Evolution of Neural Complexity

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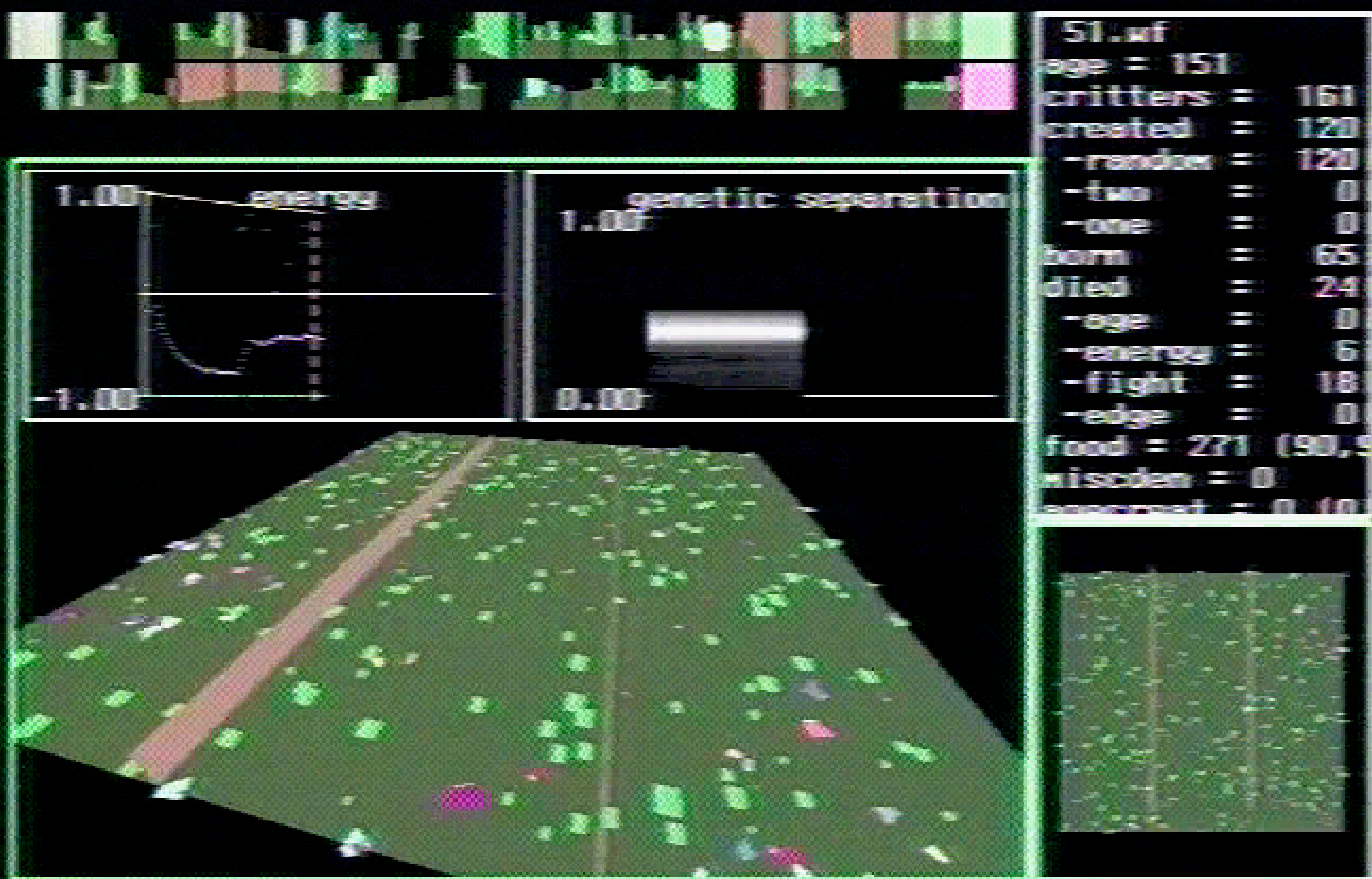
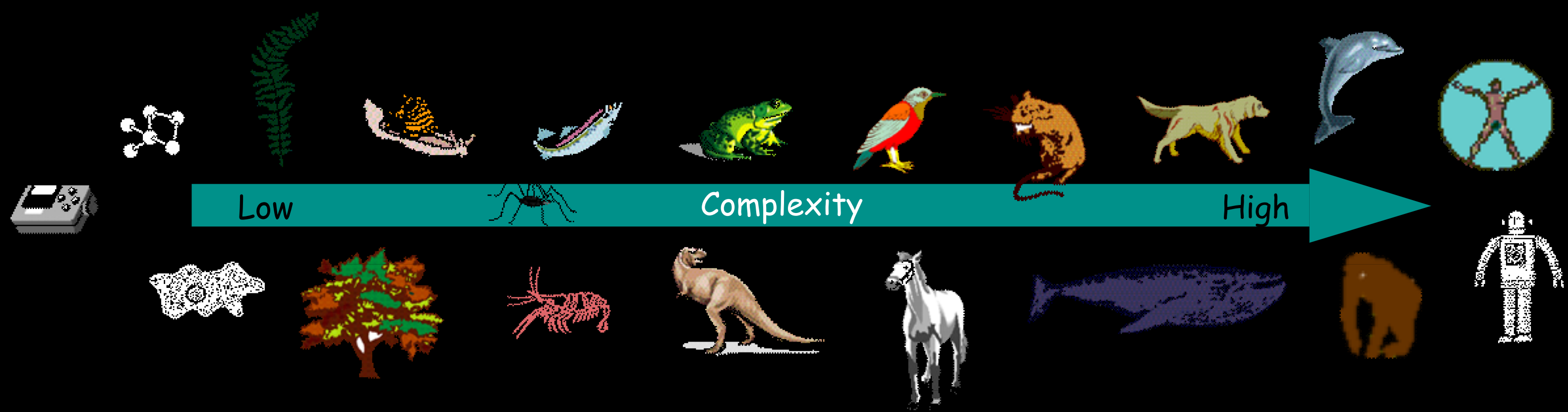
Evolution of Machine Intelligence

- Follow the path leading to natural intelligence
- *Evolution* of *nervous systems* in an *ecology*
    - *Evolution*, because it is an incredibly powerful innovator and problem solver
    - *Nervous systems*—collections of neurons and their internal, sensory, and motor connections—because that's how biological evolution has produced all known examples of natural intelligence
    - *Ecology*, because intelligence only makes sense in context
- Allows us to evolve simple intelligences (adaptive behaviors) first, along a spectrum of intelligences

Emergent Behaviors:
Foraging, Grazing, Swarming



Measuring Progress



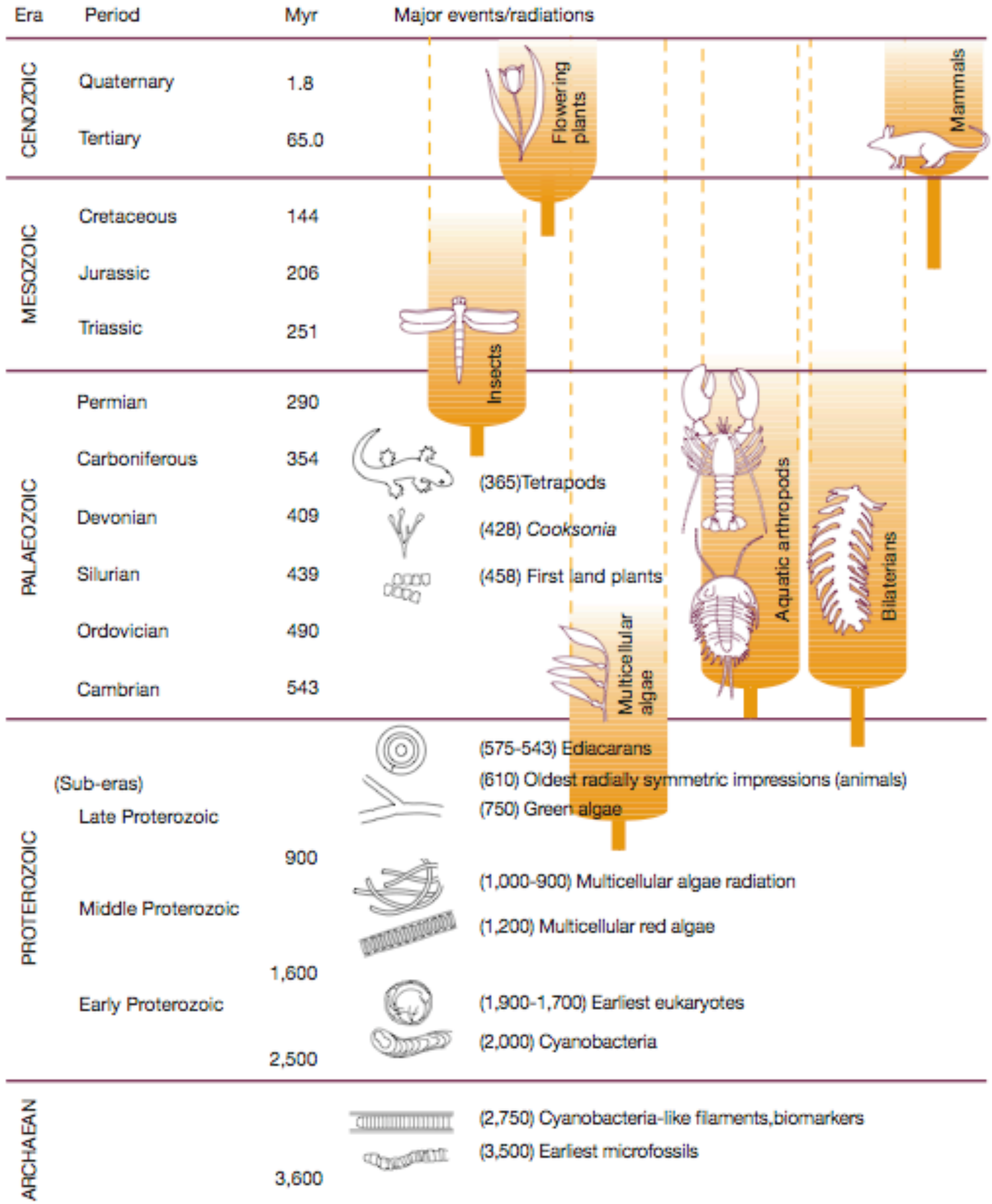
Spectrum of Life and Intelligence

Spectrum of Intelligence

- Laboratory evidence exists for self-awareness in humans, chimpanzees, and orangutans, based on the classic red-dot and mirror test
- Koko the gorilla, Washoe the chimp, and Kanzi the bonobo ape all demonstrate language skills comprehensible to humans
- Dolphins demonstrate intelligent behavior and learning in the field and in the "lab"
- Alex the parrot demonstrates language skills, and Betty the crow demonstrates tool creation (as well as use)
- Honeybees (1M neurons) exhibit associative recall and learn the abstract concepts ***same*** and ***different***
- Fruit flies (250K neurons) learn by association and exhibit a ***salience*** mechanism akin to human attention
- *Aplysia* (20K neurons) demonstrate sensitization, habituation, classical, and operant conditioning

History of Major Evolutionary Events from the Fossil Record

Carroll (2001)



The Great Chain of Being

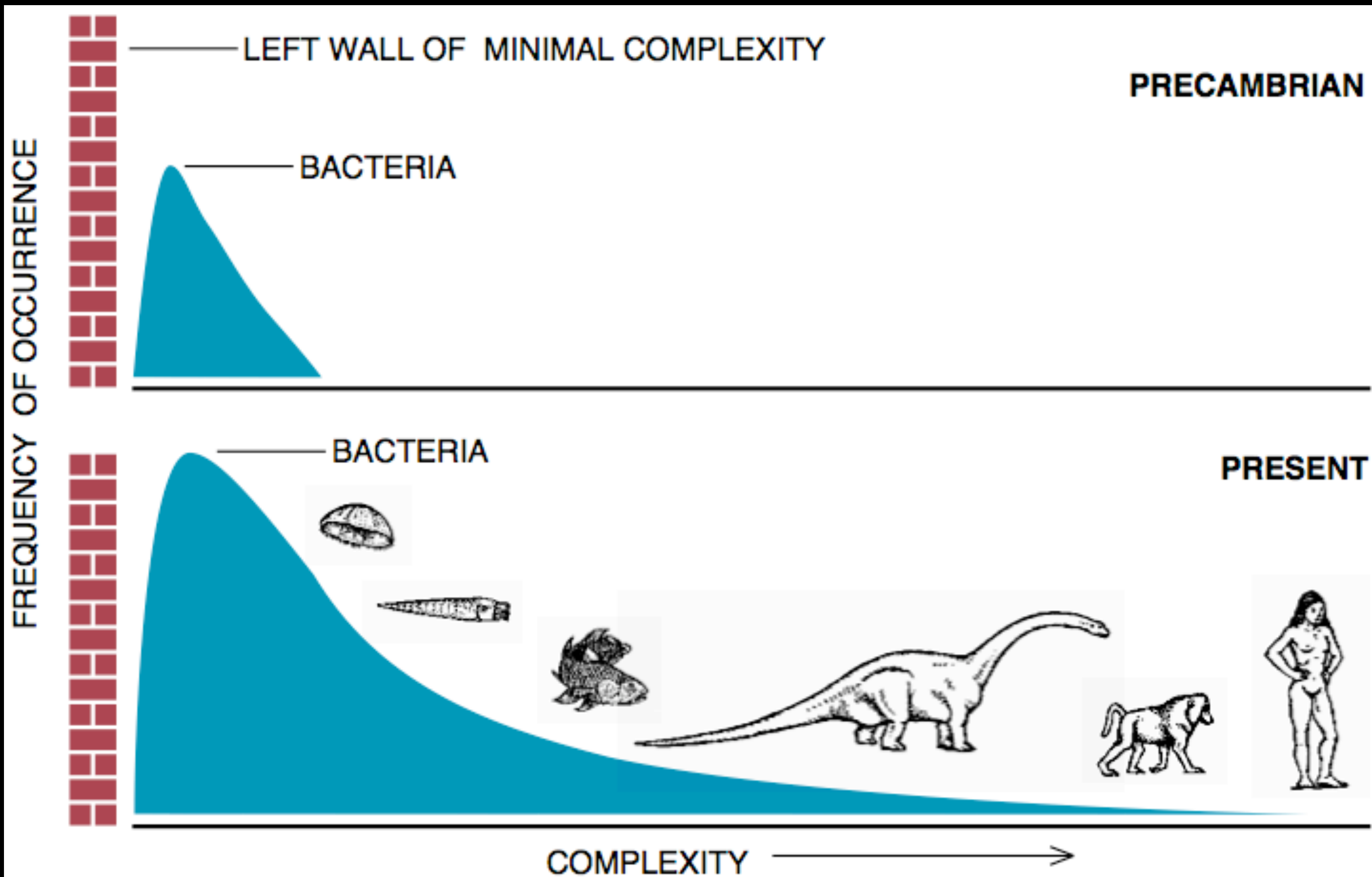
- Concerns exist about whether all such explanations might merely encode an anthropocentric bias, where "human-like" is the real measure of some loosely-defined complexity

Didacus Valades,
Rhetorica Christiana
1579

Evolutionary Trends in Complexity?

- In a 1994 Scientific American article, Steven J. Gould famously argued against an evolutionary trend towards increasing complexity
- However, he actually acknowledges the appearance of greater complexity over evolutionary time scales

Evolutionary Trends in Complexity?



Evolutionary Trends in Complexity?

- In a 1994 Scientific American article, Steven J. Gould famously argued against an evolutionary trend towards increasing complexity
- However, he actually acknowledges the appearance of greater complexity over evolutionary time scales
- The focus and conclusion of his argument is that evolution is better viewed as a branching tree or bush, rather than a purely gradualist ladder, with punctualist winnowing and accident being as important as growth in the natural record

What Kind of Complexity?

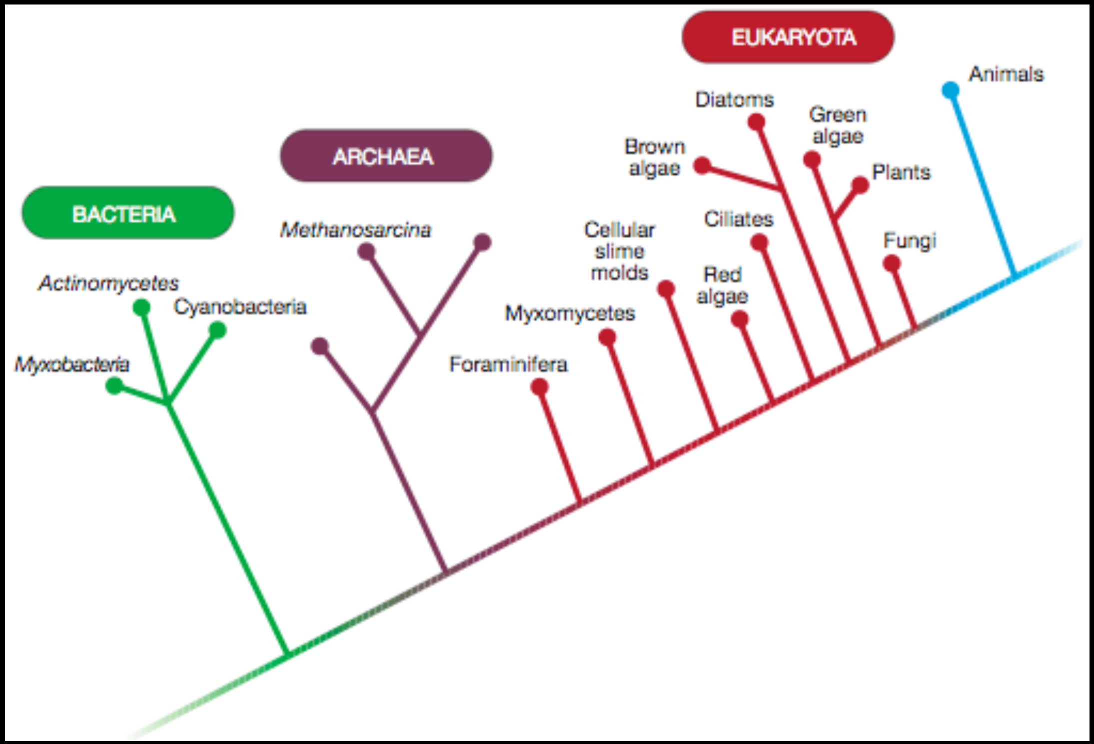
- McShea (1996) observes that loose and shifting definitions of complexity allow sloppy reasoning and highly suspect conclusions about evolutionary trends
- Defines two (or three) distinctions that produce four (or eight) types of complexity
  - Hierarchical vs. non-hierarchical
  - Morphological (objects) vs. developmental (processes)
  - (Differentiation vs. Configuration)
- Distinguishes *driven* vs. *passive* trends, using changes in minimum values and ancestor-descendent differences
- 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

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) 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

Convergent Diversification

- Multicellularity, subsequent specialization, and a resulting body-plan radiation have evolved independently in every domain of life
- Modularity and genetic regulatory evolution mirror these phenomena at a higher level of organization



Carroll (2001)

Evolutionary Trends in Complexity?

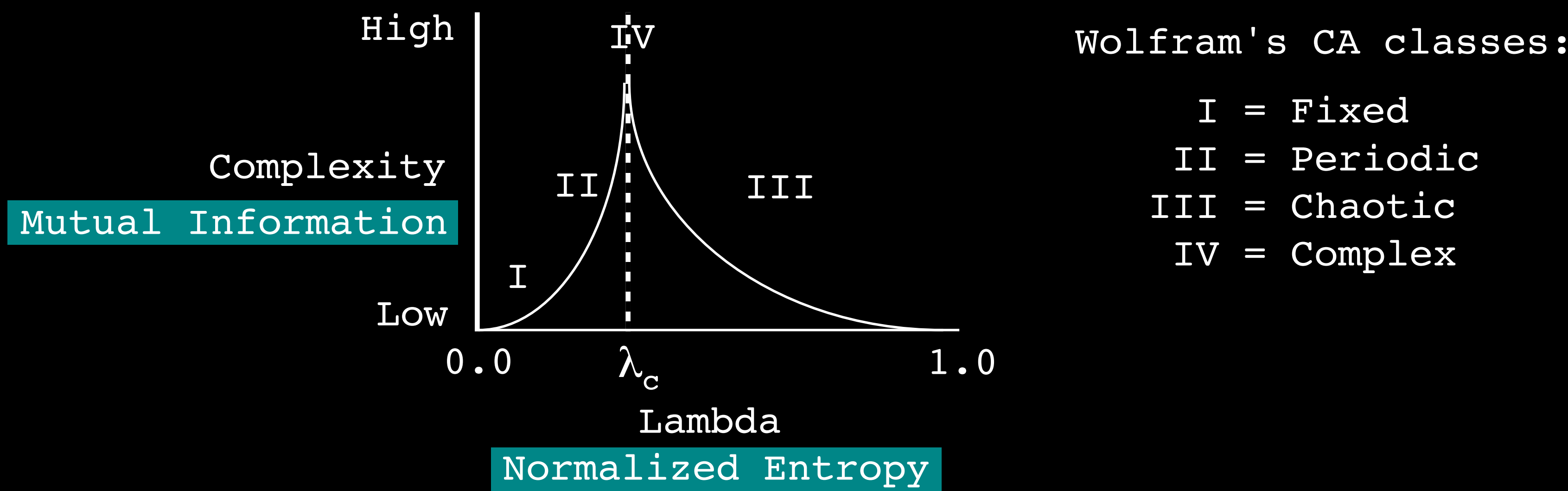
- Adami (2000, 2002) defines complexity as the information that an organism's *genome* encodes about its environment and demonstrates that asexual agents in a fixed, single niche always evolve towards greater complexity
- Turney (1999) uses a simple evolutionary model to suggest that *evolvability* is central to progress in evolution, and predicts an accelerating increase in biological systems
- 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

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)
- John Avery derives a formal relation between physical entropy and Shannon entropy/information (*Information Theory and Evolution*, 2003)
- *Informational functionalism*
  - It's the process, not the substrate
  - What can information theory tell us about life and complexity?

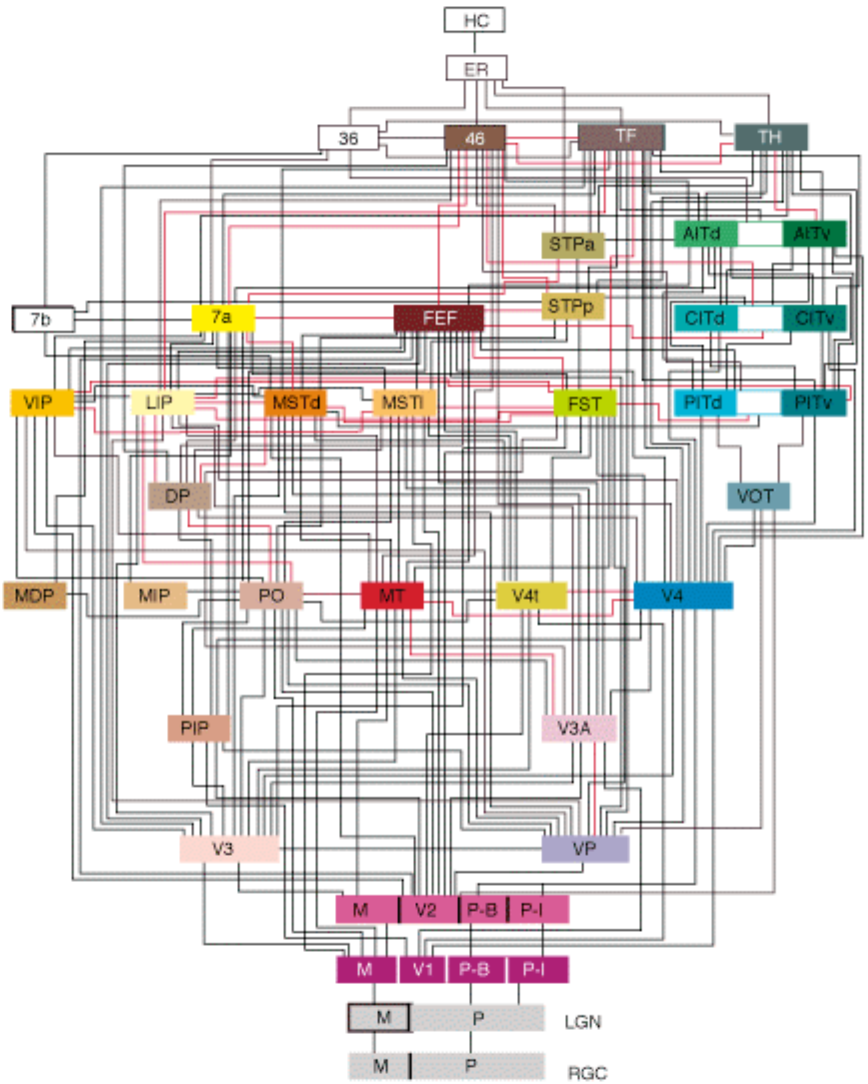
Information and Complexity

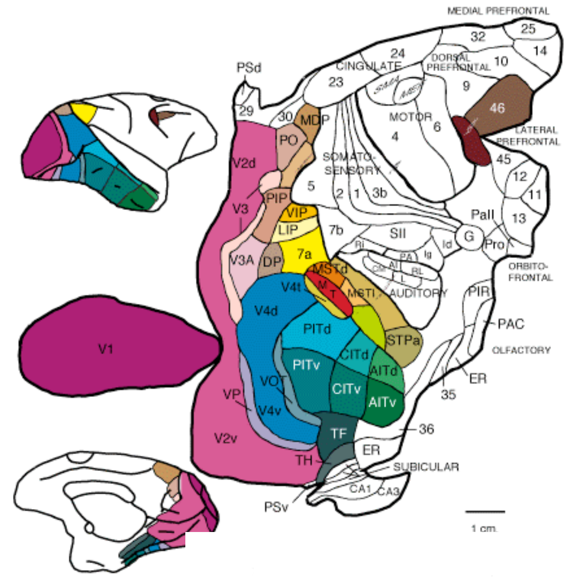
- Chris Langton's "lambda" parameter (ALife II)
  - Complexity = length of transients
  - λ = # rules leading to nonquiescent state / # rules

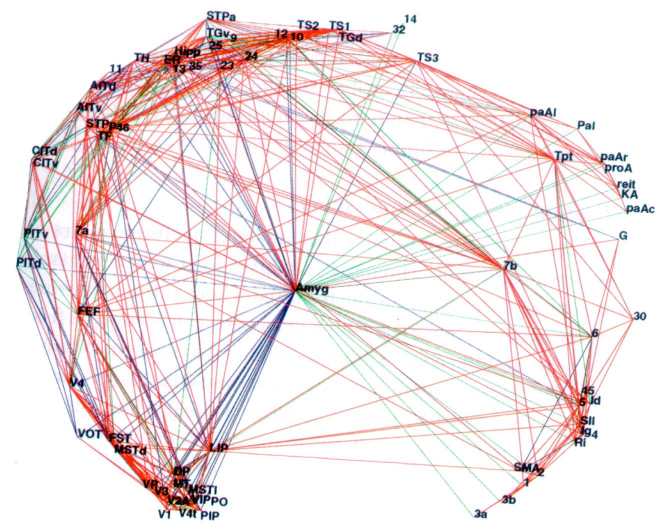


- Crutchfield: Similar results measuring complexity of finite state machines needed to recognize binary strings
- Olaf Sporns: Similar results measuring complexity of dynamics in artificial neural networks

Complex Brain Networks







Interregional connectivity of macaque visual cortex (Felleman and Van Essen, 1991)

Nonlinear multidimensional scaling of macaque cortex (Young, 1993)

Segregation and Integration

There are (at least) two complementary principles of brain structure and brain dynamics:

functional segregation and functional integration

Segregation and integration have information-theoretical connotations and characteristic dynamic signatures.

We need segregation **and** integration for effective perceptual and cognitive function.

Complexity emerges from their co-existence, generating a mixture of randomness and regularity…

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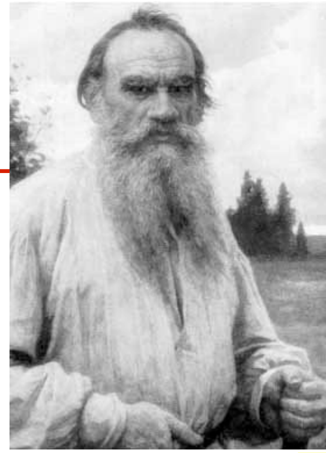


"All work and no play makes Jack a dull boy.
All work and no play makes Jack a dull boy.
All work and no play makes Jack a dull boy."

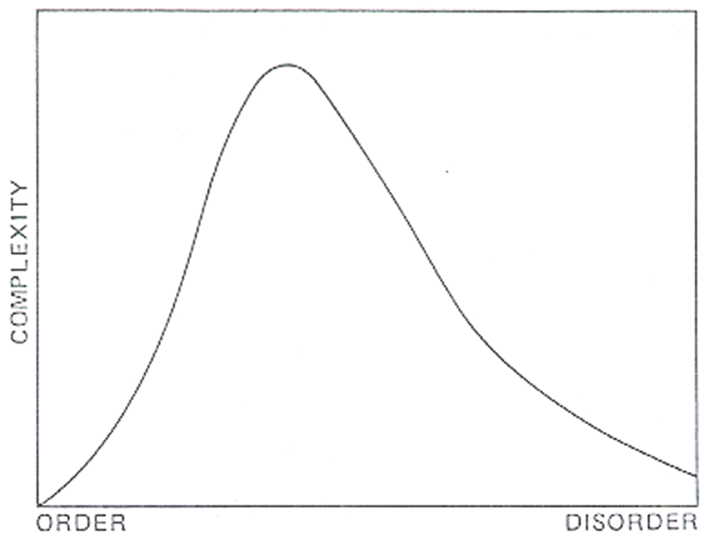
"What clashes here of wills gen wonts, oystrygods gaggin fishygods! Brékkek Kékkek Kékkek Kékkek! Kóax Kóax Kóax! Ualu Ualu Ualu! Quáouauh!"

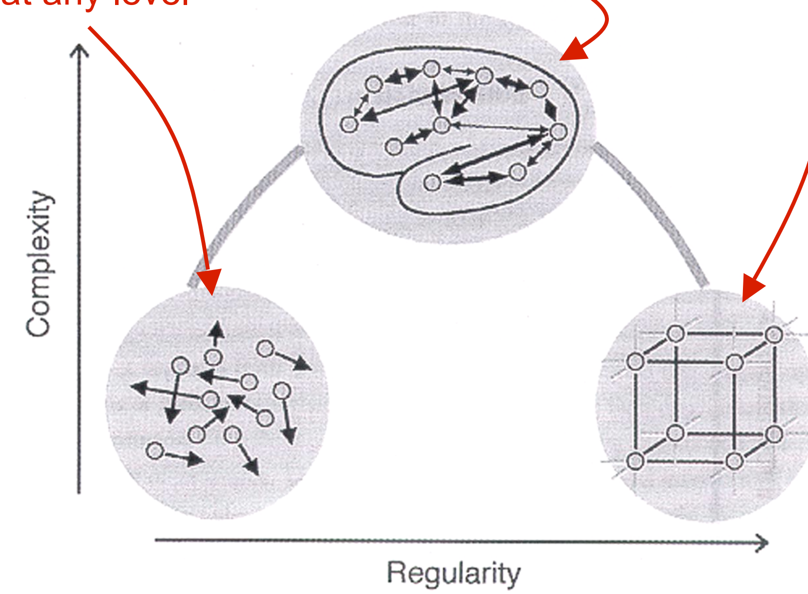
"Happy families are all alike; every unhappy family is unhappy in its own way."

identical structure
at all levels

non-repeating structure
at multiple levels

randomness,
no structure at any level





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

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

Information and Complexity

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

$$I(X) = \sum_{i=1}^{n} H\{x_i\} - H(X)$$

$$MI(x_1,x_2) = H(x_1) + H(x_2) - H(x_1x_2)$$

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

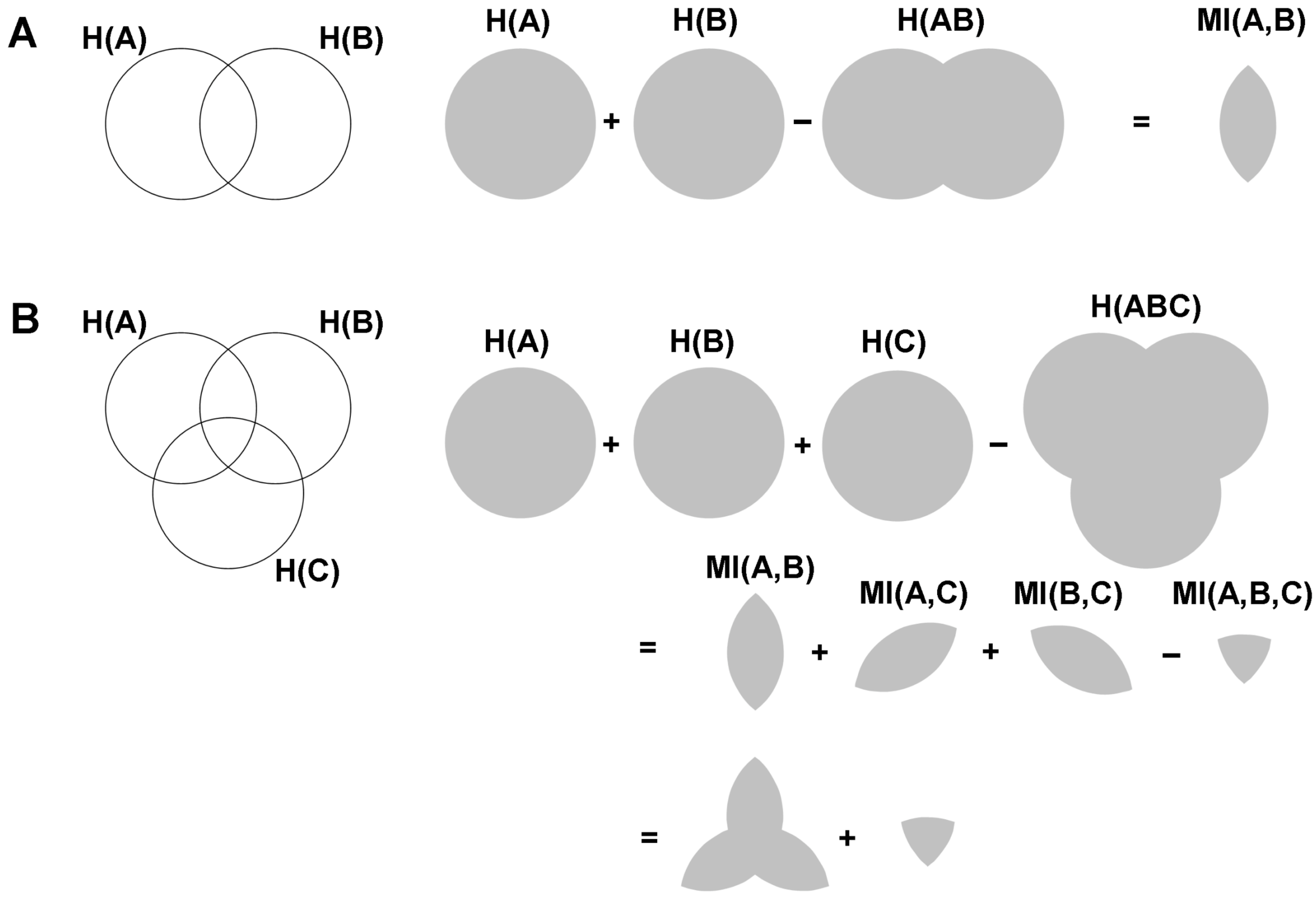
Note, $I(X) \geq 0$.
Note, $I(X) = 0$ if all elements are statistically independent

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

Tononi, Sporns, Edelman, PNAS (1994)

Information and Complexity

Mutual information (A) and multi-information (integration, B)

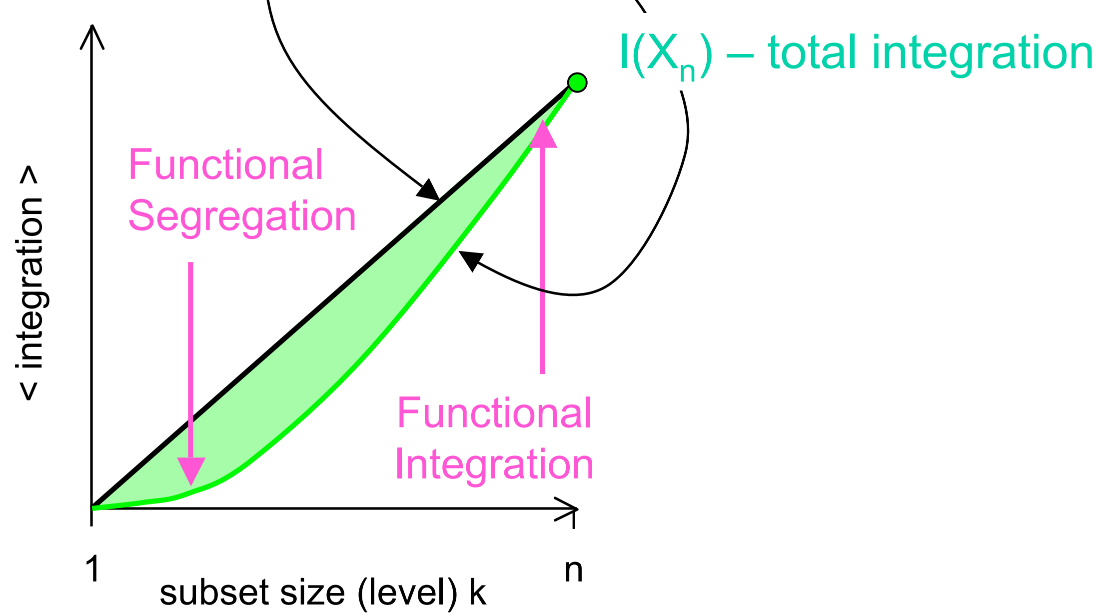


Sporns and Tononi (2006)

Information and Complexity

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

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



Tononi, Sporns, Edelman, PNAS (1994)

Information and Complexity

Equivalent mathematical expressions and relationship of complexity to mutual information (MI) (i.e. information transmission).

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

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

$$C_N(X) = \sum_{k=1}^{n/2} \langle MI(X_k;\, X-X_k) \rangle$$

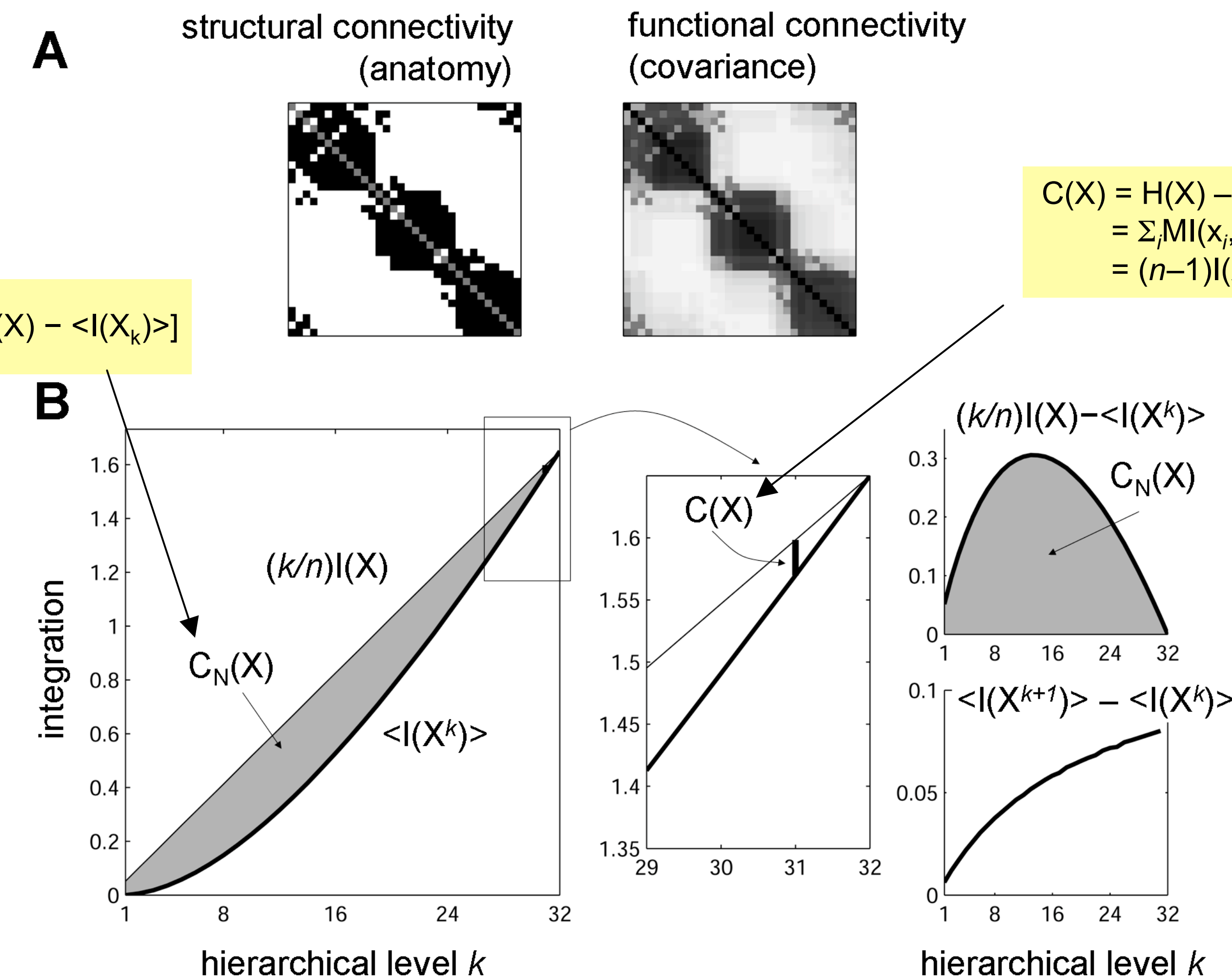
The complexity of X is the sum of the mutual information across <u>all</u> bipartitions within X (**total information transmission or integration of information within the system**).

Tononi, Sporns, Edelman, PNAS (1994)
Sporns, Tononi, Edelman, Cerebr Cortex (2000)

Information and Complexity

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

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



Sporns and Tononi (2006)

Complexity and Connectivity

Complexity captures the interplay between segregation and integration within a network, expressed in a pattern of mutual information or entropy.

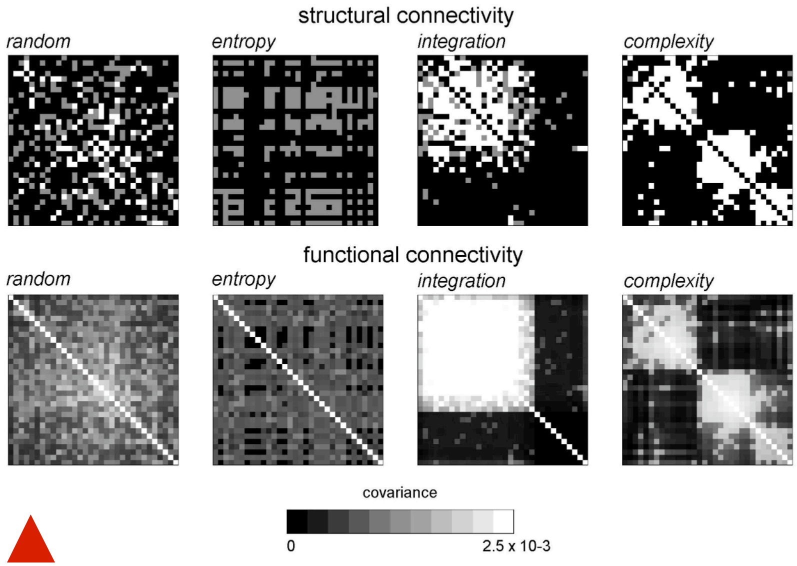
Patterns of mutual information in networks depend on structural connections.

Which patterns of structural connections give rise to high (low) complexity?

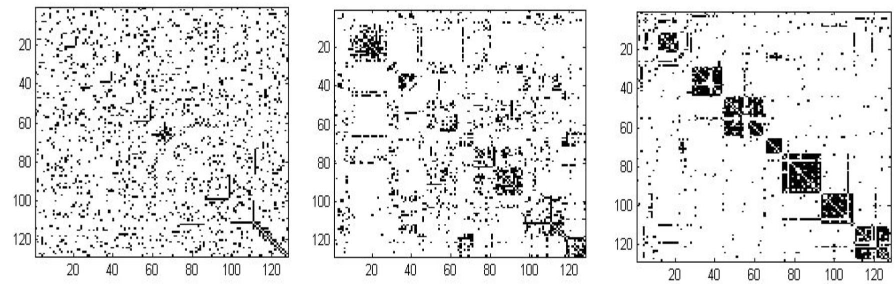
Multiple approaches:

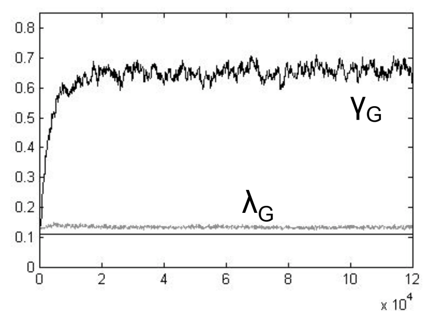
1) Optimization of networks using informational cost functions
2) Learning and rewiring rules
3) Examination of neural connectivity data sets
4) Evolution in a computational ecology (main topic of this talk)

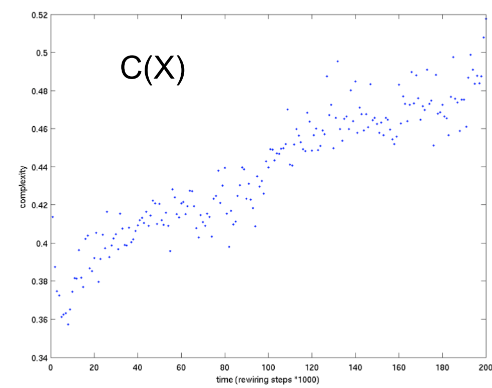
Complexity and Connectivity



Optimization of information-theoretical measures (Sporns and Tononi, *Complexity* 2002)



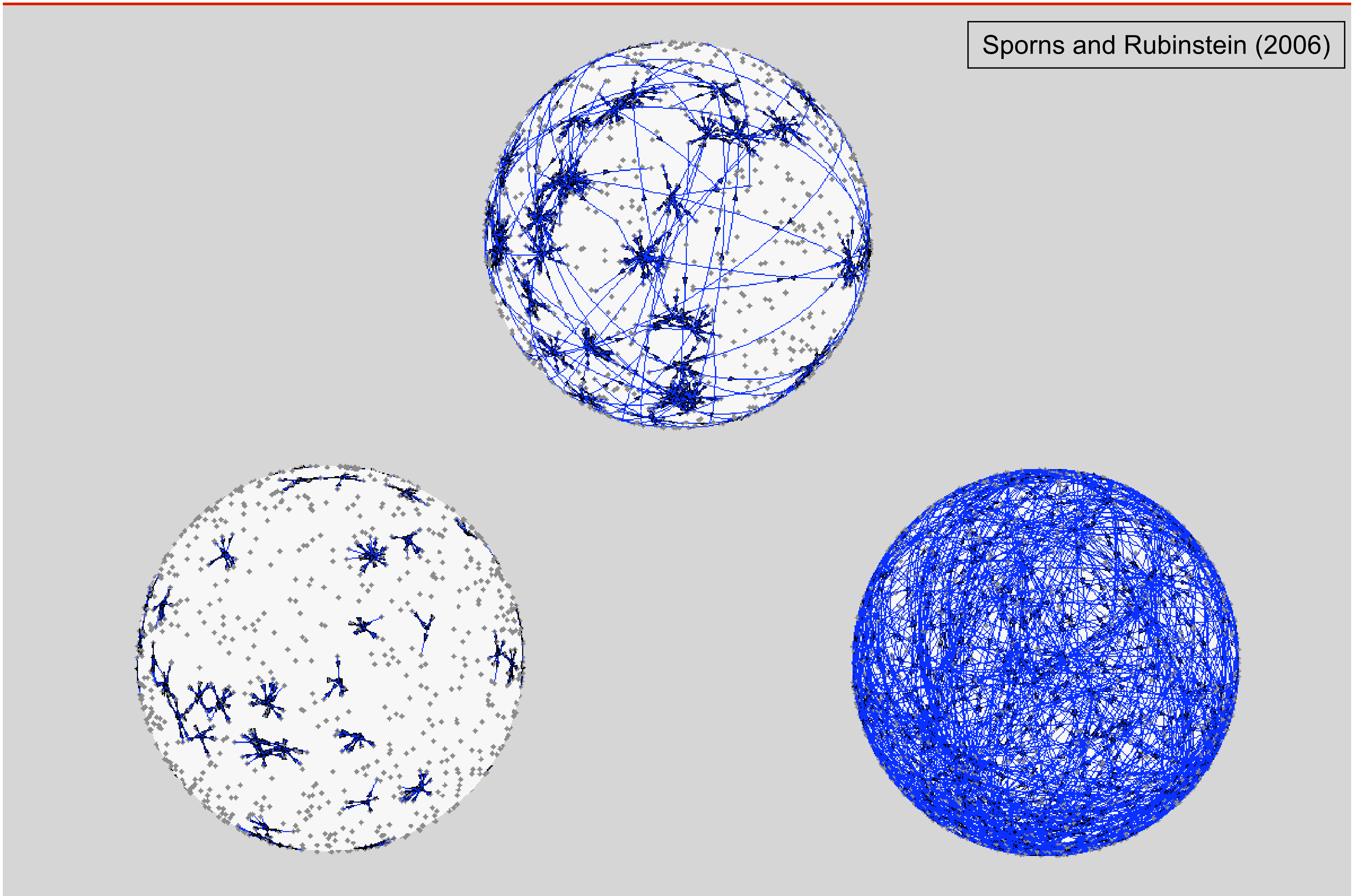




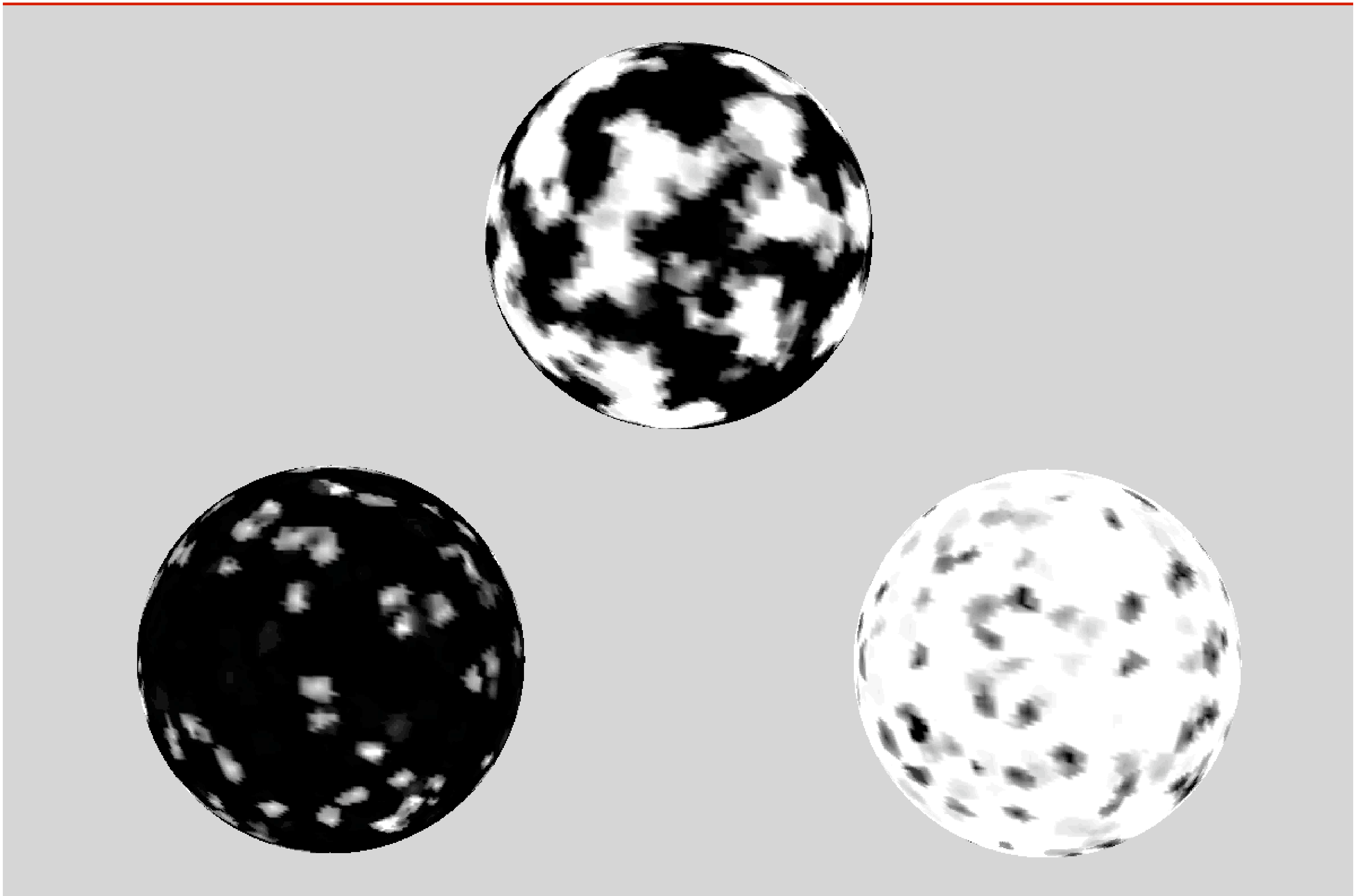
Emergence of small-world attributes and high complexity in a nonlinear neural network, using a synchrony-based rewiring rule (Breakspear, Sporns et al., *Network* 2006)

Large-scale connection matrices of the mammalian cerebral cortex generate dynamics with high complexity.
(Sporns et al., *Cerebral Cortex* 2000)
They also incoporate “small-world” attributes.
(Sporns and Zwi, *Neuroinformatics* 2004)

Complexity and Connectivity



Complexity and Connectivity



Polyworld Overview

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

Genetics: Neurophysiology Genes

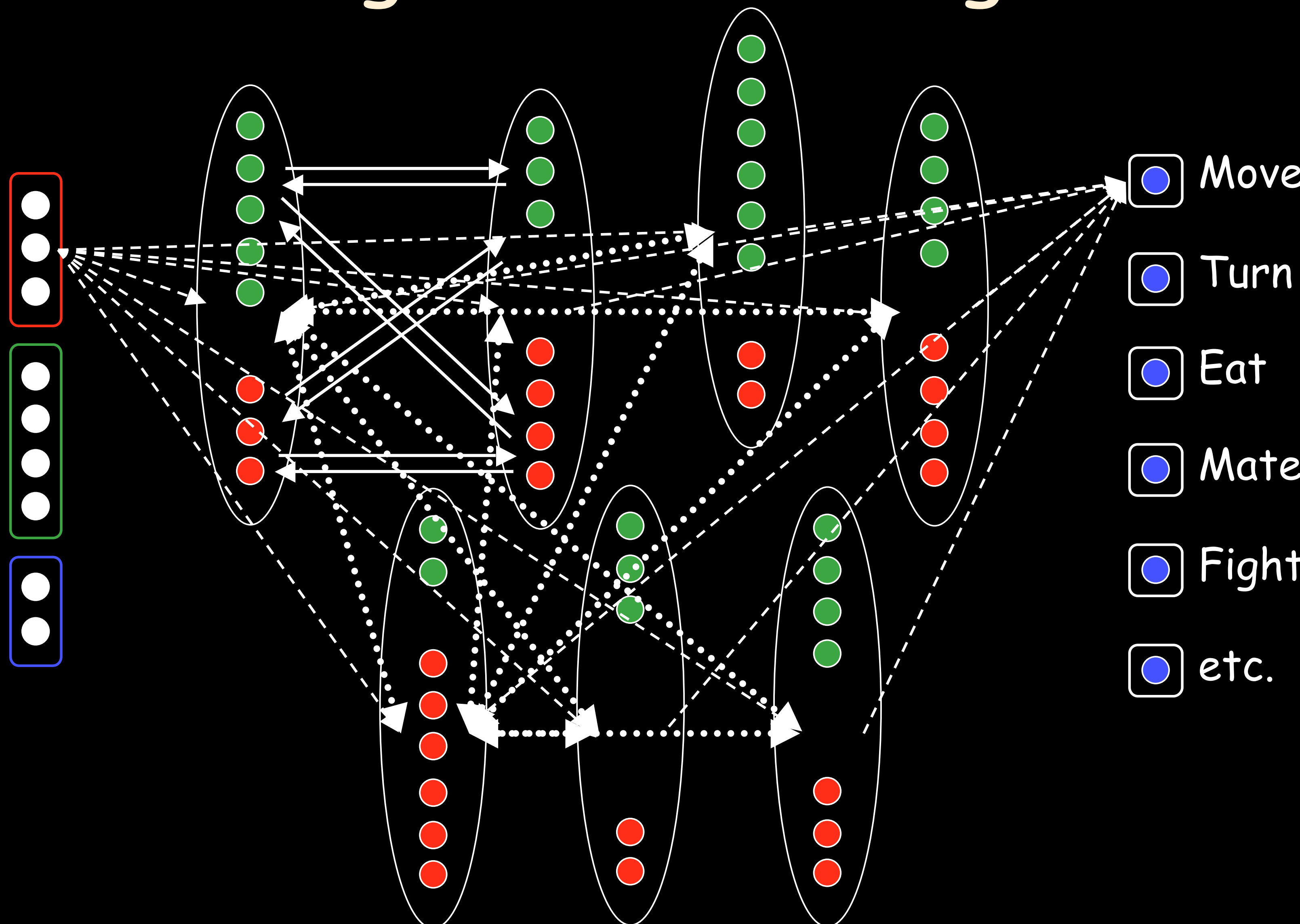
- # of neurons for red component of vision
- # of neurons for green component of vision
- # of neurons for blue component of vision

- # 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



Perception: Neural System Inputs

- Vision
- Internal energy store
- Random noise

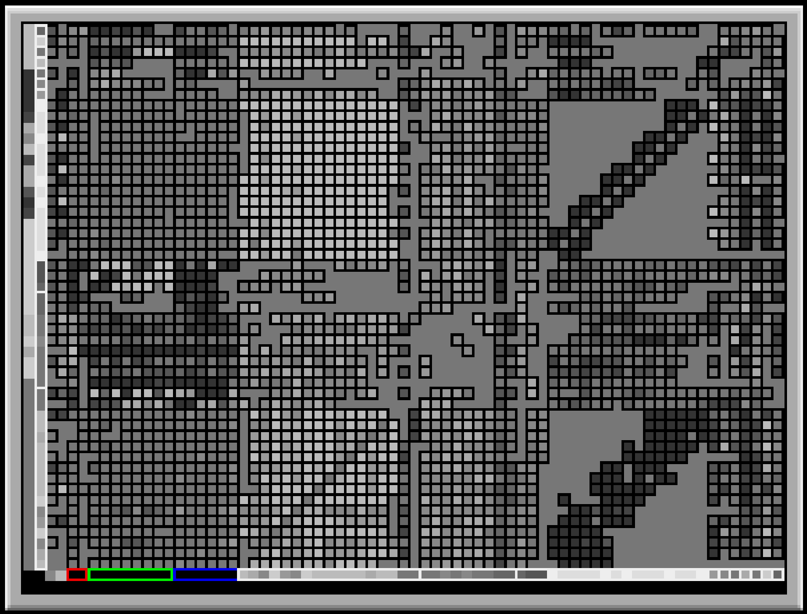
Behavior: Neural System Outputs

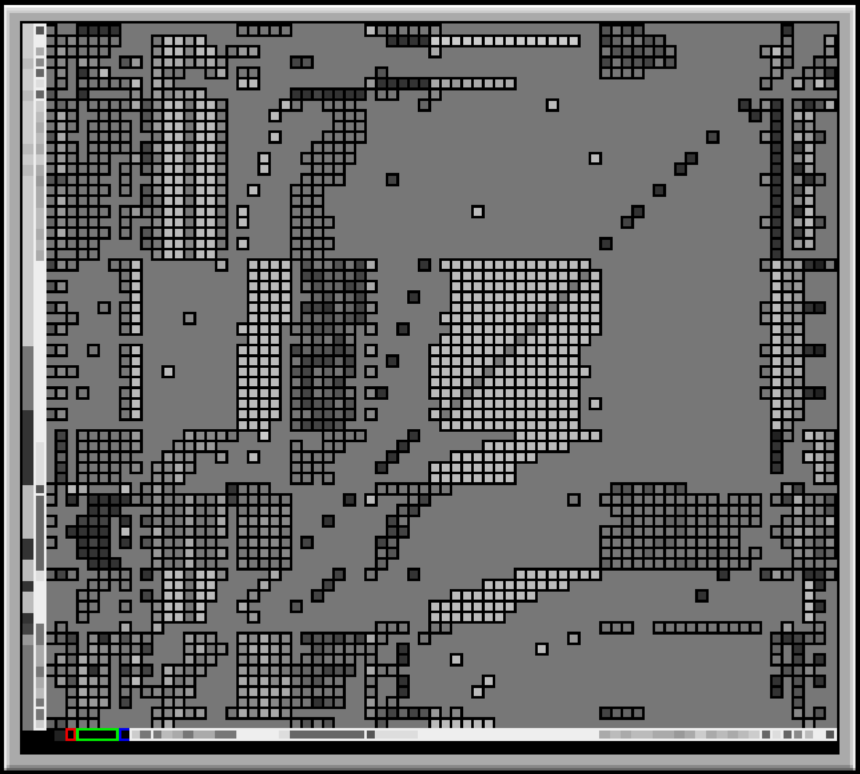
- Primitive behaviors controlled by single neuron
  - "Volition" is level of activation of relevant neuron
- Move
- Turn
- Eat
- Mate (mapped to body's blue color component)
- Fight (mapped to body's red color component)
- Light
- Focus

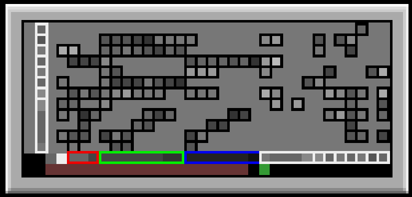
Neural System: Internal Units

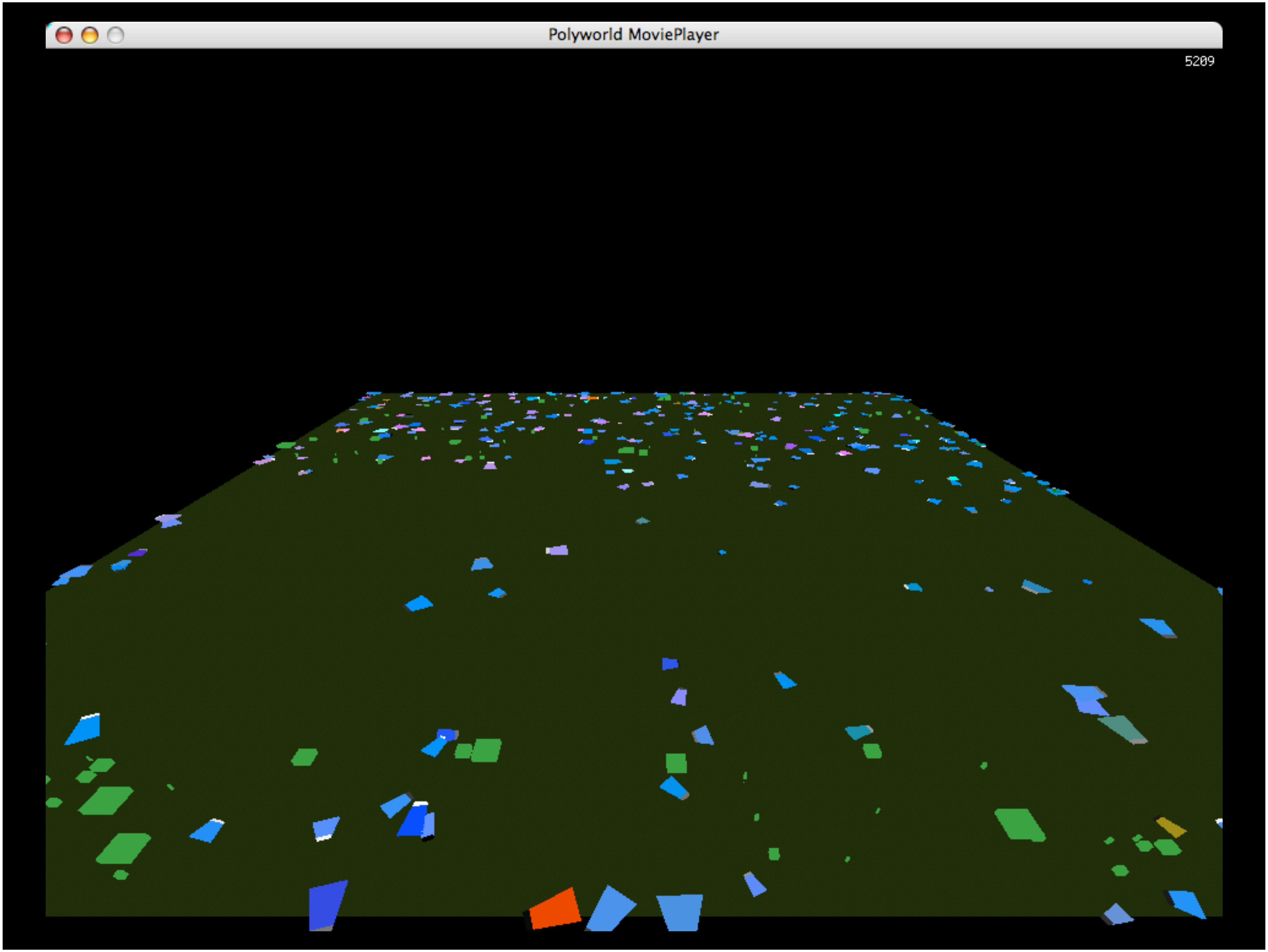
- No prescribed function
  - Neurons
  - Synaptic connections

Evolving Neural Architectures








Polyworld MoviePlayer
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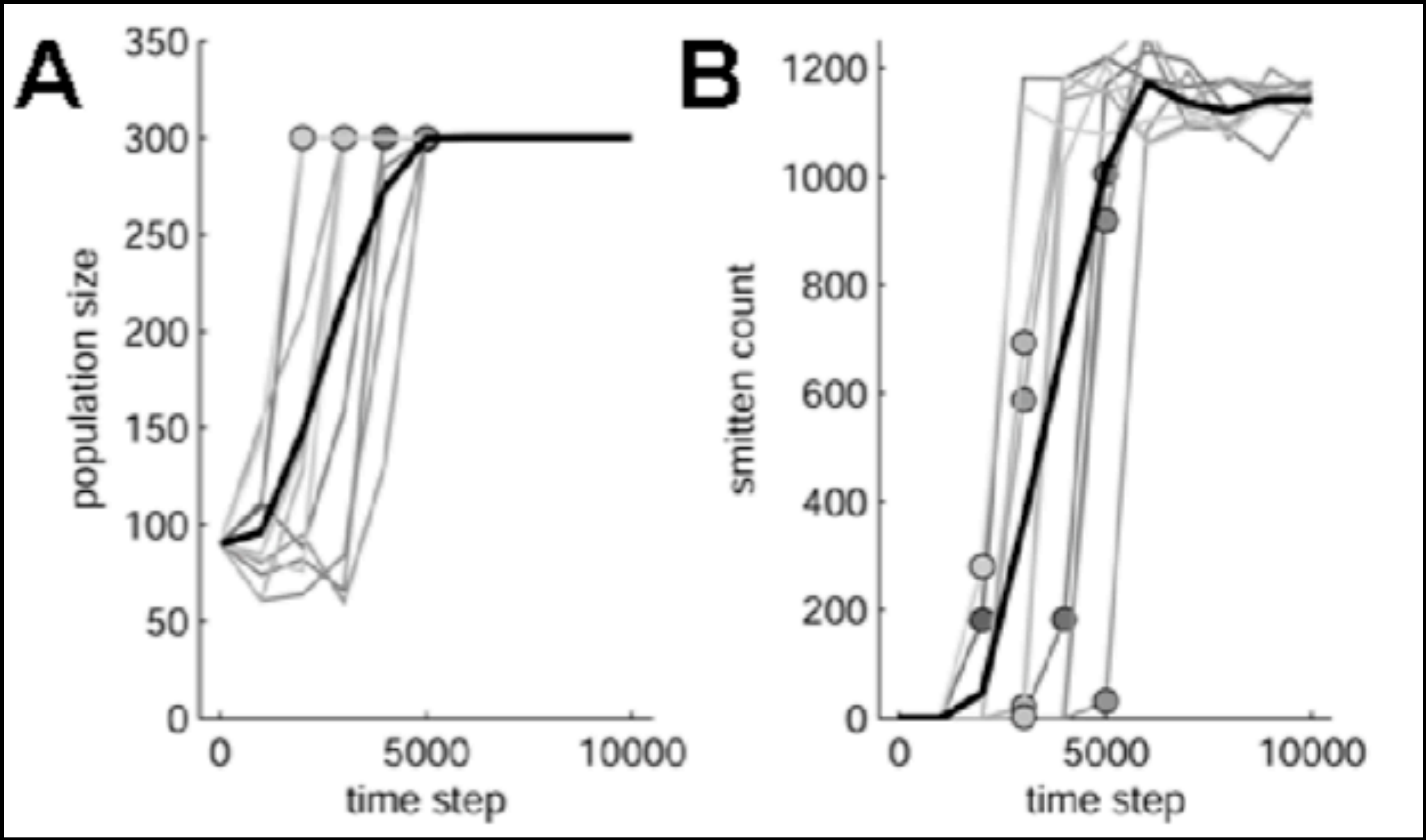
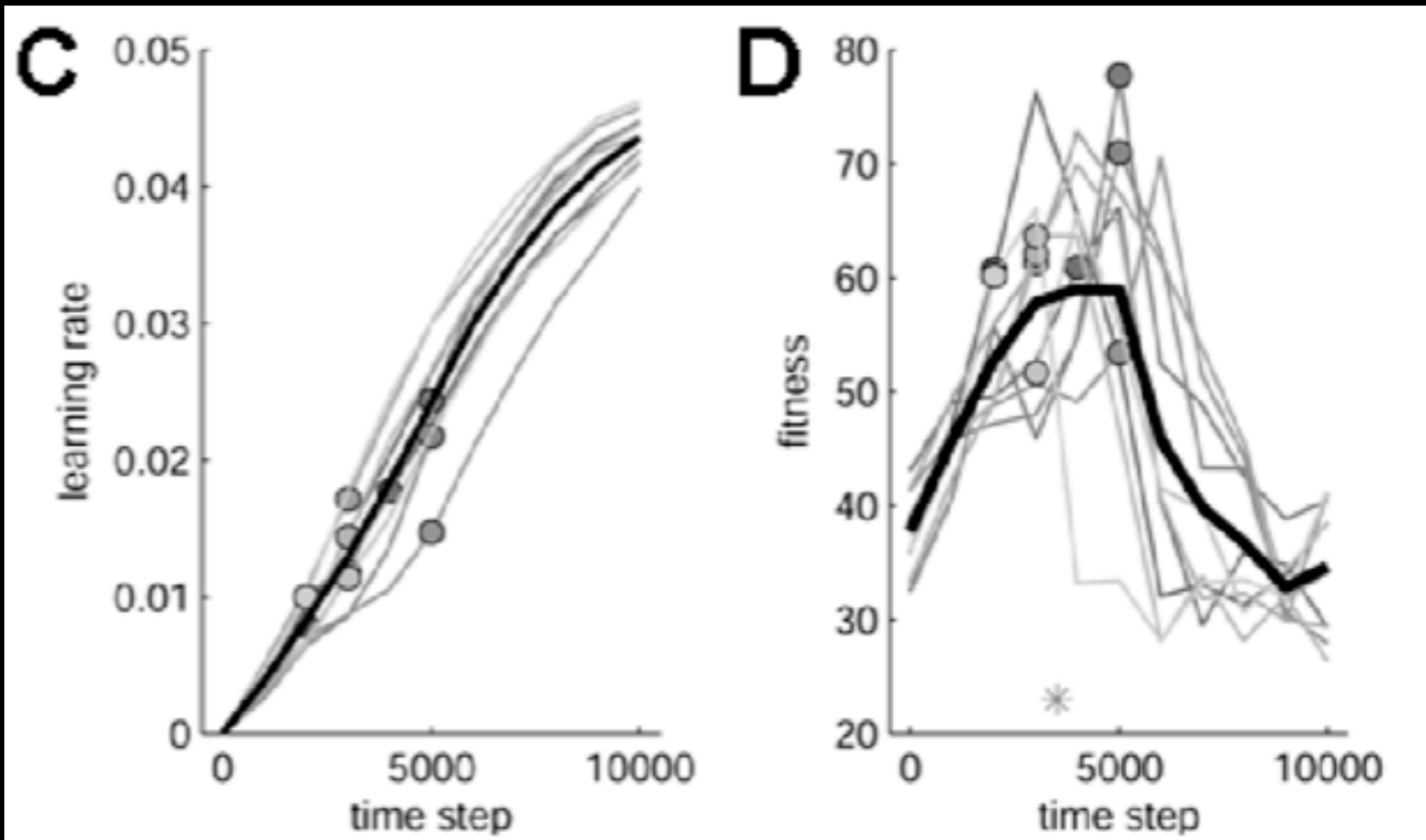
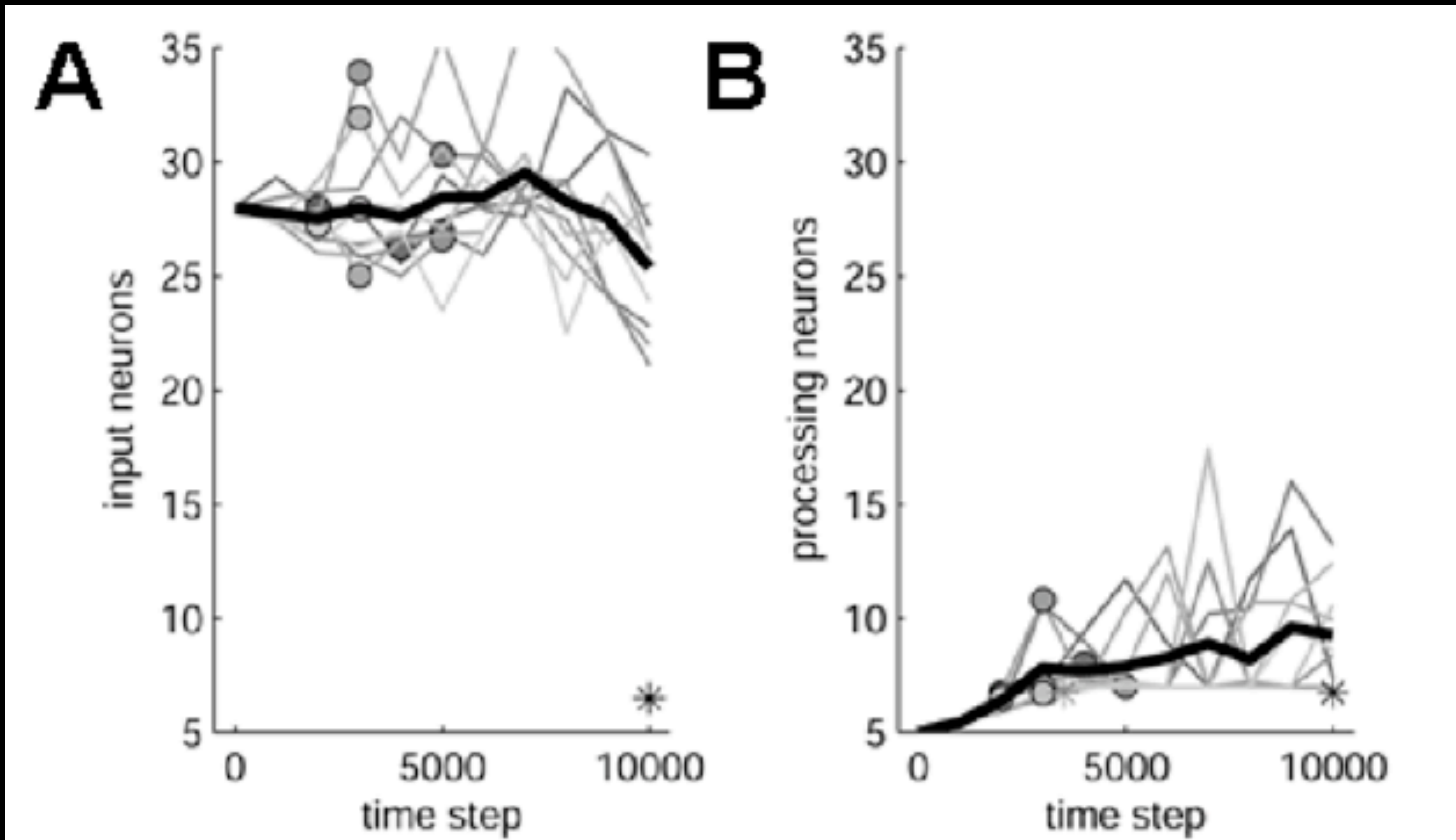
Simulation Metrics: Population & Smite Count



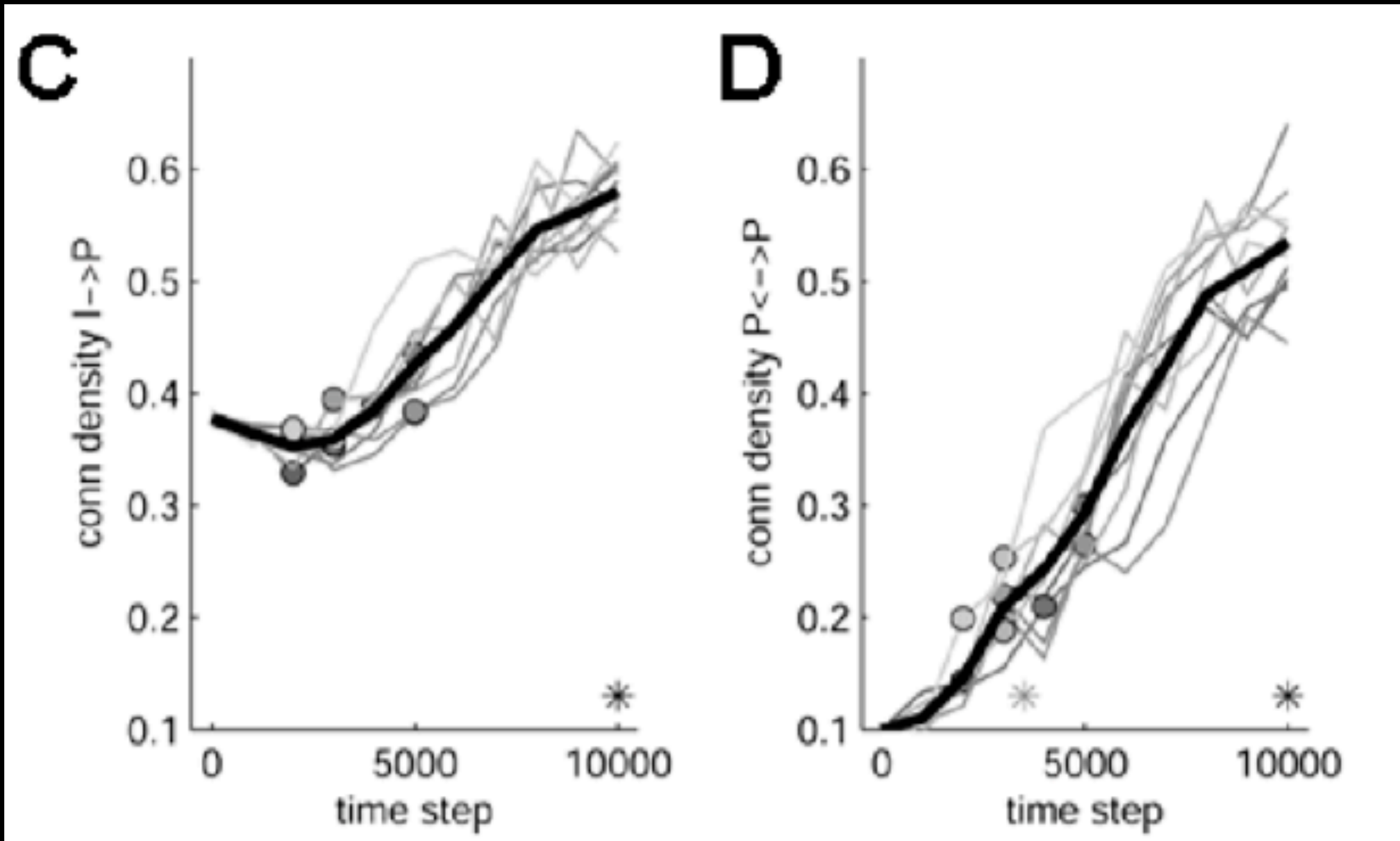
Simulation Metrics: Learning Rate & Fitness



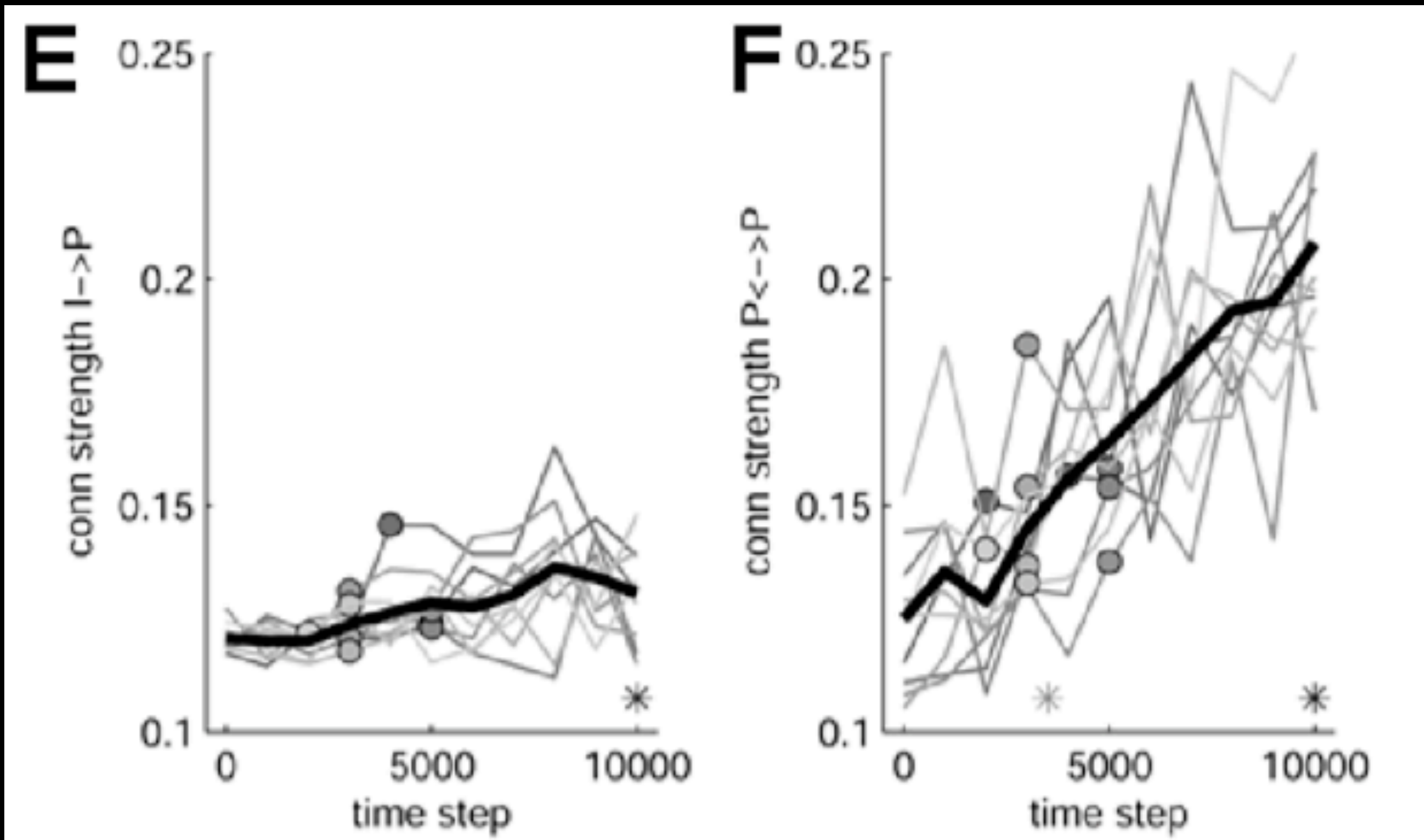
Network Metrics: Neuron Counts



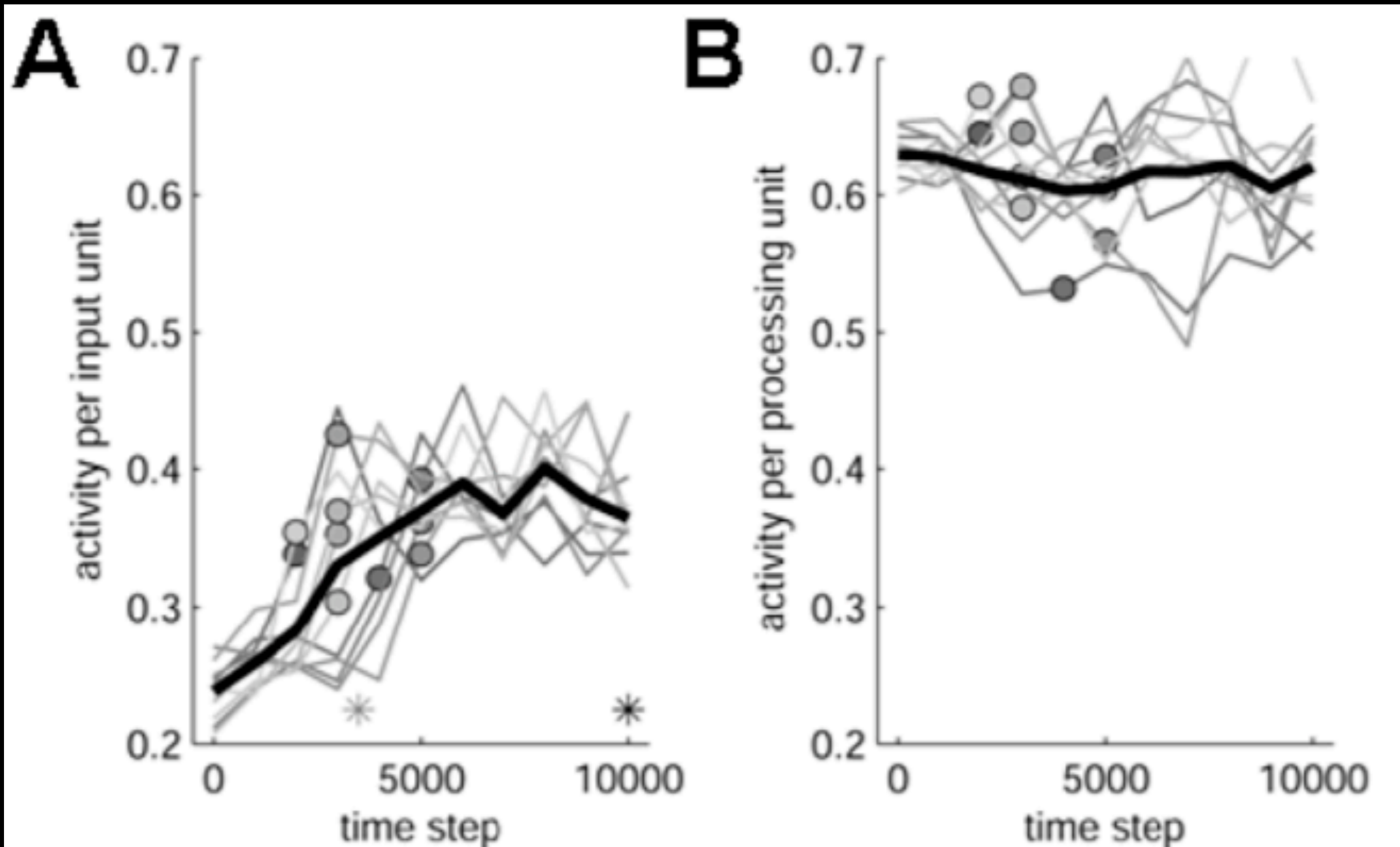
Network Metrics: Connection Densities



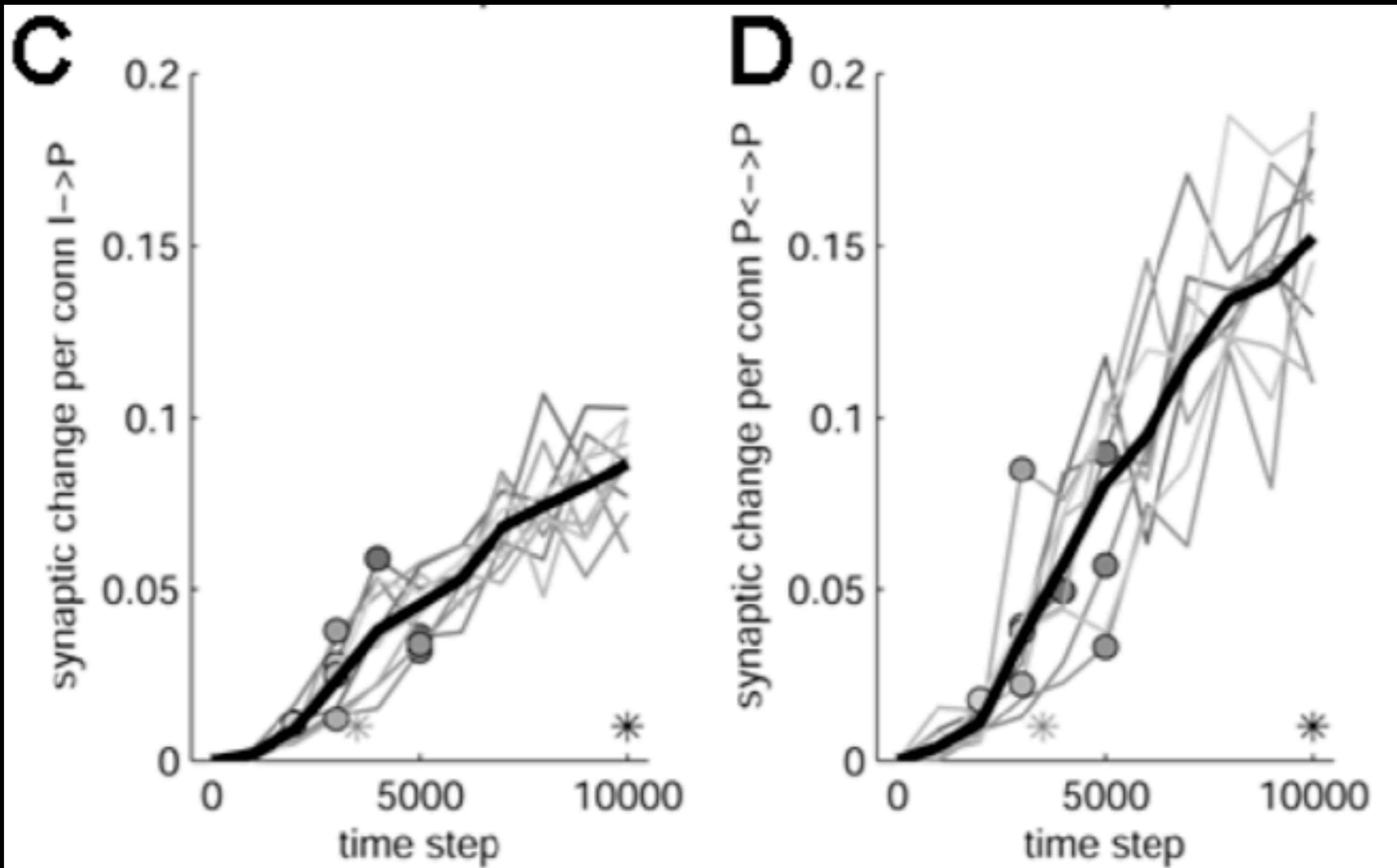
Network Metrics: Connection Strengths



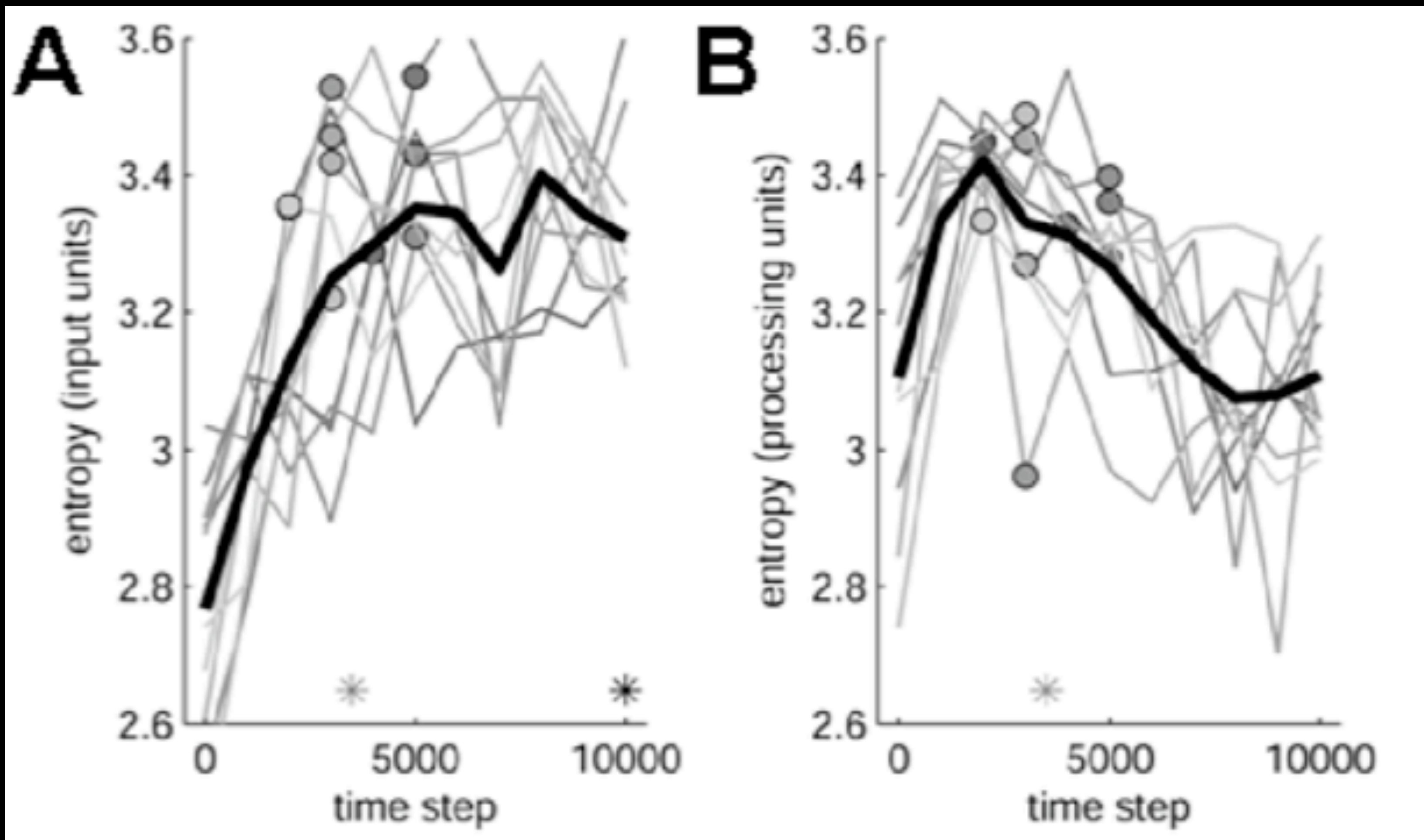
Network Metrics: Neural Activations



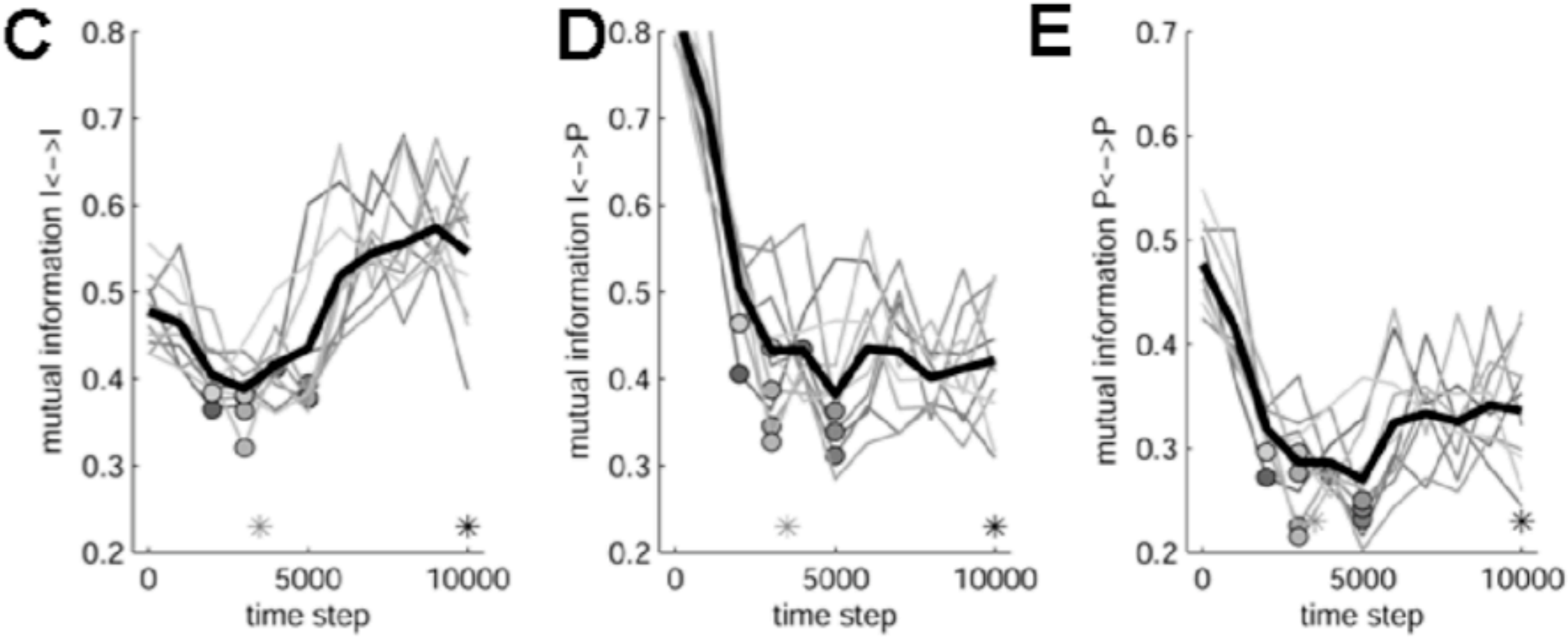
Network Metrics: Synaptic Efficacy Change



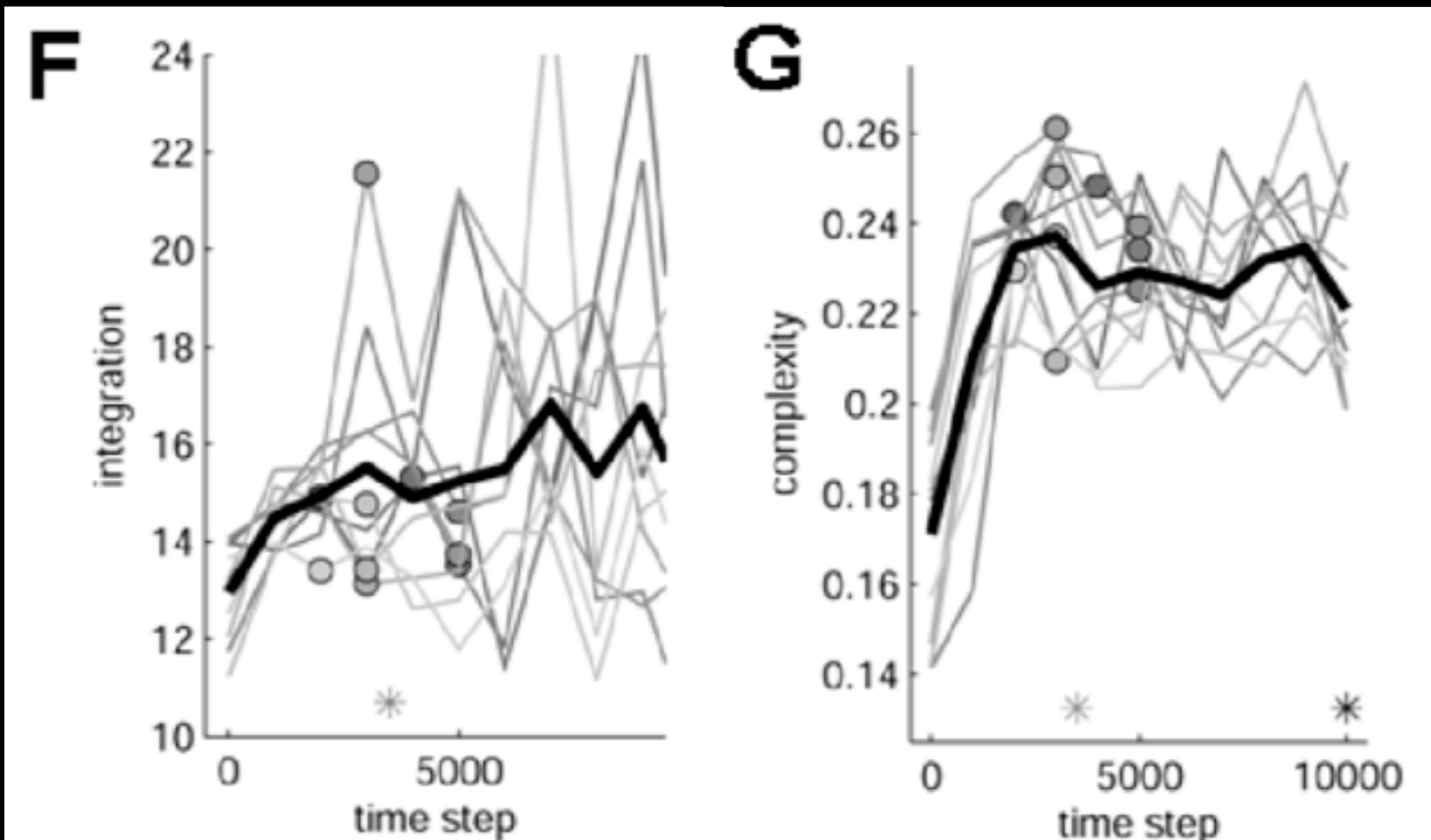
Information Metrics: Entropy



Information Metrics: Mutual Information



Information Metrics: Integration & Complexity



Conclusions & Discussion

- Demonstrated an evolved, statistically significant increase in structural elaboration and neural complexity
  - Based on increases in connection density, connection strength, and a balance of excitatory and inhibitory connections
  - Consistent with observed trends in Mutual Information and global Integration
- We speculate that this represents an active trend towards greater complexity within a single niche, and that a greater diversity of niches may lead to additional increases in global complexity
- Additional “complications” of the simulation environment should produce increases in Complexity
- Demonstrated strong trend for increased learning

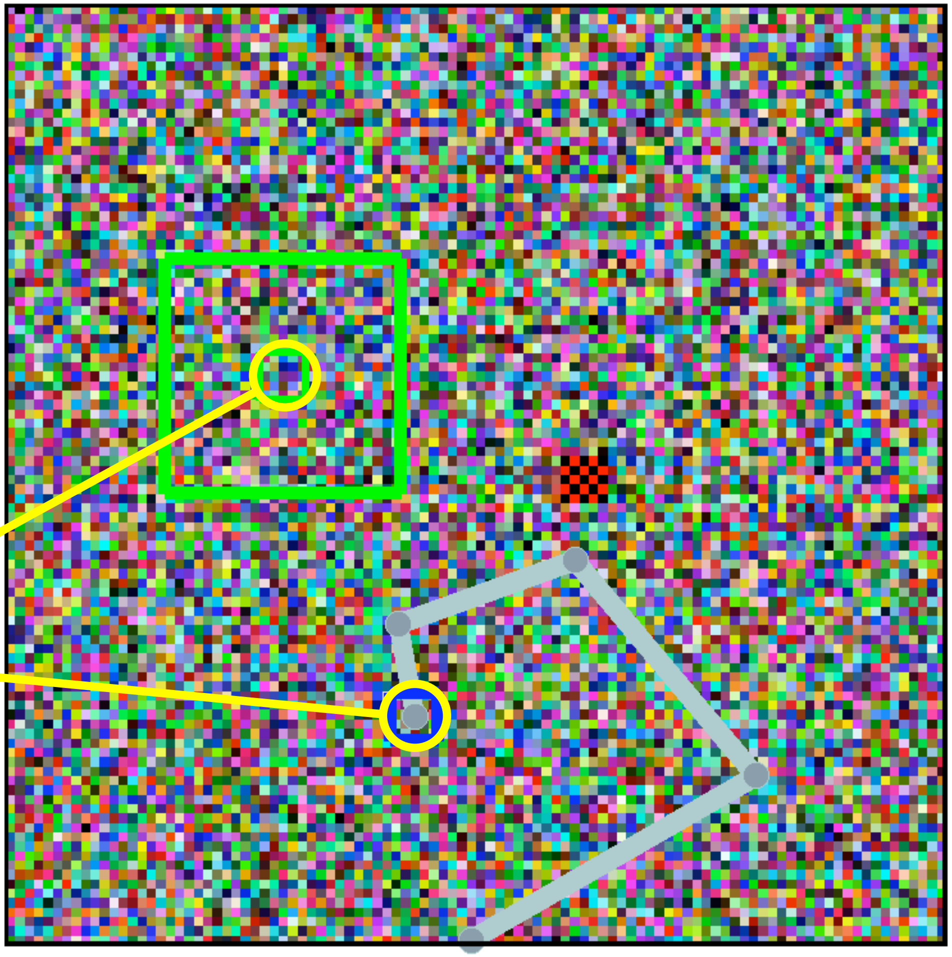
Future Directions

- Move the measurement of Complexity into Polyworld
  - Measure it routinely
  - Quantitatively assess changes to the system
- Use Complexity as a fitness function
  - Study the course of evolution in a computational ecology specifically designed to optimize for neural complexity
  - Sporns and Lungarella (2006) have demonstrated Complexity can work as effectively as a fitness function tailored to a behavioral task in a simulated robotic environment

Evolving (for) Complexity

Can we use complexity as a fitness (cost) function directly? If we evolve simple agents to maximize complexity, what sort of behavior will emerge?

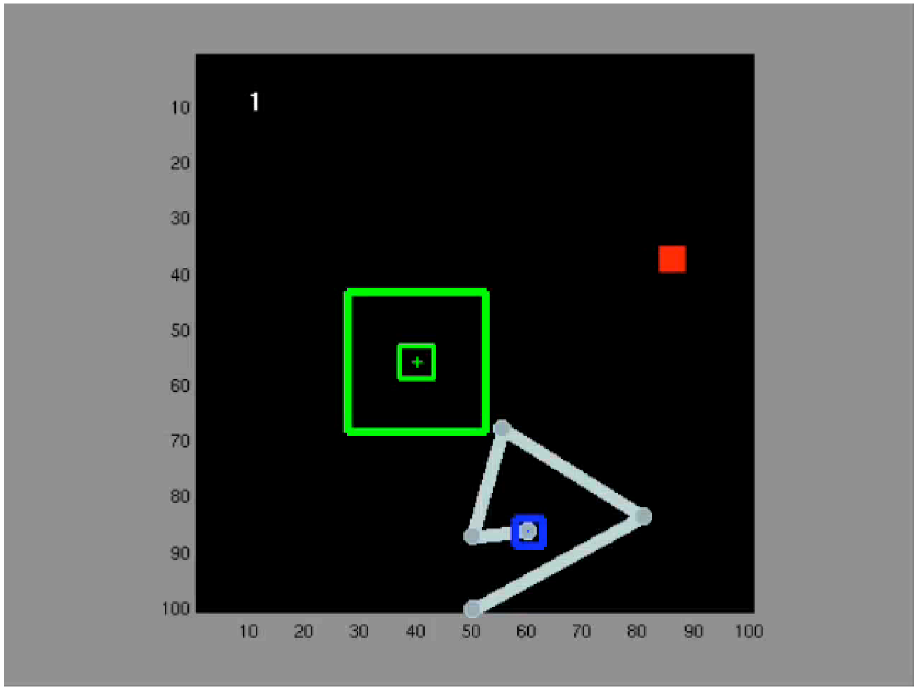
neural signals are sampled here – then we evolve and select for complexity and other cost functions



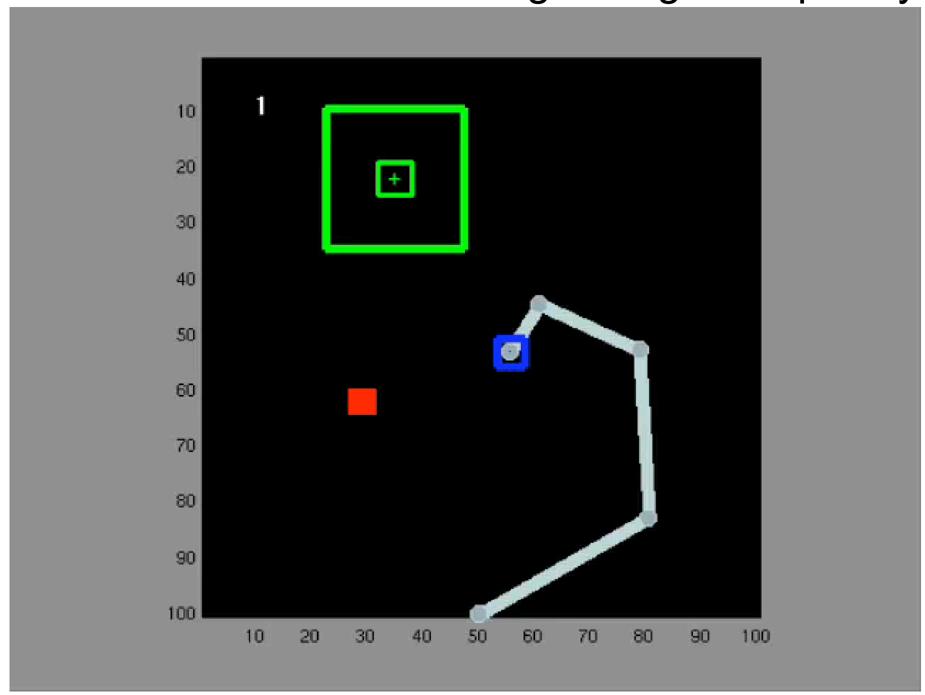
Sporns, Lungarella, ALifeX (2006)

Evolving (for) Complexity

“random” behavior



behavior after evolving for high complexity



Maximizing information structure is highly effective in producing coordinated behavior in a simple sensorimotor creature, similar to that obtained with behavioral cost functions that directly evaluate behavioral success or error.

Different information measures produce subtle differences in behavior.

Sporns, Lungarella, ALifeX (2006)

Evolution of Neural Complexity

Polyworld source code for Mac/Windows/Linux (on Qt):
http://sourceforge.net/projects/polyworld/

Polyworld technical papers:
http://www.beanblossom.in.us/larryy/Polyworld.html

Complexity paper and MATLAB toolbox:
http://www.indiana.edu/~cortex/intinf_toolbox.html

References

- Adami, C., Ofria, C., and Collier, T. 2000. Evolution of biological complexity. PNAS 97(9):4463-4468.
- Adami, C. 2002. What is complexity? BioEssays 24:1085-1094.
- Arthur, B. 1994. On the evolution of complexity, in Cowan, G. A. et al eds. Complexity: Metaphors, Models, and Reality. Addison-Wesley, Reading, MA 65-81
- Bedau, M.A., Snyder, E., Brown, C.T., and Packard, N.H. 1997. A Comparison of Evolutionary Activity in Artificial Evolving Systems and in the Biosphere, in Proceedings of the Fourth European Conference on Artificial Life, 125-135. Cambridge, MA, MIT Press.
- Bonner, J.T. 1988. The Evolution of Complexity by Means of Natural Selection. Princeton, NJ, Princeton Univ. Press.
- Carroll, S.B. 2001. Chance and necessity: the evolution of morphological complexity and diversity. Nature 409:1102-1109.
- Crutchfield, J.P. and Young, K. 1990. Computation at the onset of chaos, in Complexity, Entropy, and Physics of Information, ed. Zurek, W. Reading, MA, Addison-Wesley.
- Gould S.J. 1994. The Evolution of Life on Earth. Scientific American 271(4): 62-69.
- Huynen, M. A. 1995. Exploring Phenotype Space through Neutral Evolution, Technical Report Preprint, Santa Fe Institute.
- Huynen, M. A. 1996, Exploring phenotype space through neutral evolution, Journal of Molecular Evolution 43(3) 165-169.

References

- Katz, M. J. 1987. Is evolution random? In R. A. Raff and E. C. Raff eds. Development as an Evolutionary Process, Alan R. Liss, New York, 285-315.
- Kimura, M. 1983. The Neutral Theory of Molecular Evolution. Cambridge University Press.
- McShea, D.W. 1996. Metazoan complexity and evolution: is there a trend? Evolution 50:477–492.
- Newman M.E.J., Engelhardt Robin. 1998. Effects of neutral selection on the evolution of molecular species. In Proc. R. Soc. London B, 1333-1338.
- Rensch, B. 1960a. Evolution above the species level. Columbia Univ. Press, New York.
- Rensch, B. 1960b. The laws of evolution, in Tax, S. ed. The Evolution of Life. Univ. of Chicago Press, Chicago. 95-116.
- Saunders, P. T. and Ho, M. W. 1976. On the increase in complexity in evolution. J. Theor. Biol. 63:375-384.
- Turney, P. 1999. Increasing Evolvability Considered as a Large-Scale Trend in Evolution, in Wu, Annie, eds. Proceedings Workshop on Evolvability at the 1999 Genetic and Evolutionary Computation Conference (GECCO-99), Orlando, Florida, 43-46.
- Waddington, C. H. 1969. Paradigm for an evolutionary process, in Waddington, C. H. ed. Towards a Theoretical Biology, Vol. 2, Aldine, Chicago, 106-128.