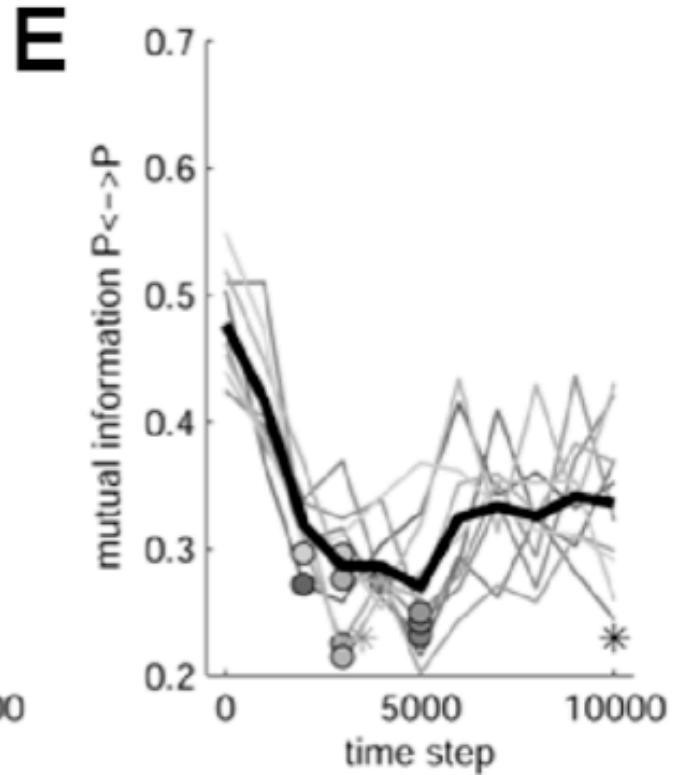
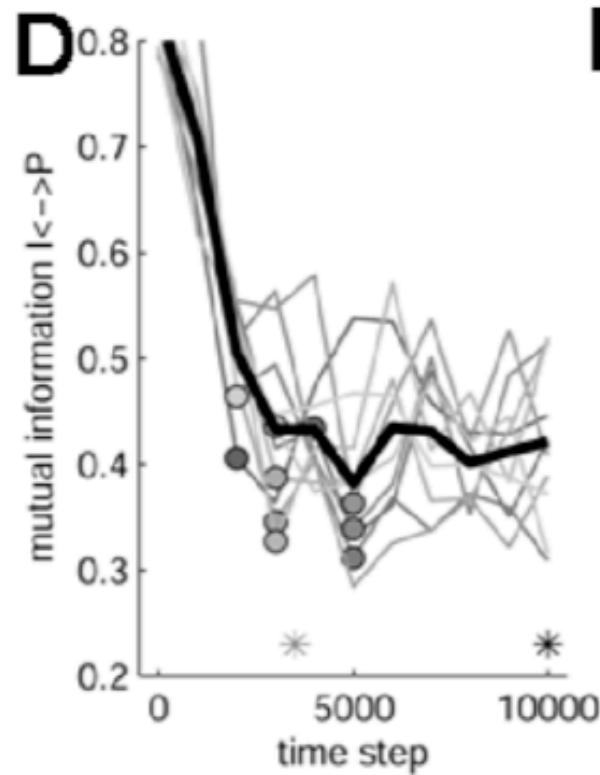
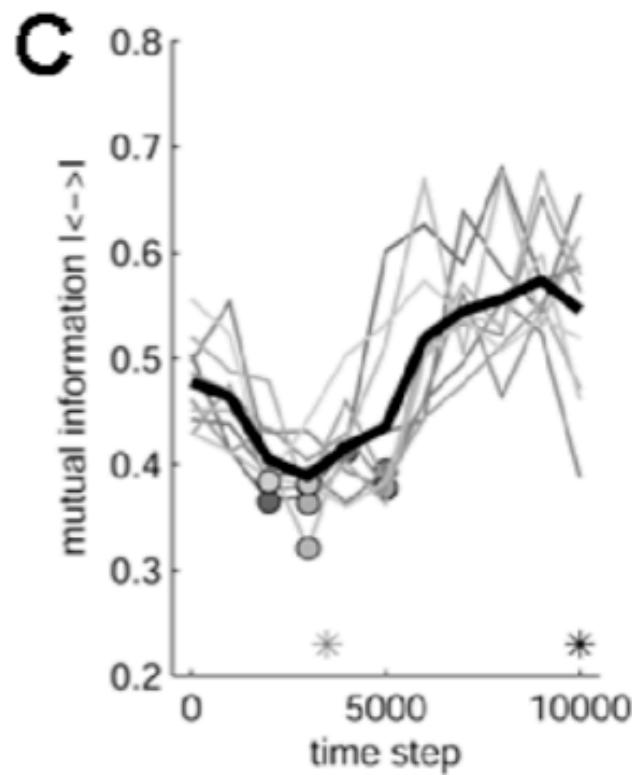
Quantifying Life and Intelligence

- Measure state and compute complexity
- What complexity?
 - Mutual Information
 - Sporns's functional complexity
 - Tononi's Phi
 - Adami's "physical" complexity
 - Gell-Mann & Lloyd's "effective" complexity
- What state?
 - Chemical composition
 - Electrical charge
 - Aspects of behavior or structure
 - Neuronal states
- Other issues
 - Scale, normalization, sparse data

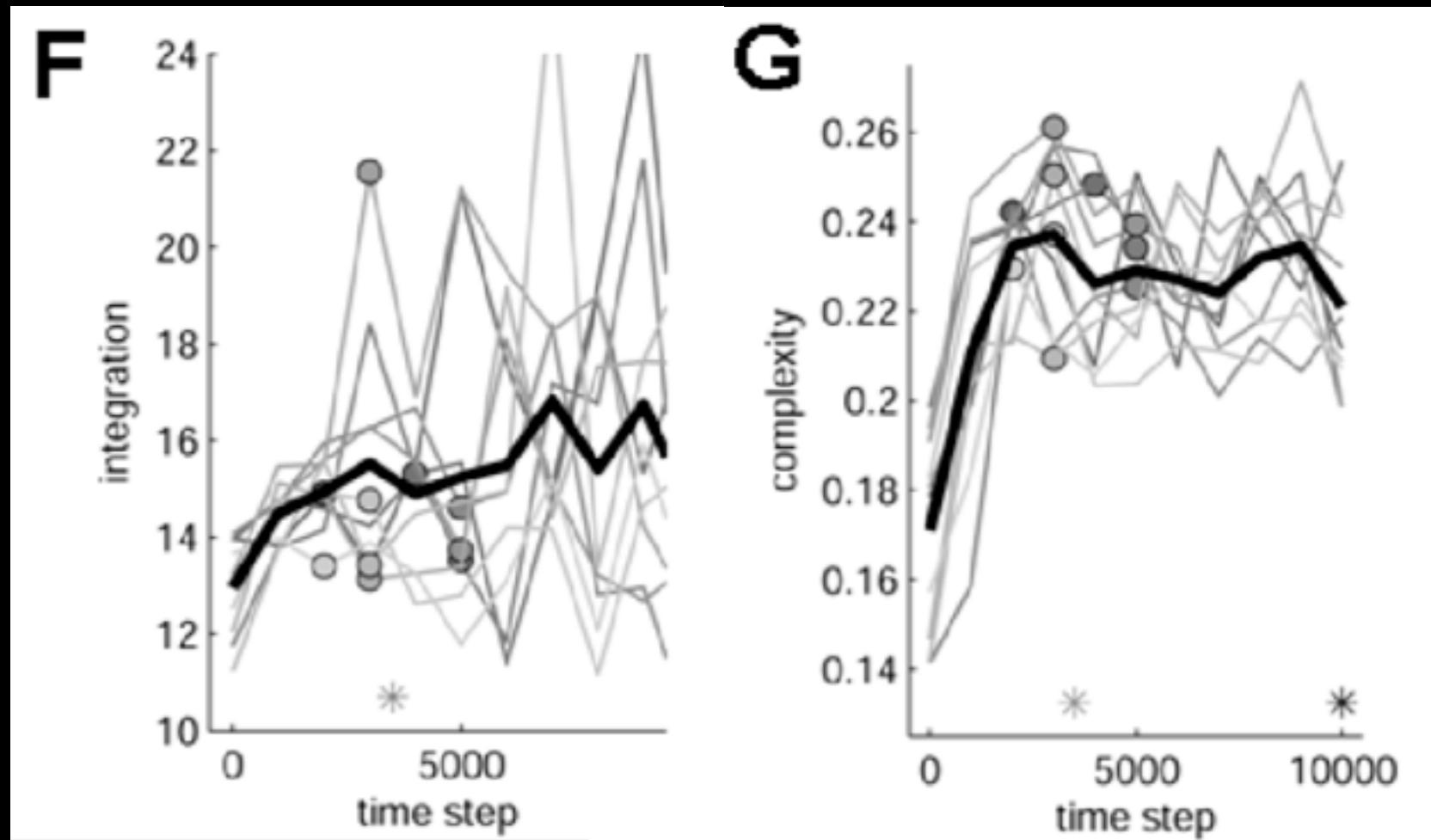
Information Metrics: Entropy



Information Metrics: Mutual Information

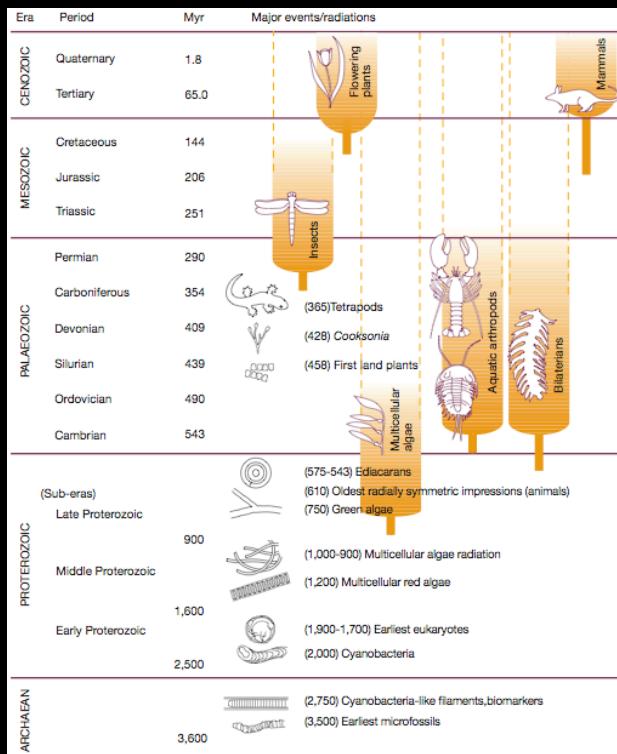


Information Metrics: Integration & Complexity

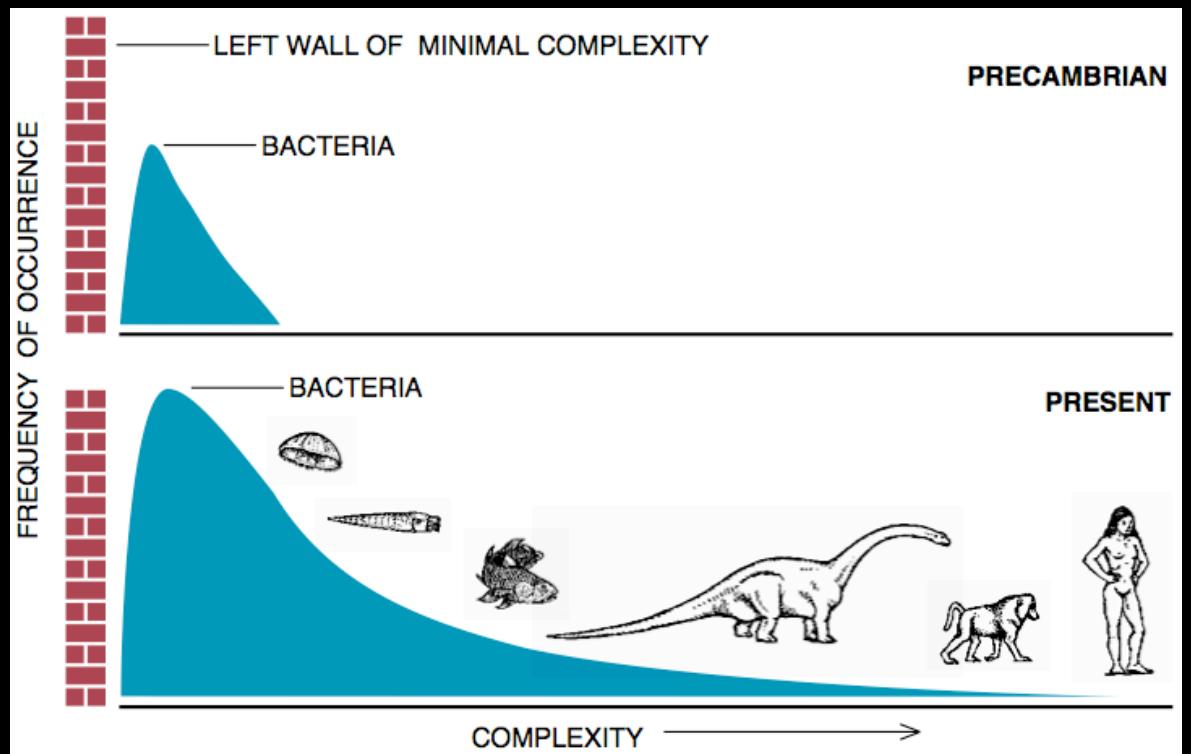


Is there an evolutionary “arrow of complexity”?

- Yes - Darwin, Lamarck, Cope, Spencer, Huxley, Rensch, Stebbins, Waddington, Saunders and Ho, Wake, Bonner, Ayala, Arthur, Lewin, Valentine, McShea
- No - Williams, Lewontin, Levins, Slobodkin, Gould, McShea



Carroll (2001)



Gould (1994)

Natural and Artificial Trends in Complexity

- Bedau (et al. 1997, Rechsteiner and Bedau 1999) provides evidence of an increasing and accelerating "evolutionary activity" in biological systems not yet demonstrated in artificial life models
- Turney (1999) uses a simple evolutionary model to suggest that *evolvability* is central to progress in evolution, and predicts an accelerating increase in biological systems
- Adami (2000, 2002) defines complexity as the information that an organism's genome encodes about its environment and demonstrates that asexual agents in a fixed, single niche evolve towards greater complexity

Sources of Complexity Growth

- Rensch (1960a,b; Bonner 1988) argued that more parts will allow a greater division of labor among parts
- Waddington (1969; Arthur 1994; Knoll and Bombach 2000) suggested that due to increasing diversity niches become more complex, and are then filled with more complex organisms
- Saunders and Ho (1976; Katz 1987) claim component additions are more likely than deletions, because additions are less likely to disrupt normal function
- Kimura (1983; Huynen 1995; Newman and Englehardt 1998) demonstrated value of neutral mutations in bridging gulfs in fitness landscape, through selection for function in previously neutral changes

What Kind of Complexity?

- McShea (1996) observes that loose and shifting definitions of complexity allow sloppy reasoning and highly suspect conclusions about evolutionary trends
- Identifies four distinct categories of complexity
 - Number of different parts (genes, cells, organs)
 - Number of different interactions between parts
 - Number of hierarchical levels
 - Number of parts or interactions at a given scale
- Suggests there may be upper limits to complexity
- Discusses (limited) evidence for increases in number of cell types, arthropod limb types, and vertebrae sizes
- Acknowledges complexity of human brain, but otherwise ignores nervous systems
- Distinguishes *driven* vs. *passive* trends, using changes in minimum values and ancestor-descendent differences

Driven or Passive?

- Original experiments did not address the distinction between *driven* and *passive* sources of complexity
 - Established ability to compute neural complexity of Polyworld agents
 - Demonstrated increase in complexity as evolution proceeds
- Current experiments directly assess driven vs. passive contributions to complexity resulting from natural selection

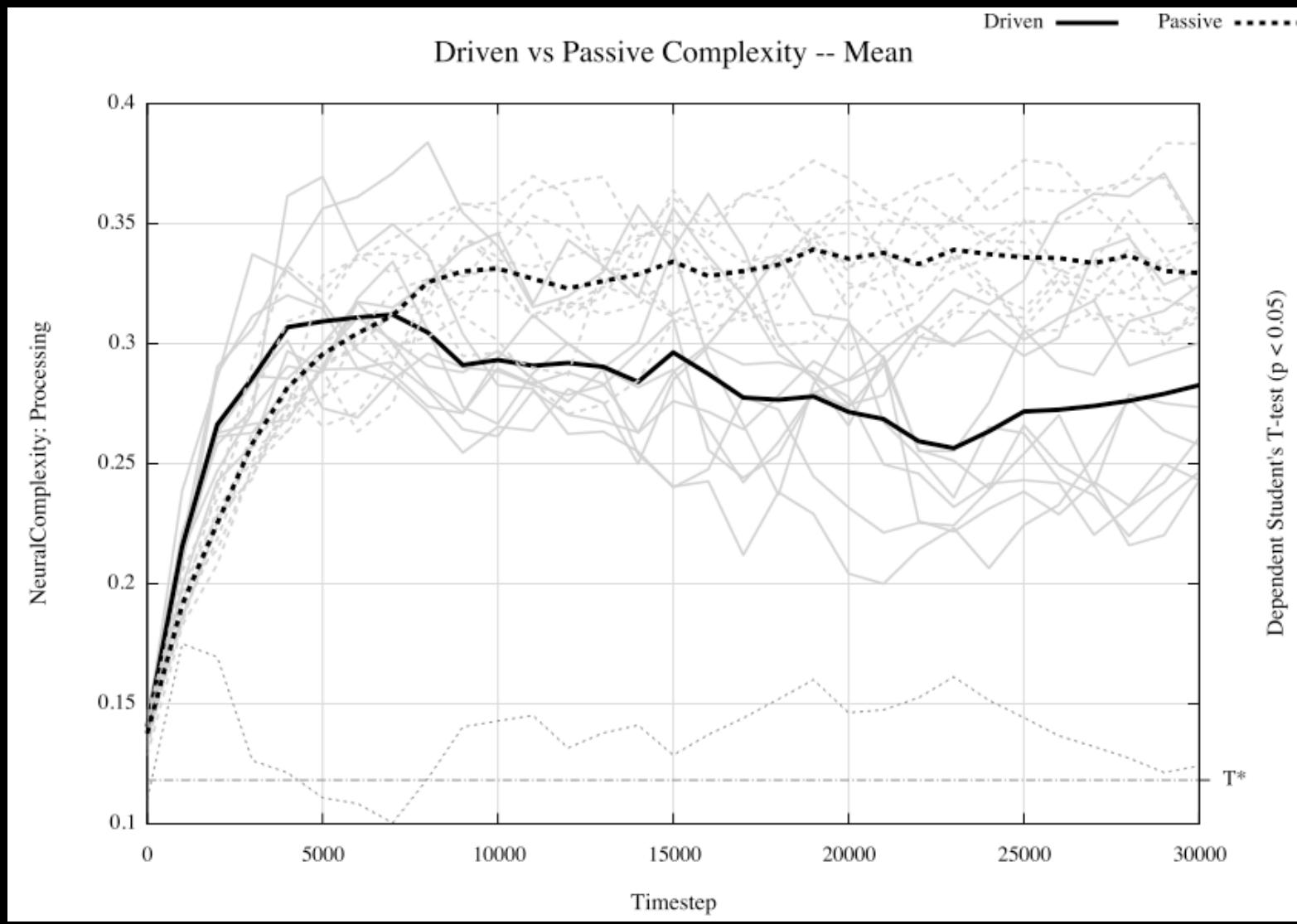
Natural Selection vs. Random Drift

- By default Polyworld agents are subject to natural selection
 - Genes are passed on as a direct result of success at survival and reproduction
- Goal: Produce a random drift of agent genes in Polyworld in a simulation that is directly comparable to a standard, natural selection run
 - Same initial conditions
 - Same population statistics
 - Same statistics for genetic mutations and crossover operations

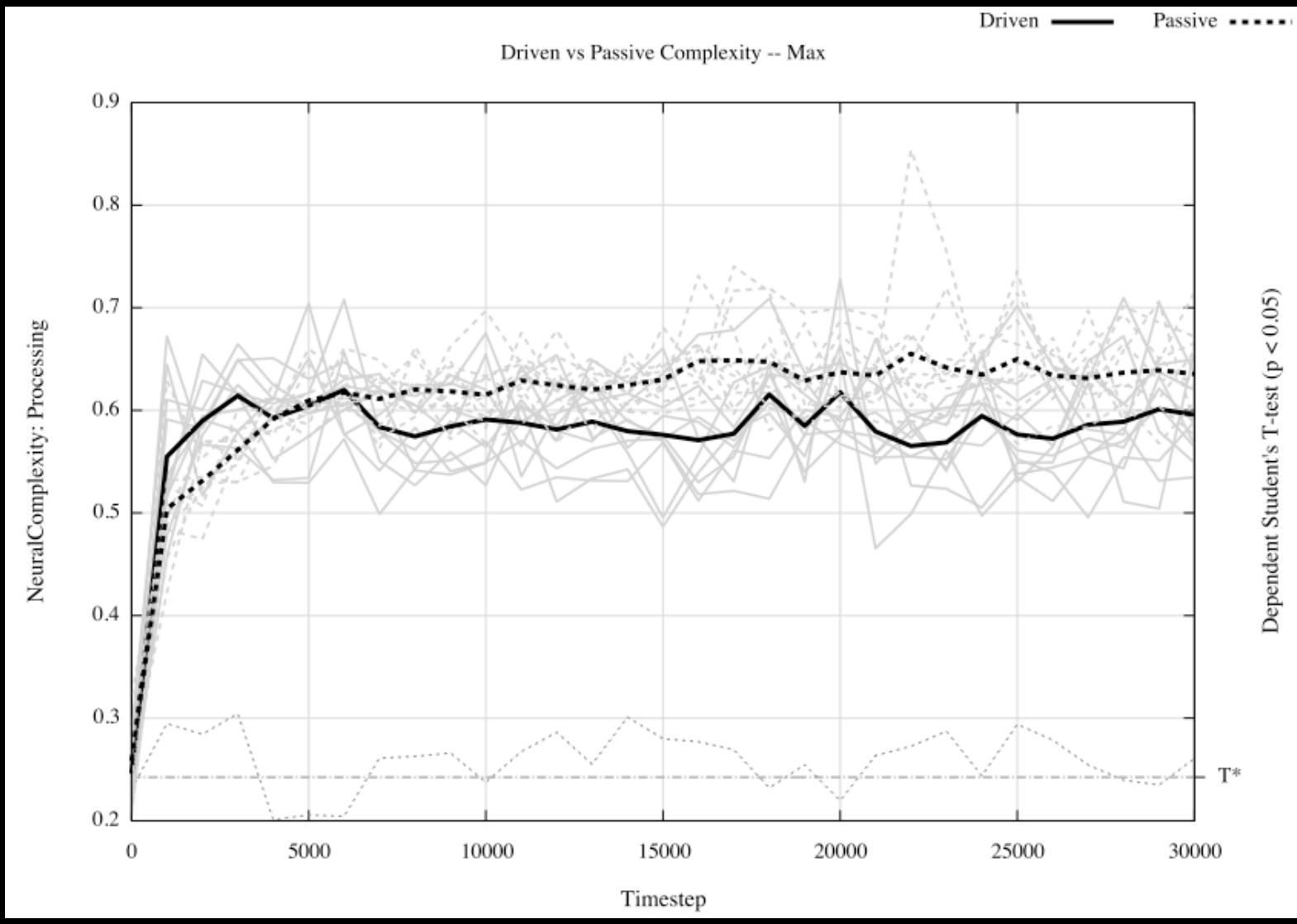
Eliminating Natural Selection

- Run standard simulation, logging all births and deaths
- Run random-drift simulation, with following conditions:
 - Use identical initial conditions
 - Eliminate behaviorally generated births and deaths
 - At each time step, for every birth in the standard run, select two parents at random and produce their offspring
 - Deposit the offspring at a random location
 - At each time step, for every death in the standard run, select one agent at random and kill it
- Produces identical statistics for population genetics and comparable visual inputs ("life experiences") to agents in the two simulations
- Natural selection no longer affects gene histories

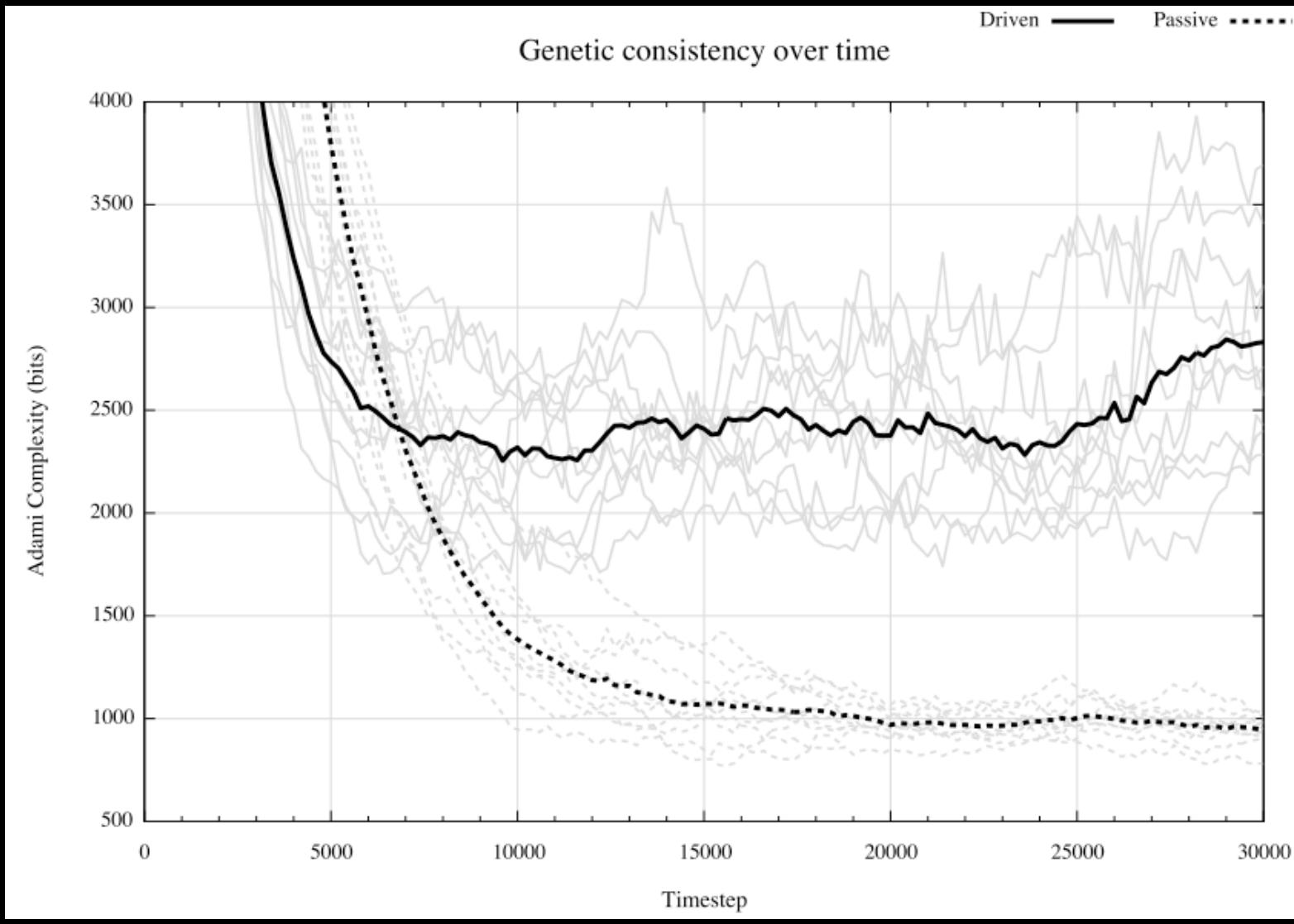
Driven vs. Passive Mean Complexity



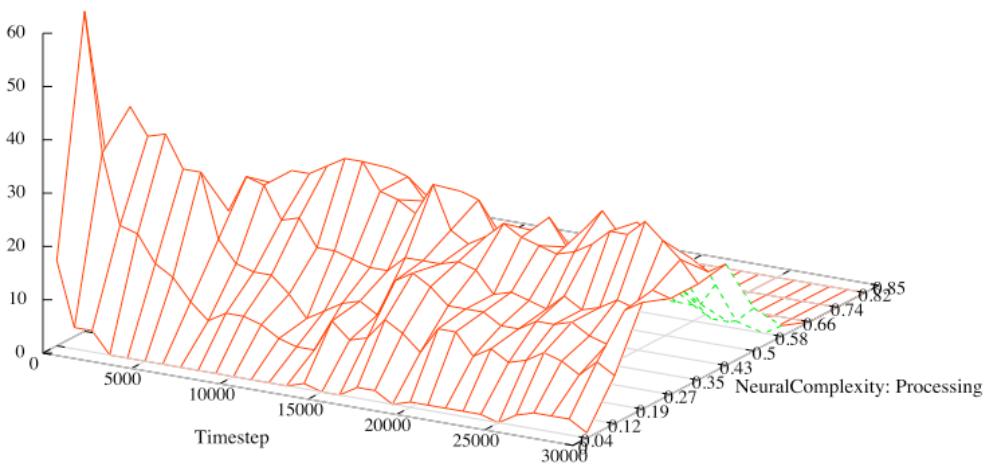
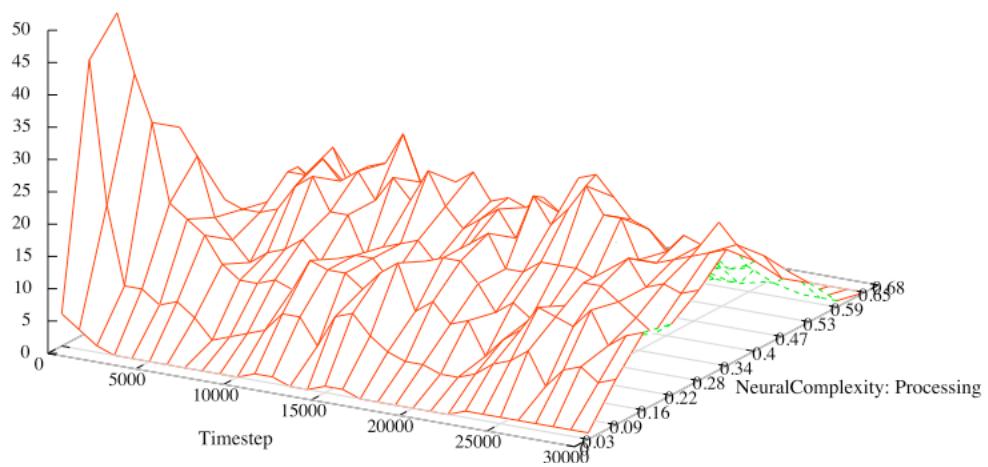
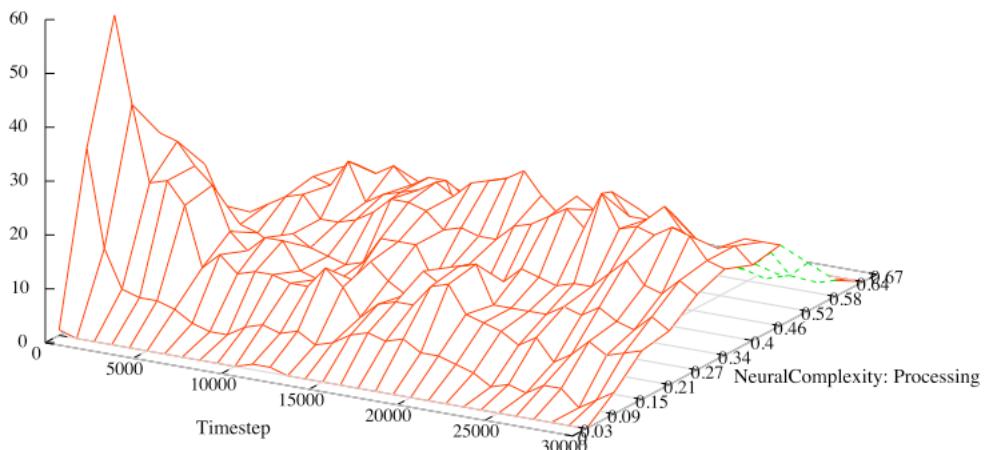
Driven vs. Passive Max Complexity



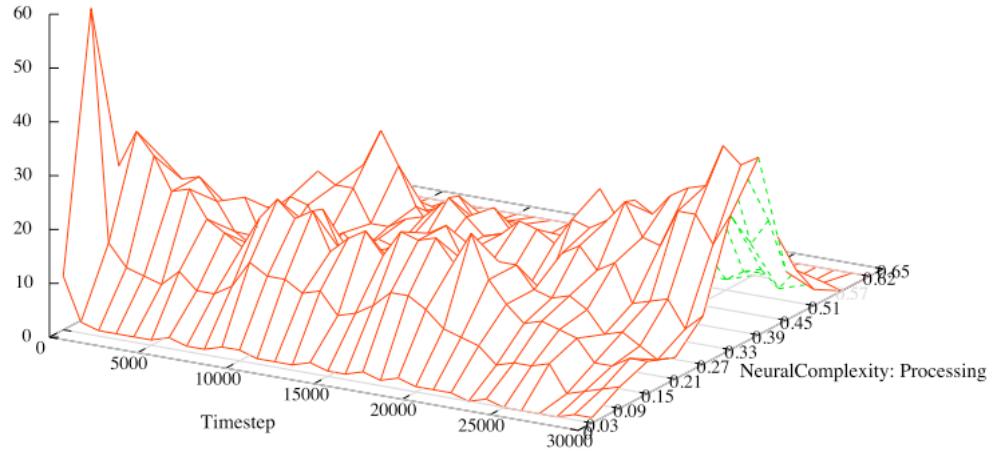
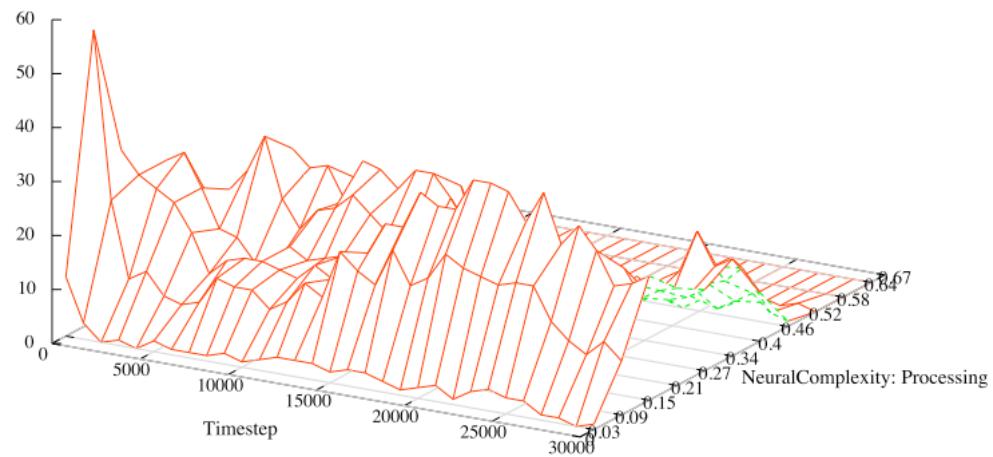
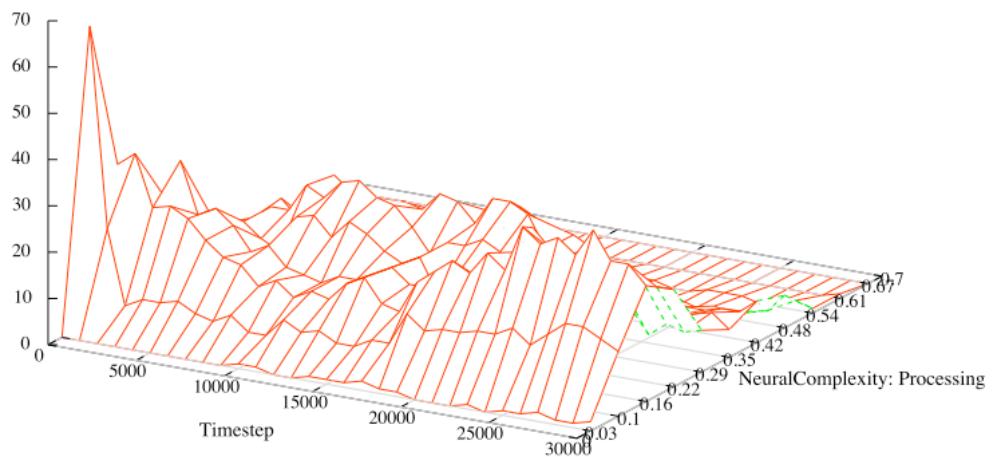
Genetic Similarity



Complexity Histogram Over Time - Passive



Complexity Histogram Over Time - Driven



Conclusions

- Evolution selects FOR a complexity increase when it enhances the ability to survive and reproduce
- Evolution selects mildly AGAINST a complexity increase when existing characteristics are “good enough”
 - Though not shown by these experiments, evolution is known to select AGAINST unneeded but costly complexity
- At the level of species, evolution of complexity is almost always driven
 - Just not in a single direction
- Integrating these opposing tendencies over the history of life, may appear passive
 - But ever-increasing “ecospace” may provide an overarching drive towards complexity as well
- Conflicting evidence for complexity growth in the biological record is to be expected
- Seemingly conflicting intuitions about a clear evolution of complexity in the paleontological record vs., for example, the longevity of the cockroach and its extreme suitability to its ecological niche are not actually in conflict

Speculation

- Though current experiments effectively explore complexity dynamics only in a single niche, for hardly more than a single species...
 - Multiple niches, niche creation, and potential arms races associated with competition within a niche are all likely to confer an evolutionary advantage on at least some complexity increases
 - Inherently more complex niches will require greater biological complexity
 - All niches are *not* created equal
 - Increasing the complexity of Polyworld's ecology—the range of organism-environment interactions and available niches—will allow a measurable selection towards greater neural complexity

Future Directions

- Explore use of complexity measure as fitness function
- More environmental interaction
 - Pick up and put down
 - Pieces of food
 - Pieces of barrier
 - Other agents
- More complex environment
 - More control over more organic food growth patterns
 - Multiple food types
- Additional senses (definitely touch, perhaps smell)
- More complex, spiking neural models
- Assess progress by routinely measuring complexity

Future Directions

- Behavioral Ecology benchmarks
 - Optimal foraging (profitability vs. predation risk)
 - Patch selection/depletion (Ideal Free Distribution)
 - Vancouver whale populations
- Evolutionary Biology problems
 - Speciation = f (population isolation)
 - Altruism = f (genetic similarity)
- Classical conditioning, intelligence assessment experiments

Future Directions

- Source code is available
for Mac/Windows/Linux (on Qt) at
<http://sourceforge.net/projects/polyworld/>
- Papers and other materials at
<http://beanblossom.in.us/larryy/Polyworld.html>