Guiding the Self-organization of Random Boolean Networks

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Contenido

Self-organization

- Pervasive concept, many definitions. Depends partly on observer.
- A notion: *A system described as self-organizing (SO) is one in which elements interact, achieving dynamically a global function or behavior* [Gershenson, 2007, p. 32].
- i.e. a *global* pattern is produced from *local* interactions.


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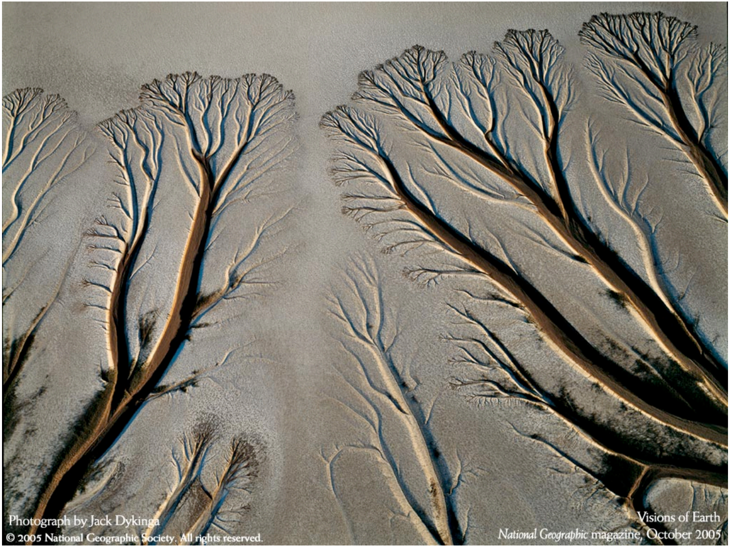
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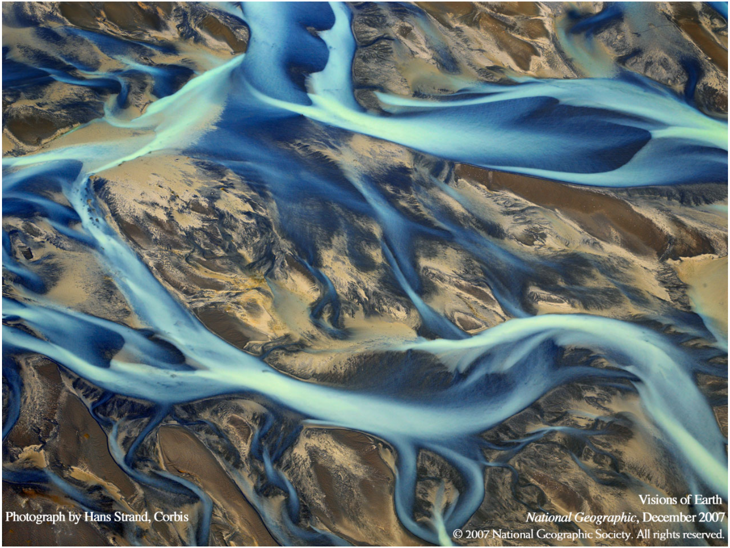
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Examples

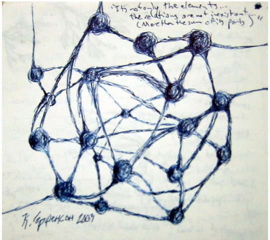
- a cell (molecules interact to produce life)
- a brain (neurons interact to produce cognition)
- a colony (insects interact to perform collective tasks)
- flocks, schools, herds (animals interact to coordinate collective behavior)
- a market (agents interact to define prices)
- traffic (vehicles interact to determine flow patterns)
- an ecosystem (species interact to achieve ecological homeostasis)
- a society (members interact to define social properties e.g. language, culture, fashion, esthetics, ethics, politics).

So... SO

- Almost any system *can* be described as SO [Ashby, 1962].
- When is it *useful*? [Gershenson and Heylighen, 2003]
  - Properties at more than one scale.
  - Undefined or non-stationary spaces.
  - Interested in adaptation and robustness.
- Guided self-organization (GSO) [Prokopenko, 2009]: balance between design and self-organization.
- My GSO notion: *The steering of the self-organizing dynamics of a system towards a desired configuration*.
- GSO for understanding how natural systems achieve SO and for building artificial systems capable of SO.
- This talk: How can evolution guide the SO of genetic regulatory networks? How can we guide RBN self-organization towards a desired regime?

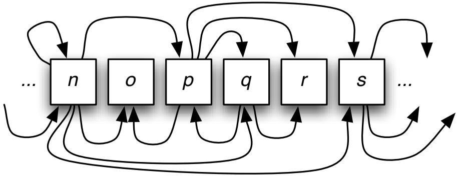
Random Boolean Networks (RBNs)

- RBNs originally models of genetic regulatory networks (GRNs) [Kauffman, 1969, Kauffman, 1993].
- Random connectivity and functionality + ensemble approach.
  - Useful when specific topology and functions cannot be defined.
- Possibility to explore possibilities of living and computational systems.
- Very general computational models.
  - Generalizations of Boolean CA.



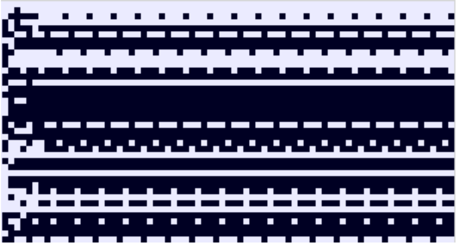
Classic RBNs (several different flavors)

- N Boolean nodes linked by K connections each.
- The state of a node at time $t+1$ depends on the states of its K inputs at time t by means of a Boolean function.
- Connections and functions are chosen randomly when the RBN is generated and remain fixed during its temporal evolution.



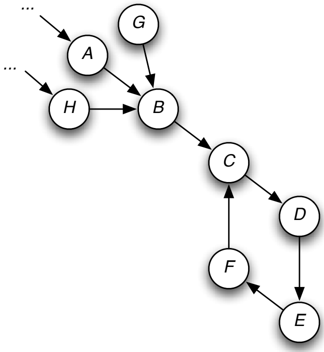
E.g.

n(t)	p(t)	o(t+1)
0	0	1
0	1	0
1	0	0
1	1	1



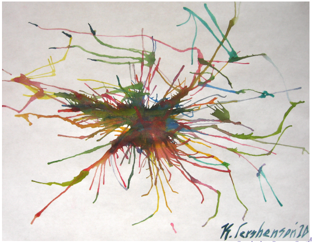
Dynamics on state space

- Attractors, basins.
- Dissipative systems, deterministic.
    - Only one successor, several or no predecessors.
- What is relationship between topological and state networks?



RBNs as self-organizing systems

- Dynamics "self-organize" towards attractors.
- Useful description to understand how the interactions between nodes (lower scale) affect the network dynamics and properties (higher scale).
- Complexity reduction.
  - $\sim 30,000$ genes in humans, only ~ 300 cell types (attractors).
- In which ways can the self-organization of random Boolean networks be guided?



Dynamical regimes I

- Ordered, chaotic, and critical (near phase transition).
- *Ordered*: most nodes are static. Robust. Convergence of similar states.

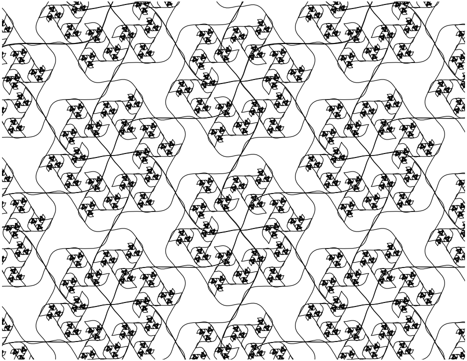
- *Chaotic*: most nodes are changing. Fragile. Divergence of similar states.

Dynamical regimes II

- *Critical*: balance: some nodes static, some changing. Changes spread locally. Maximization of information storage, coherent information transfer [Lizier et al., 2008], and Fisher information [Wang et al., 2010].

- Computation and life @ "edge of chaos" [Langton, 1990, Kauffman, 1993, Crutchfield, 1994, Kauffman, 2000].
  - Evidence from four kingdoms [Balleza et al., 2008].
  - Balance between robustness, information storage and variability, computation, exploration.
- How can SO of RBNs be guided towards criticality?

The criticality of RBNs can depend on many different factors. These factors can be exploited—by engineers or by natural selection—to guide the self-organization of RBNs and related systems towards the critical regime.



p, K

GSO-RBN

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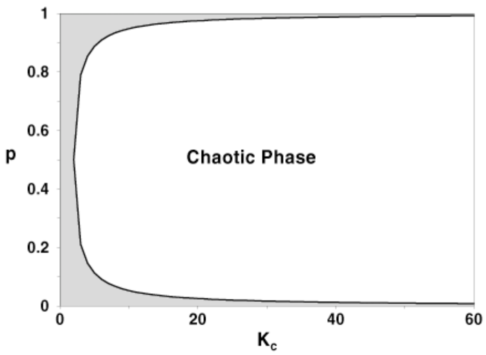
Probability p of having ones on the last column of lookup tables [Derrida and Pomeau, 1986]

$$\langle K \rangle = \frac{1}{2p(1-p)}$$



[Aldana, 2003], © Elsevier

Canalizing functions

- A canalizing function [Kauffman, 1969, Stauffer, 1987, Szejka and Drossel, 2007] is one in which at least one of the inputs has one value that is able to determine the value of the output of the function, regardless of the other inputs [Shmulevich and Kauffman, 2004].
- Non-canalizing inputs of canalizing functions are not relevant, i.e. ficticious. Altering them does not affect state space or dynamics of RBN.
- More canalization $\Rightarrow$ higher K_c.

x(t)	y(t)	z(t+1)=NOT x
0	0	1
0	1	1
1	0	0
1	1	0

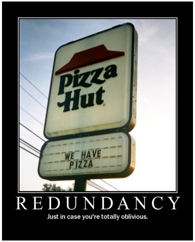
Topology

- Most RBN studies use homogeneous or normal topologies (uniform rank distributions): more and longer attractors, less correlation in expression patterns.
- Skewed topologies: less and shorter attractors, more correlations (entropy and mutual information) [Oosawa and Savageau, 2002].
- Balance achieved with scale-free topologies.
- RBNs with a scale-free topology expand the advantages of the critical regime into the ordered phase [Aldana, 2003]
  - Well-connected elements can lead to the propagation of changes
  - i.e. adaptability even when the average connectivity would imply a static regime.
  - Scale-free topology "expands the range of the critical regime".

Modularity

- Prevalent property in natural systems [Callebaut and Rasskin-Gutman, 2005], desired in artificial ones [Simon, 1996].
- Modules offer a level of organization that promotes at the same time robustness and evolvability [Wagner, 2005b].
  - Damage within one module usually does not propagate through the whole system (robustness).
  - Useful changes can be exploited to find new configurations without affecting the functionality of other modules.
- Modules broaden the range of the critical regime in RBNs [Poblanno-Balp and Gershenson, 2010] towards the chaotic phase, since changes do not propagate as easily between modules.

Redundancy



- Redundancy consists of having more than one copy of an element type.
- Redundancy of nodes prevents mutations from propagating in RBNs [Gershenson et al., 2006]
- Can "smoothen" rough landscapes, increase neutrality, useful for robustness and evolvability.
- Can be combined with modularity.

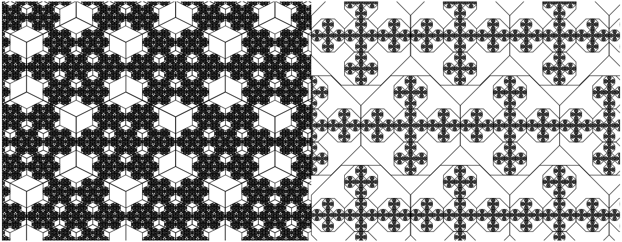
Degeneracy

- Ability of elements that are structurally different to perform the same function [Edelman and Gally, 2001, Fernández and Solé, 2004]; or ability of elements to perform different functions [Whitacre and Bender, 2010].
- Also widespread in biological systems.
- Also promotor of robustness and evolvability, even more than redundancy [Wagner, 2005a, Wagner, 2005b].
- No RBN study yet, but can be speculated that degeneracy should promote critical dynamics.

Discussion

Two categories for GSO towards criticality: ∼functions and ∼topology

- Move the phase transition (p, K, or canalizing functions).
  - If too ordered, move $p \to 0.5$, increase K, and/or decrease canalization (if any).
  - If too chaotic, move $p \to 1$ or 0, decrease K, and/or increase canalization.
- Broaden the critical regime (with a scale-free topology, modularity, redundancy, or degeneracy).
  - Promote one or more.



Why criticality?

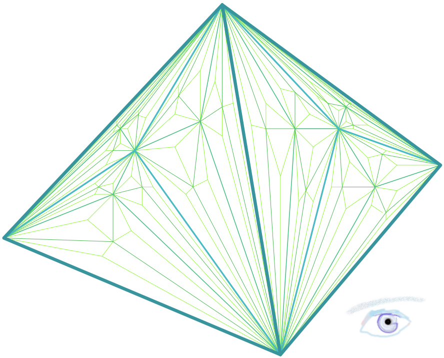
- Balance: adaptability, evolvability, robustness.
- *Adaptability*: ability of a system to produce advantageous changes in response to a state of its environment [Gershenson, 2007].
- Evolvability: ability of random variations to sometimes produce improvement [Wagner and Altenberg, 1996]. Includes scalability. Particular type of adaptability.
- A system is *robust* if it continues to function in the face of perturbations [Wagner, 2005b, Jen, 2005]. Complements adaptability, interrelated.
- Topology and modularity $\rightarrow$ evolvability.
- Redundancy and degeneracy $\rightarrow$ robustness.

Open Questions

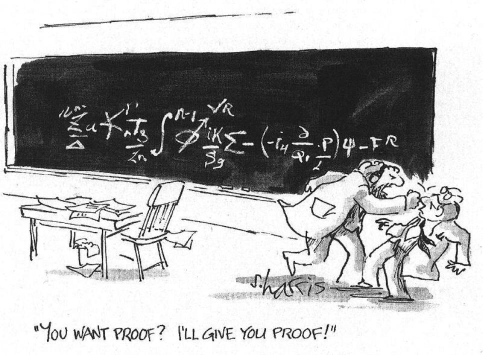
- What drove the evolution of criticality in GRNs? [Balleza et al., 2008]
- Which methods have been exploited by natural selection?
- How are the different methods related?
  - How are scale-free and modular topologies related?
  - Is there an advantage of having both a scale-free topology and modularity over only one of them?
  - When is redundancy or degeneracy preferable?
  - What are the differences and advantages of critical RBNs produced with one or several of the presented methods?
  - How are different methods related to adaptability, evolvability, and robustness?
  - What is the proper balance between evolvability and robustness?

Conclusions

- Methods for GSO in RBNs reviewed.
- Useful for understanding natural and building artificial systems.
  - Can generalize some aspects from RBNs.
- Many open research avenues.



Question time!



More details:
Gershenson, C. (In Press). Guiding the Self-organization of Random Boolean Networks. *Theory in Biosciences*.
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