

The Dynamics of Complex Systems

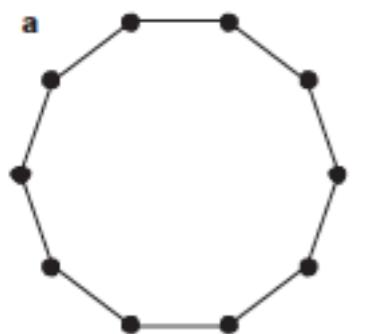
**Graph theory
Complex Networks**

**Networks of (Networks of) Complex Systems:
Extended Criticality and Biological memory**

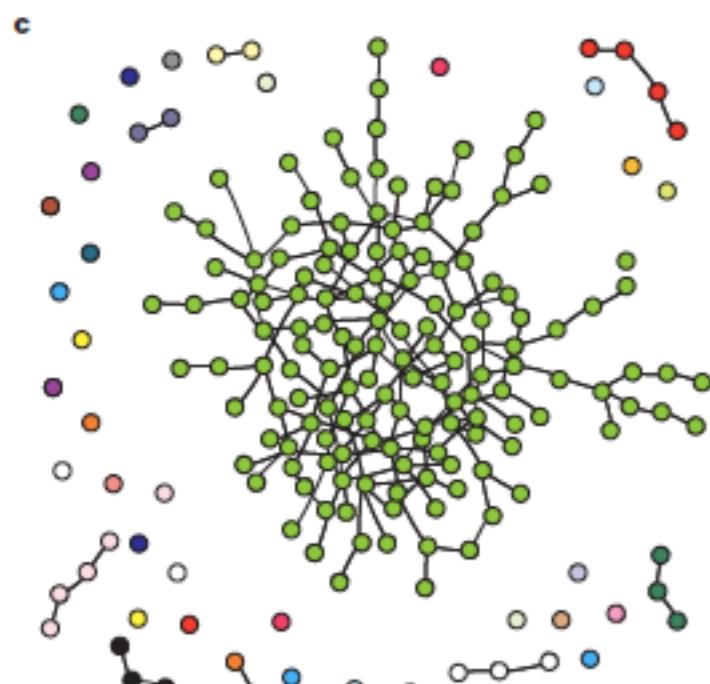
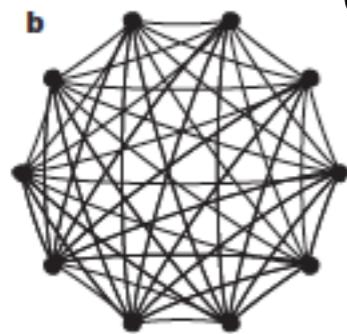


Complex Networks vs. Psychometric Networks

nearest neighbour ring



complete network



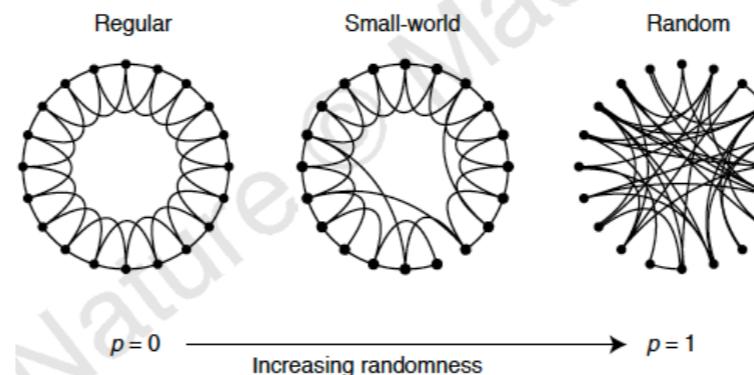
random

Compositions of Vertices and Edges

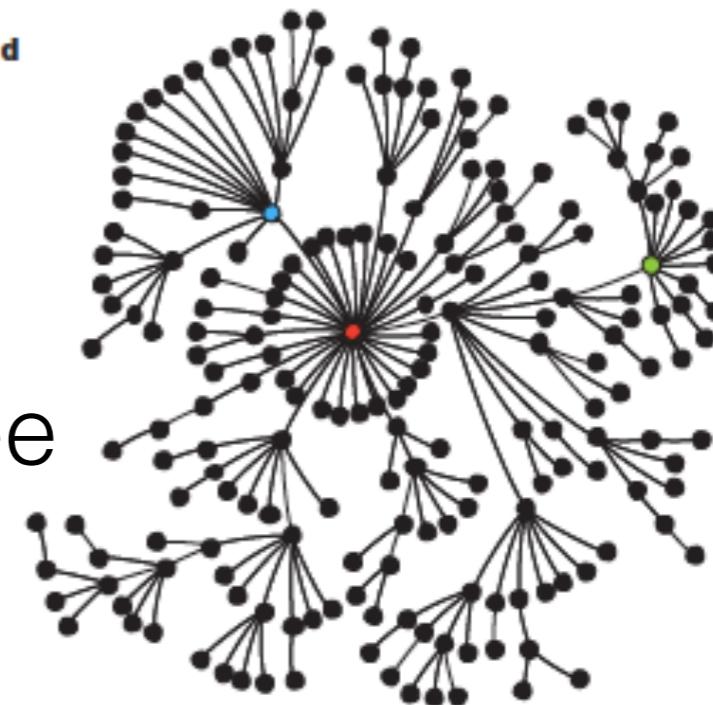
Different topologies have
different properties:
Getting from A to B

scale-free

many more topologies and varieties exist!



small world



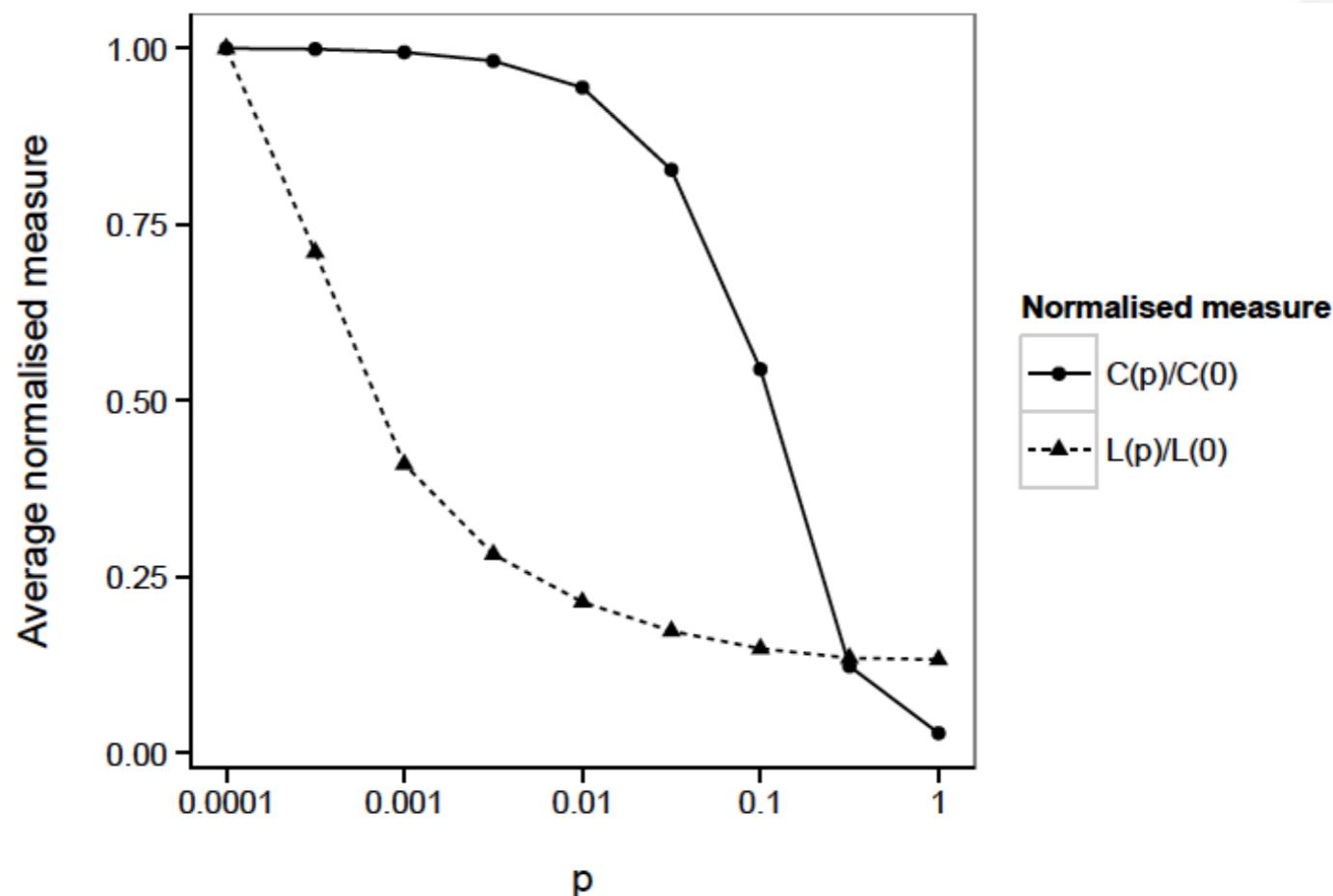
Network / Graph topology: It's a Small World After All

“small-world” test:

Average path length (L)

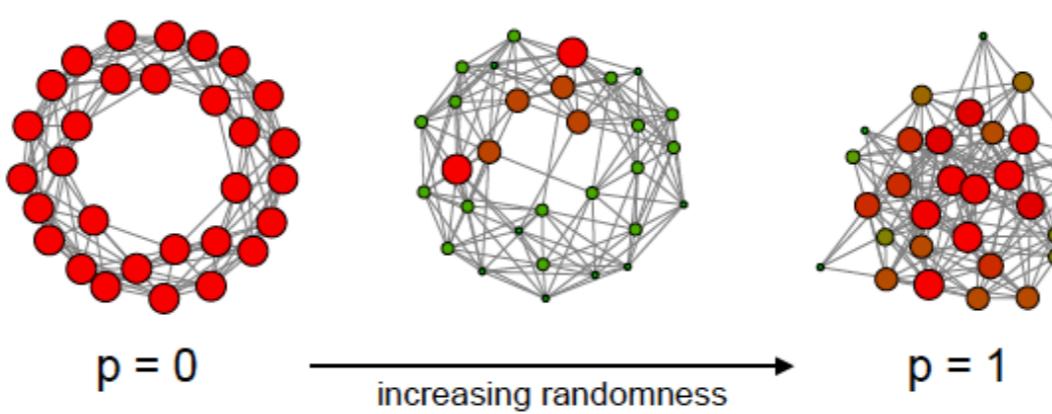
Clustering coefficient (C)

Compare to randomly
rewired version



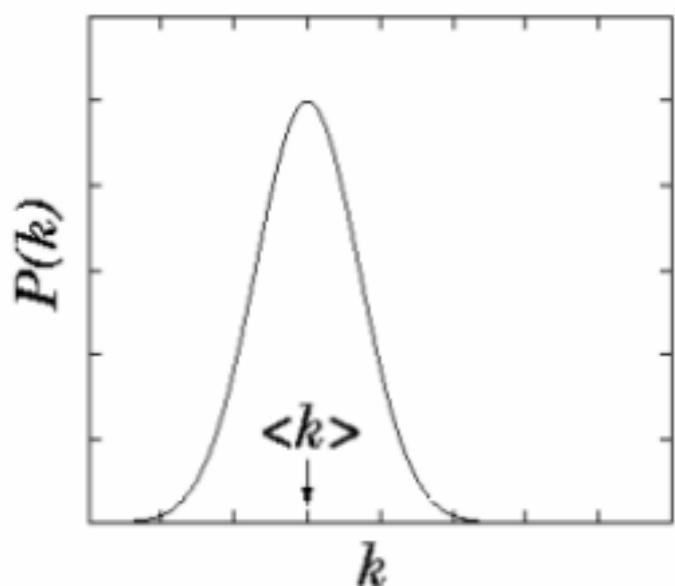
Sound familiar?

In between
fully ordered
&
completely random
=
optimal

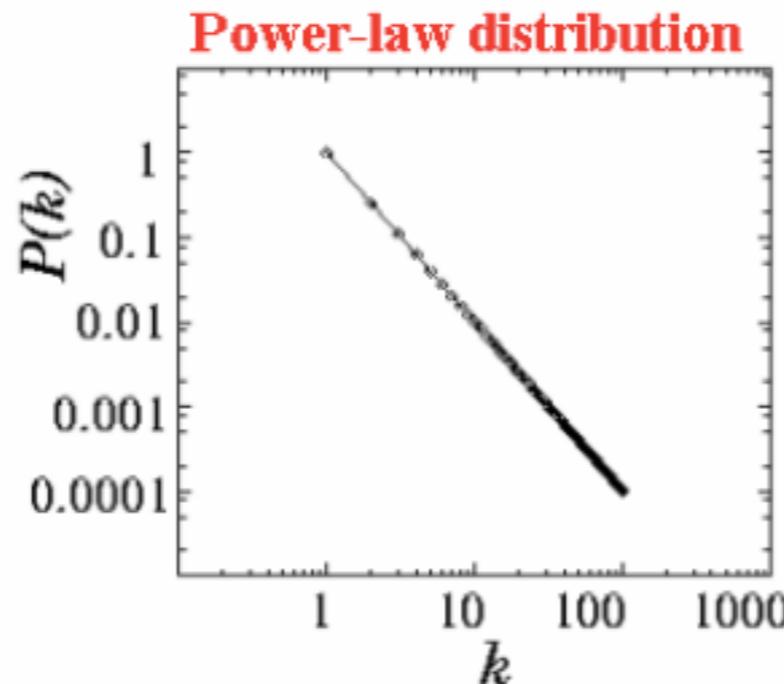


Network / Graph topology: It's a Scale Free World After All

Possion distribution



Power-law distribution



Number of connections a node in the network has: degree (δ)



Exponential Network



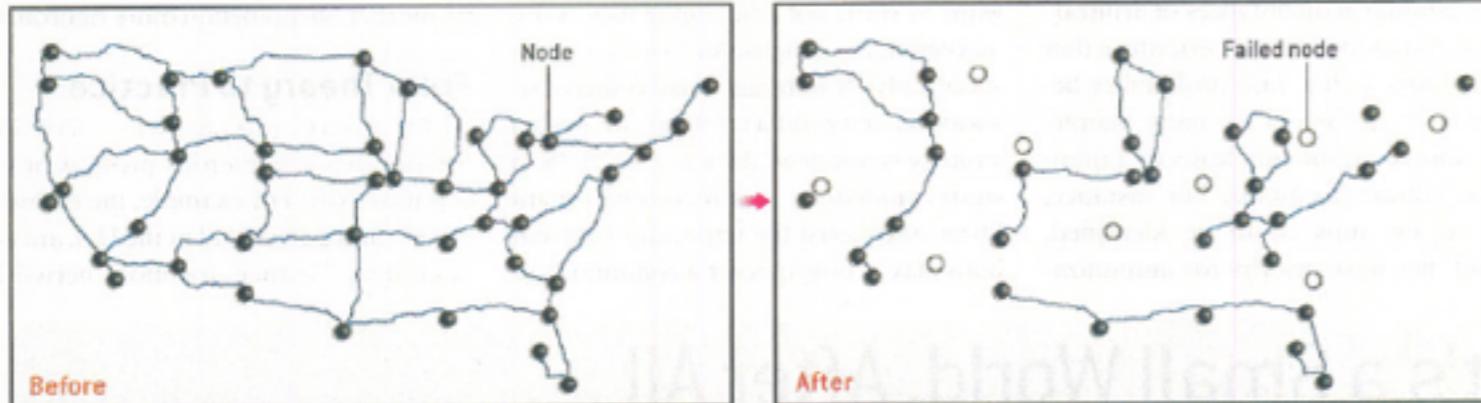
Scale-free Network

Scale-free network: degree distribution is a power law!

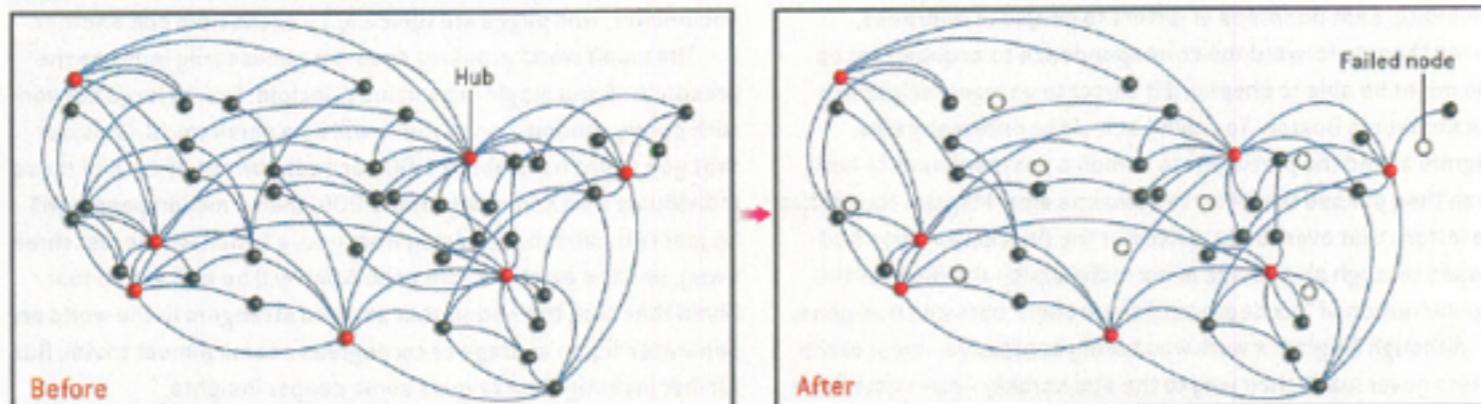


Can complex networks provide a suitable structure?

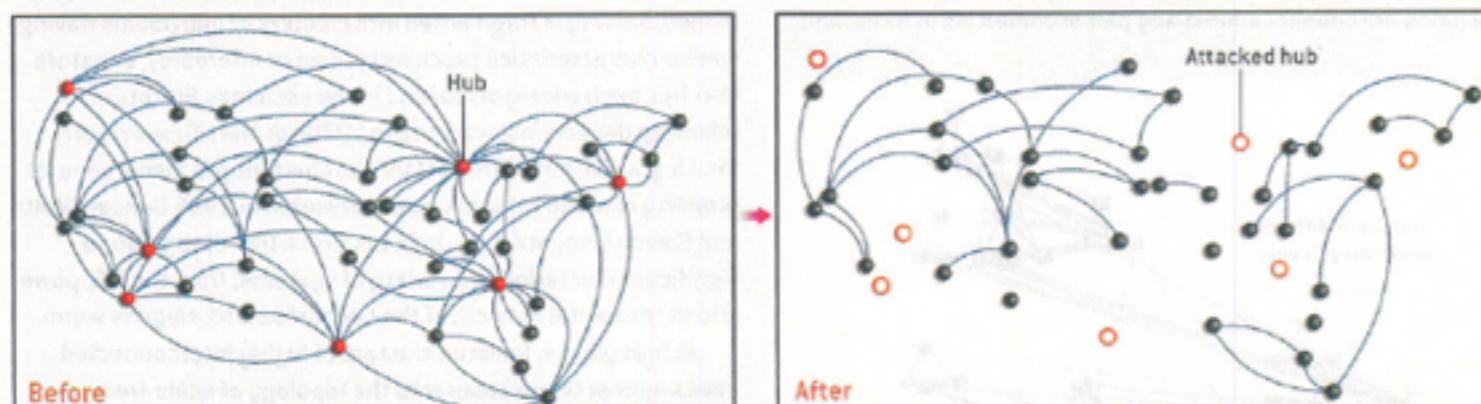
Random Network, Accidental Node Failure



Scale-Free Network, Accidental Node Failure



Scale-Free Network, Attack on Hubs



Scale free networks
are resilient to
random attacks on
nodes or node
failures

(cf. internet on 9/11)

when more hub nodes
fail though....

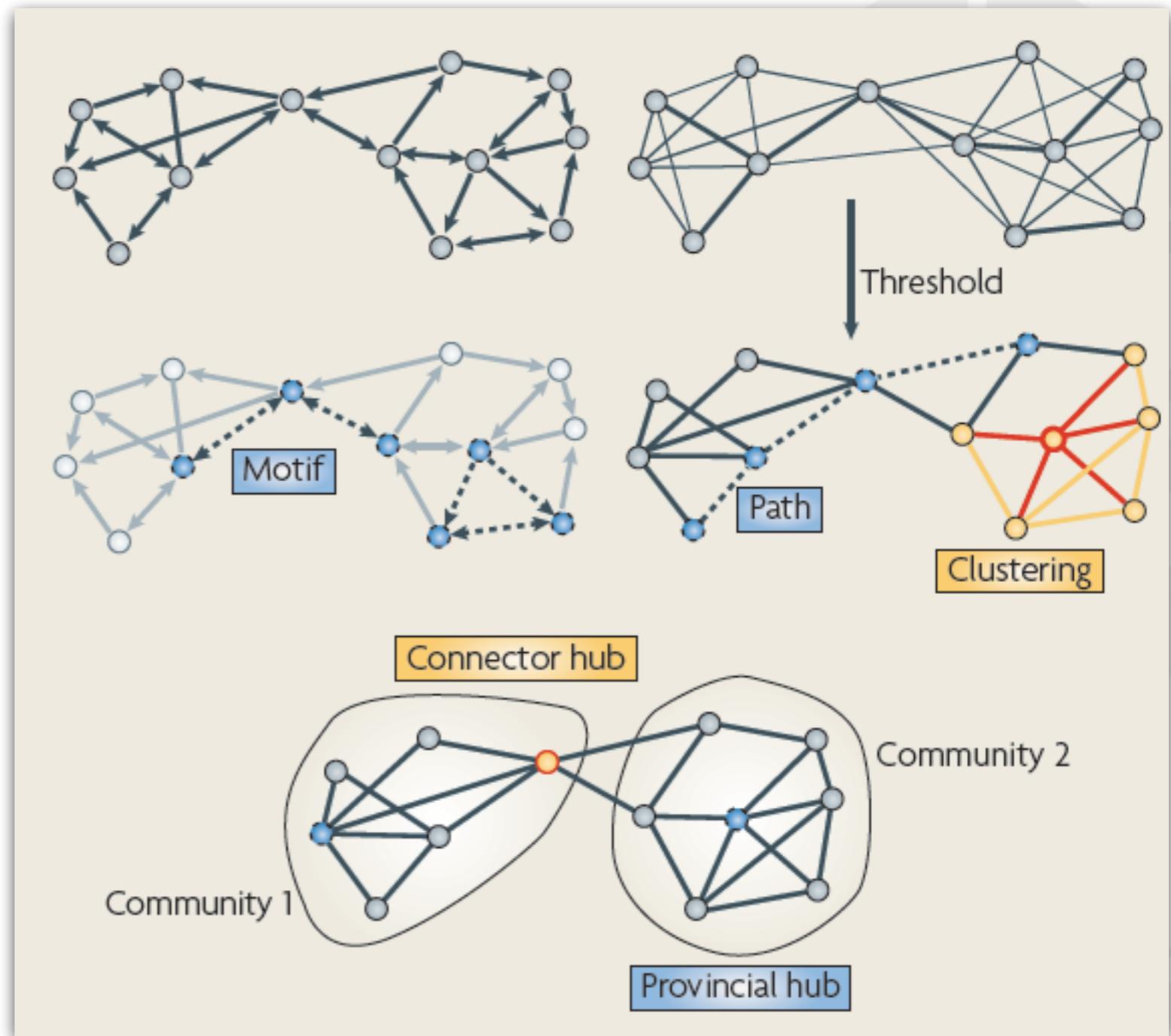
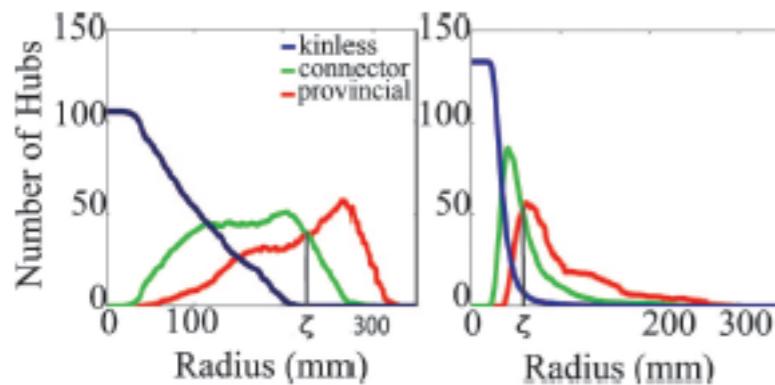
targeted attack!



Can complex networks provide a suitable structure?

A brand new zoo of complexity measures!

- Node degree
- Degree distribution
- Assortativity
- Clustering coefficient
- Motifs
- Path length
- Path efficiency
- Connection density or cost
- Hubs
- Centrality
- Robustness
- Modularity



Effectiveness / Connectivity: 6 degrees of separation

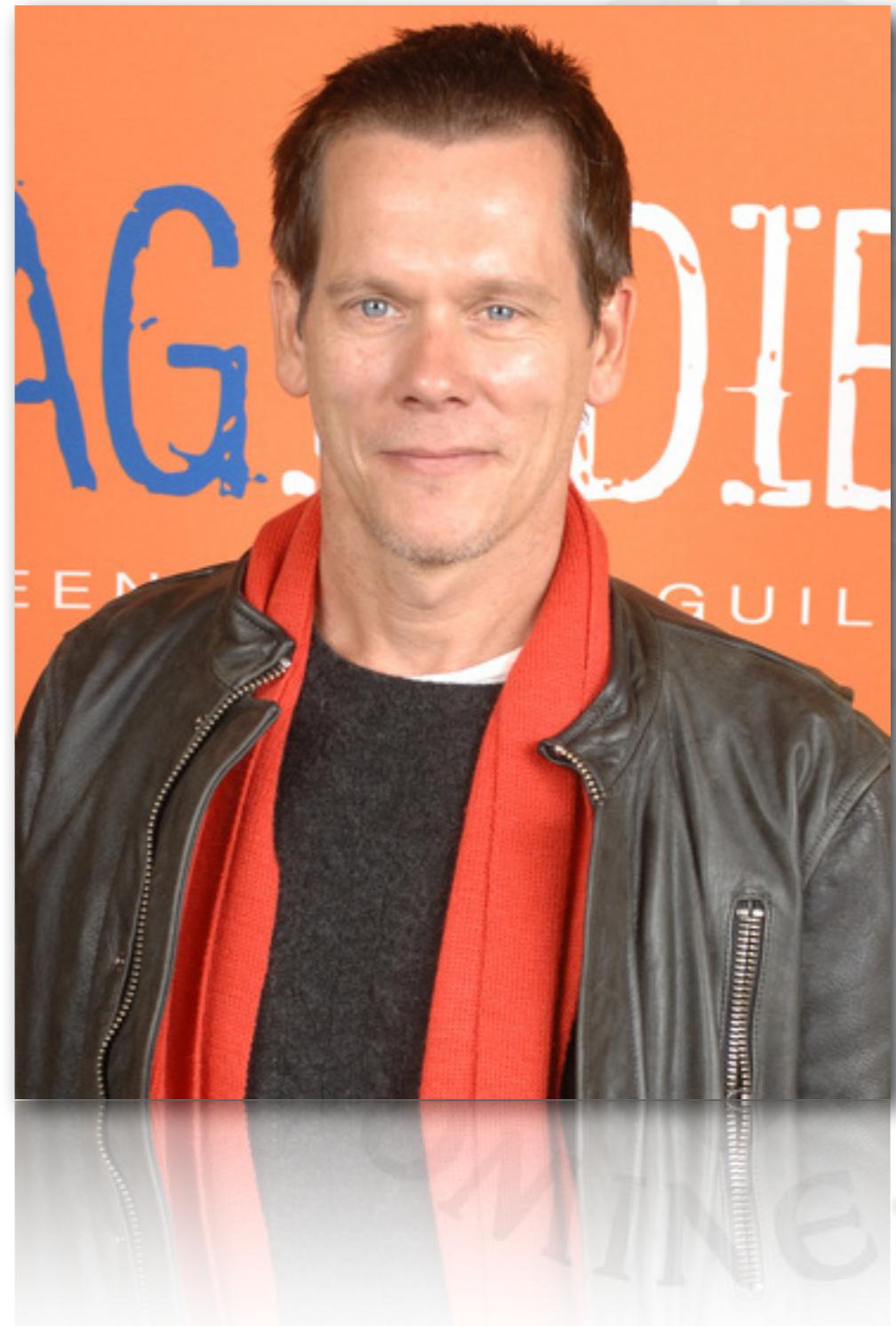
Kevin Bacon number (Erdős number)

- Node degree
- Degree distribution
- Assortativity
- Clustering coefficient
- Motifs
- Path length
- Path efficiency
- Connection density or cost
- Hubs
- Centrality
- Robustness
- Modularity

Degree of separation
(from Kevin Bacon)

'6 degrees of separation'

[http://en.wikipedia.org/wiki/
Bacon_number#Bacon_numbers](http://en.wikipedia.org/wiki/Bacon_number#Bacon_numbers)



Effectiveness / Connectivity: 6 degrees of separation

Your degree of separation from:

Nobel Laureate **1/2**

Pharrell Williams

Hillary Clinton
Donald Trump

1

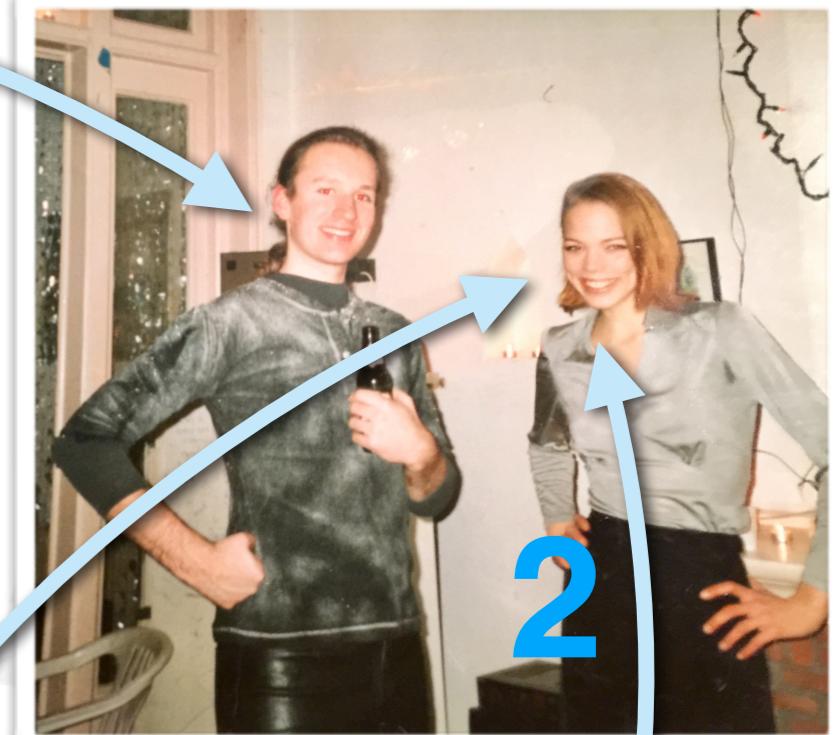
2

2

3

3/4

[http://en.wikipedia.org/wiki/
Bacon_number#Bacon_numbers](http://en.wikipedia.org/wiki/Bacon_number#Bacon_numbers)



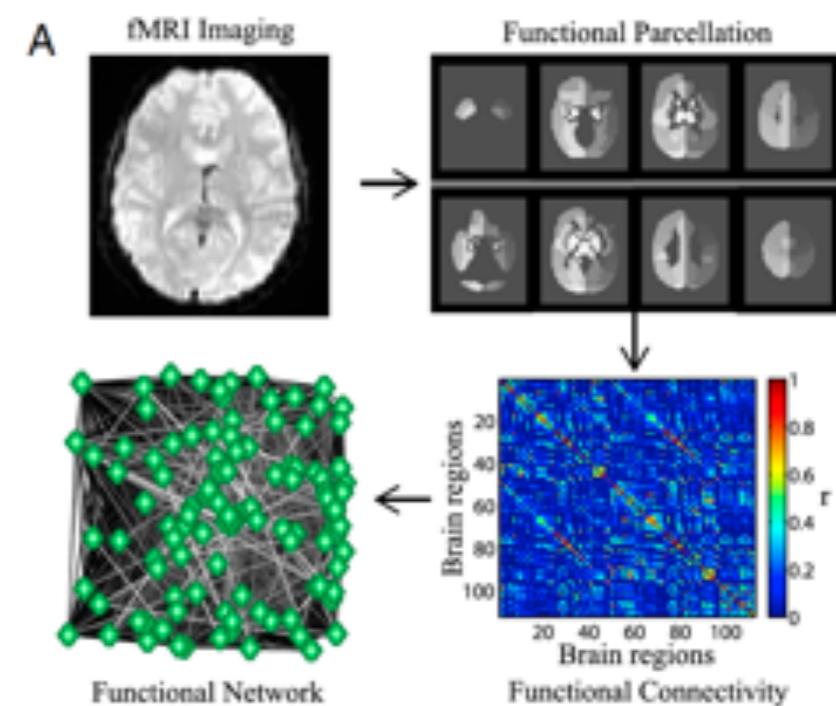
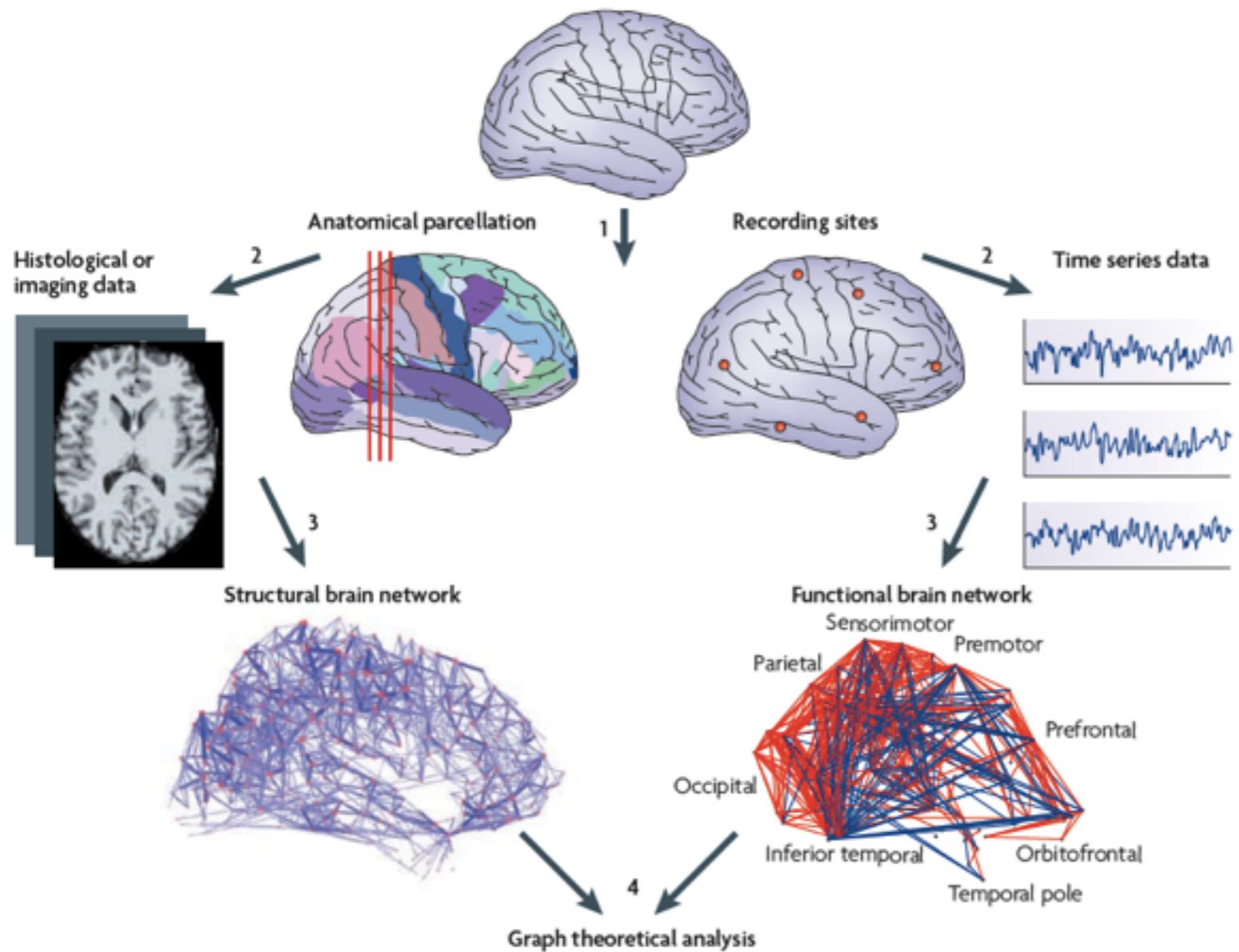
Radboud University Nijmegen



Network / Graph topology

Functional vs. Structural networks

Box 1 | Structural and functional brain networks



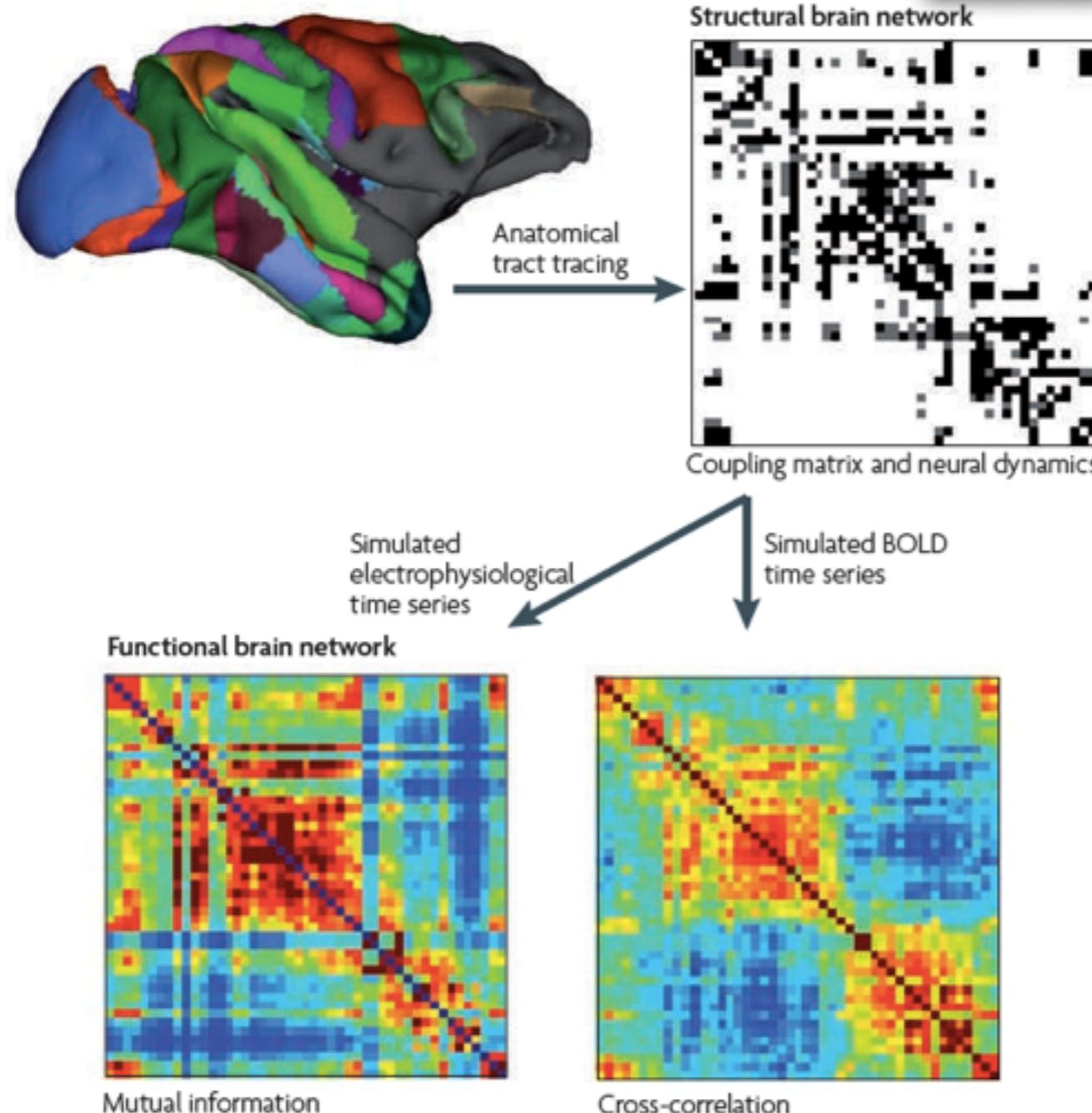
Bullmore, E., & Sporns, O. (2009). Complex brain networks: graph theoretical analysis of structural and functional systems. *Nature reviews. Neuroscience*, 10(3), 186-98. doi: 10.1038/nrn2575.

Radboud University Nijmegen



Network / Graph topology

Functional vs. Structural networks



adjacency matrix
similarity matrix
coupling matrix

Compare:
Recurrence matrix

“neural dynamics”

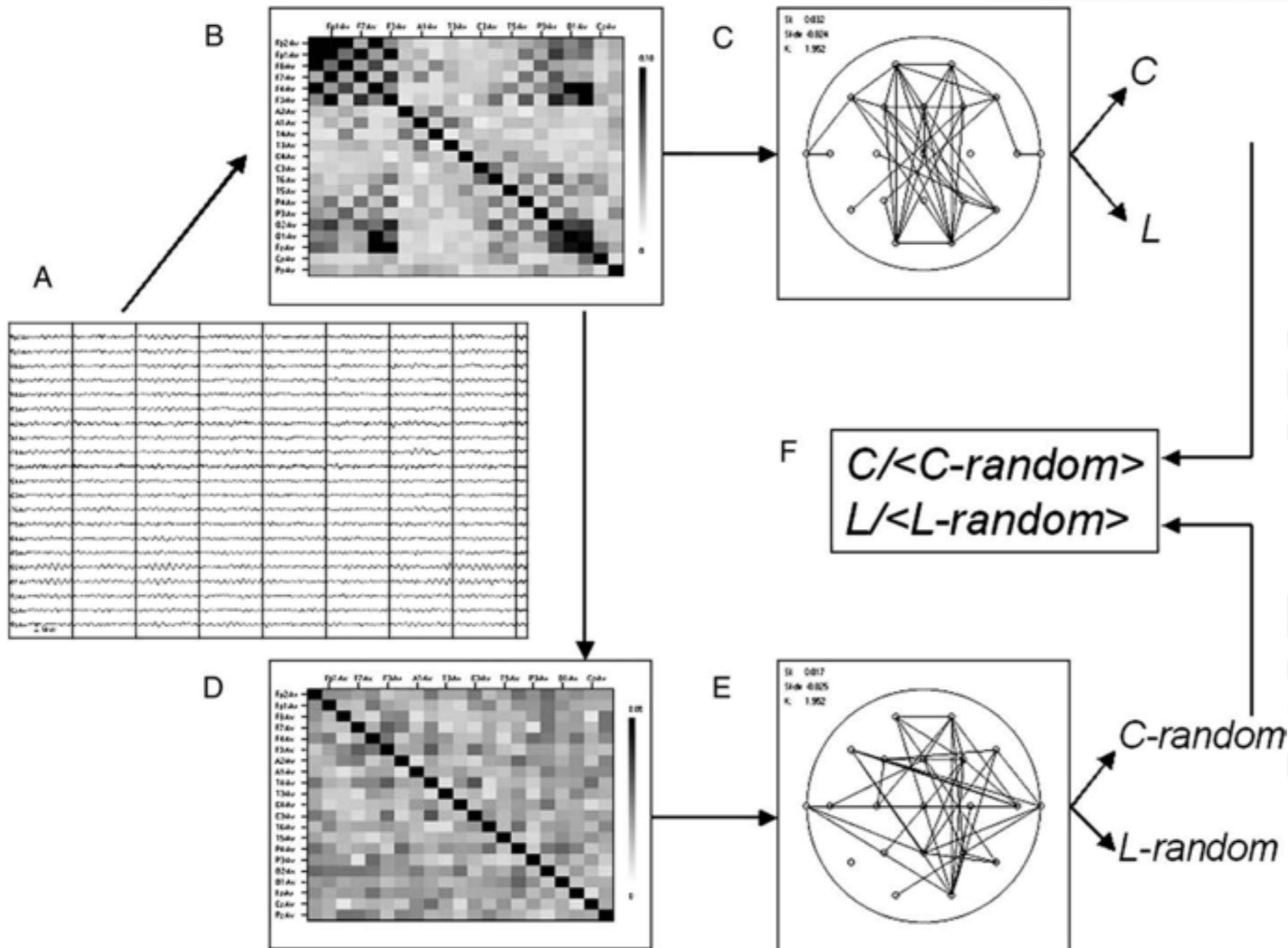
Compare:
Surrogate data generation from
recurrence matrix

Figure 1 | Computational modelling of structural and functional brain networks.



Network / Graph topology

How to get the matrices



Adjacency matrix and weighted graph can be extracted from resting state recordings:

5 min. eyes closed

find 4096 samples without artefacts

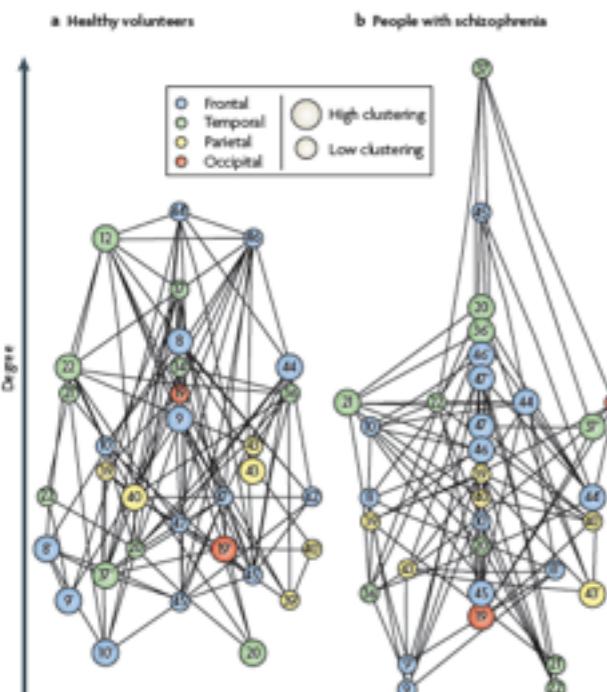
That's about 6-7 seconds!



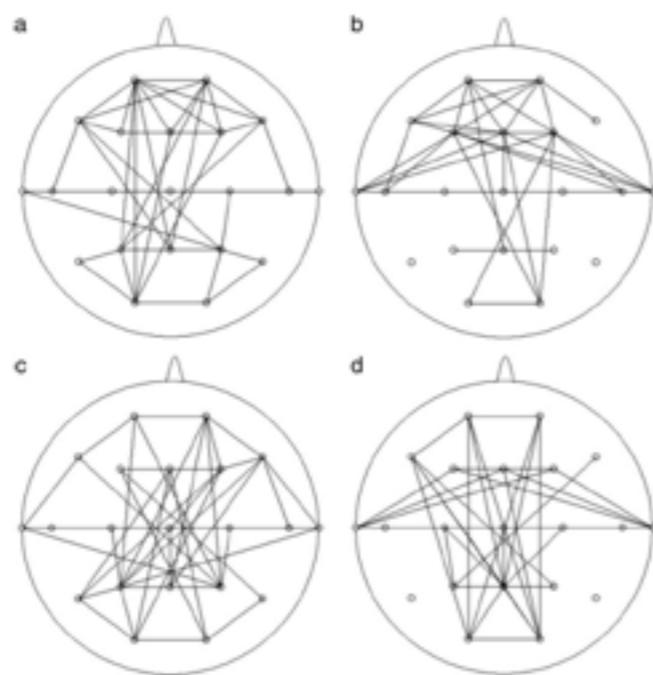
Network / Graph topology

Pathology studies

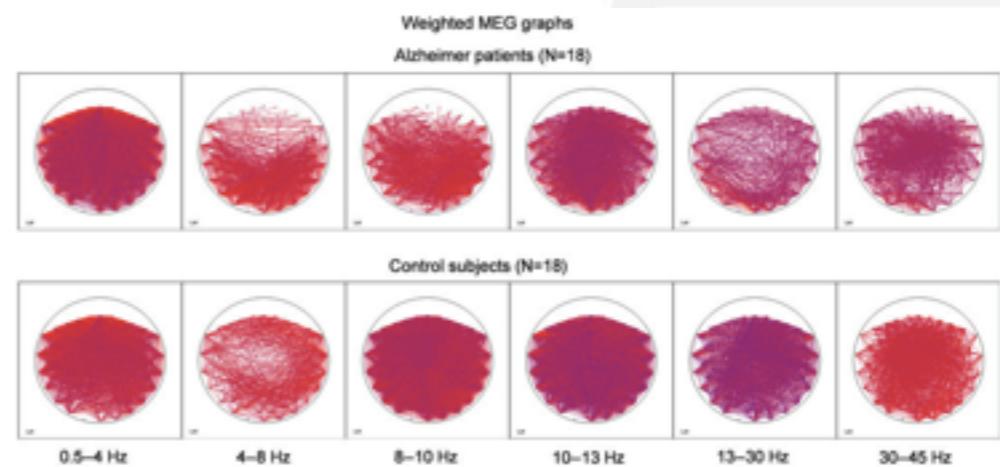
Based on a few samples we can distinguish healthy subjects from patients:



Schizophrenia



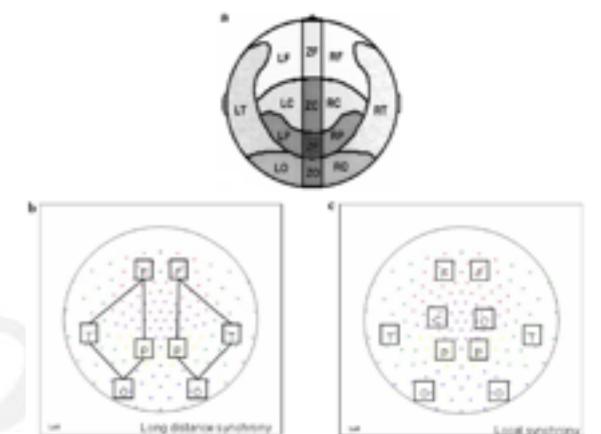
Absence seizure



Alzheimer's disease: Targeted attack on hubs!

Parkinson's

Major
depressive
disorder



Epilepsy

brain tumor patients

Bartolomei, F., Bosma, I., Klein, M., Baayen, J. C., Reijneveld, J. C., Postma, T. J., et al. (2006). Disturbed functional connectivity in brain tumour patients: evaluation by graph analysis of synchronization matrices. *Clinical neurophysiology*, 117(9), 2039-49. doi: 10.1016/j.clinph.2006.05.018.

Ponten, S. C., Douw, L., Bartolomei, F., Reijneveld, J. C., & Stam, C. J. (2009). Indications for network regularization during absence seizures: weighted and unweighted graph theoretical analyses. *Experimental neurology*, 217(1), 197-204. Elsevier Inc. doi: 10.1016/j.expneurol.2009.02.001.

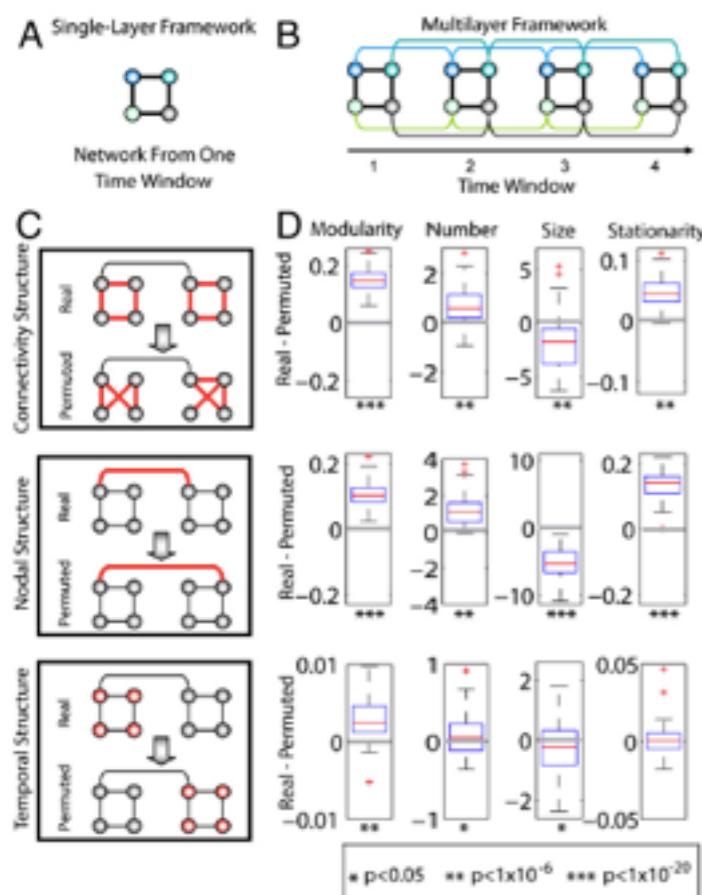
Stam, C. J., Haan, W. de, Daffertshofer, a, Jones, B. F., Manshanden, I., Cappellen van Walsum, a M. van, et al. (2009). Graph theoretical analysis of magnetoencephalographic functional connectivity in Alzheimer's disease. *Brain : a journal of neurology*, 132(Pt 1), 213-24. doi: 10.1093/brain/awn262.

Stam, C. J. (2010). Use of magnetoencephalography (MEG) to study functional brain networks in neurodegenerative disorders. *Journal of the neurological sciences*, 289(1-2), 128-34. Elsevier B.V. doi: 10.1016/j.jns.2009.08.028.

Network / Graph topology

Cognition studies

Systematic dynamic reconfiguration / topology differences during / correlated with, performance / characteristics

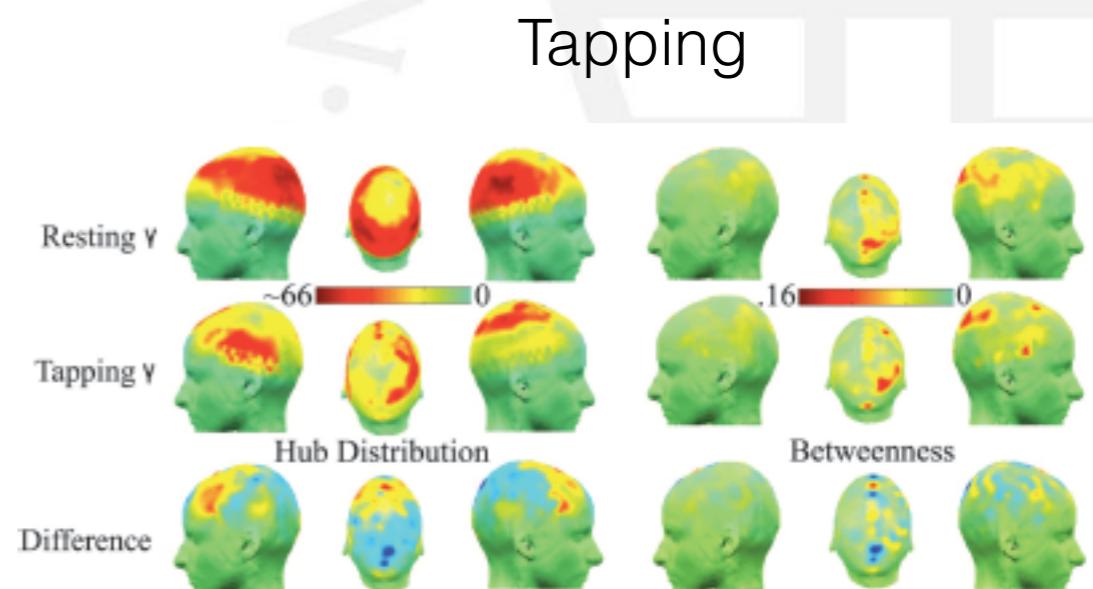


Cognitive abilities

Gender

Age

Learning



Bassett, D. S., Meyer-Lindenberg, A., Achard, S., Duke, T., & Bullmore, E. (2006). Adaptive reconfiguration of fractal small-world human brain functional networks. *Proceedings of the National Academy of Sciences of the United States of America*, 103(51), 19518-23. doi: 10.1073/pnas.0606005103.

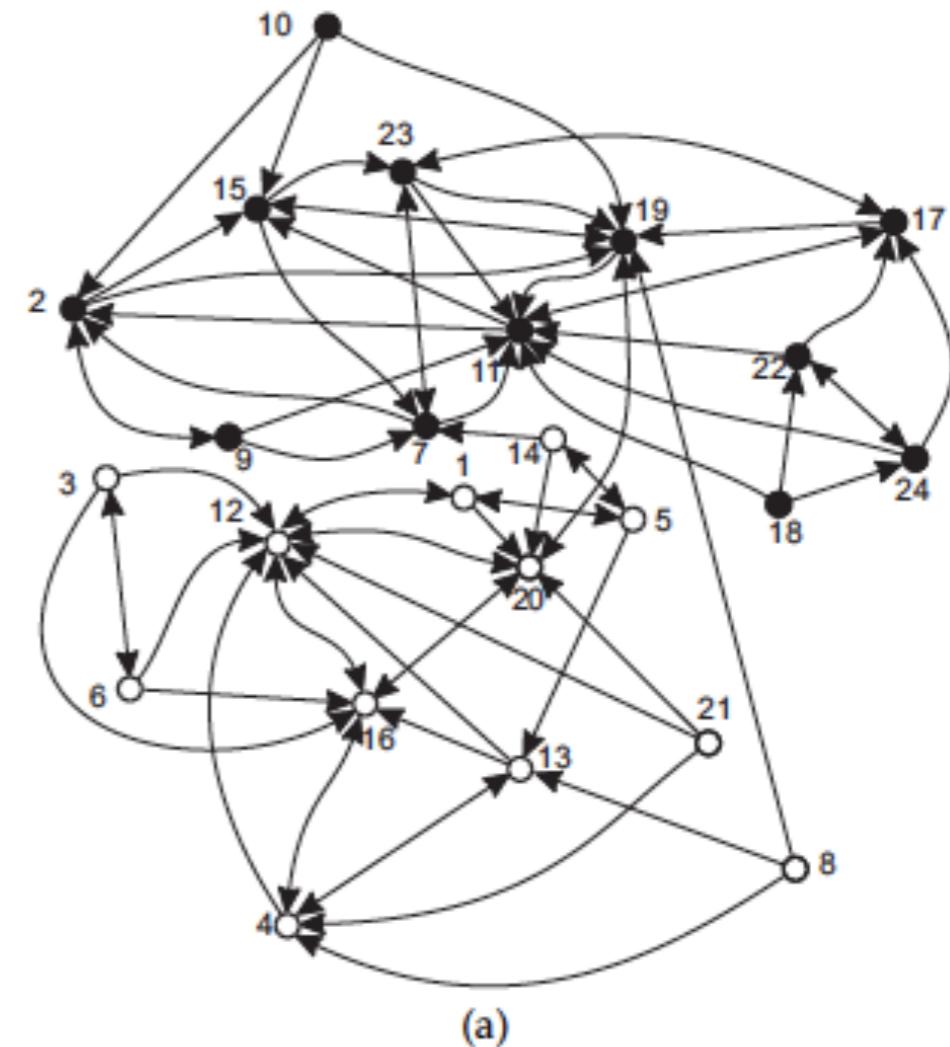
Bassett, D. S., Wymbs, N. F., Porter, M. a, Mucha, P. J., Carlson, J. M., & Grafton, S. T. (2011). Dynamic reconfiguration of human brain networks during learning. *Proceedings of the National Academy of Sciences*. doi: 10.1073/pnas.1018985108.

Douw, L., Schoonheim, M. M., Landi, D., Meer, M. L. van der, Geurts, J. J. G., Reijneveld, J. C., et al. (2011). Cognition is related to resting-state small-world network topology: an magnetoencephalographic study. *Neuroscience*, 175, 169-77. Elsevier Inc. doi: 10.1016/j.neuroscience.2010.11.039.

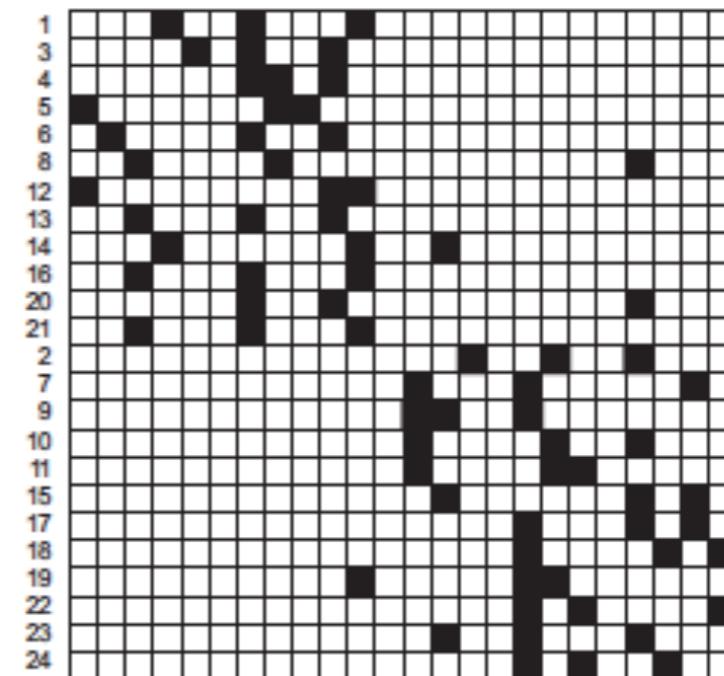
Network / Graph topology - Social networks

Sex	ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	
F	1	1							+														+	-		
M	2	-	1							+														-	-	
F	3			1					+	-			+													
F	4				1						-		+	+												
F	5	+											+	+												
F	6	-		+			1						+				-	+								
M	7		+									-	+												+	
F	8				+				-			1				+				-						
M	9	+								+							-									
M	10	+								-							+				+					
M	11	+															+				-					
F	12	+									-						+									
F	13			+												+										
F	14			+	-	+		-								+										
M	15				+													+							+	-
F	16			+							-		+					+								
M	17			-							+							+	-	-					+	
M	18										+							+	-	+					+	
M	19			-							+	-					+				+					
F	20										-		+			-	+			+						
F	21		-	-	+								+				+			-	+					
M	22				-	-						+					-	+								
M	23					+						+					-		+	-						
M	24																	+								1
+		2	4	1	4	2	1	4	0	1	0	8	8	3	1	4	6	3	0	7	6	0	2	3	2	
-		4	2	0	1	0	4	4	0	4	9	1	1	1	2	3	1	2	0	7	6	10	4	3	3	

Figure 9.6: Data on the three most liked or disliked classmates.



(a)



(b)

Figure 9.7: (a) The sociogram for positive nominations represented as a directed graph. Boys are represented by black-colored vertices; girls by white-colored vertices. (b) The same data represented as an adjacency matrix.

Network / Graph topology - Social networks

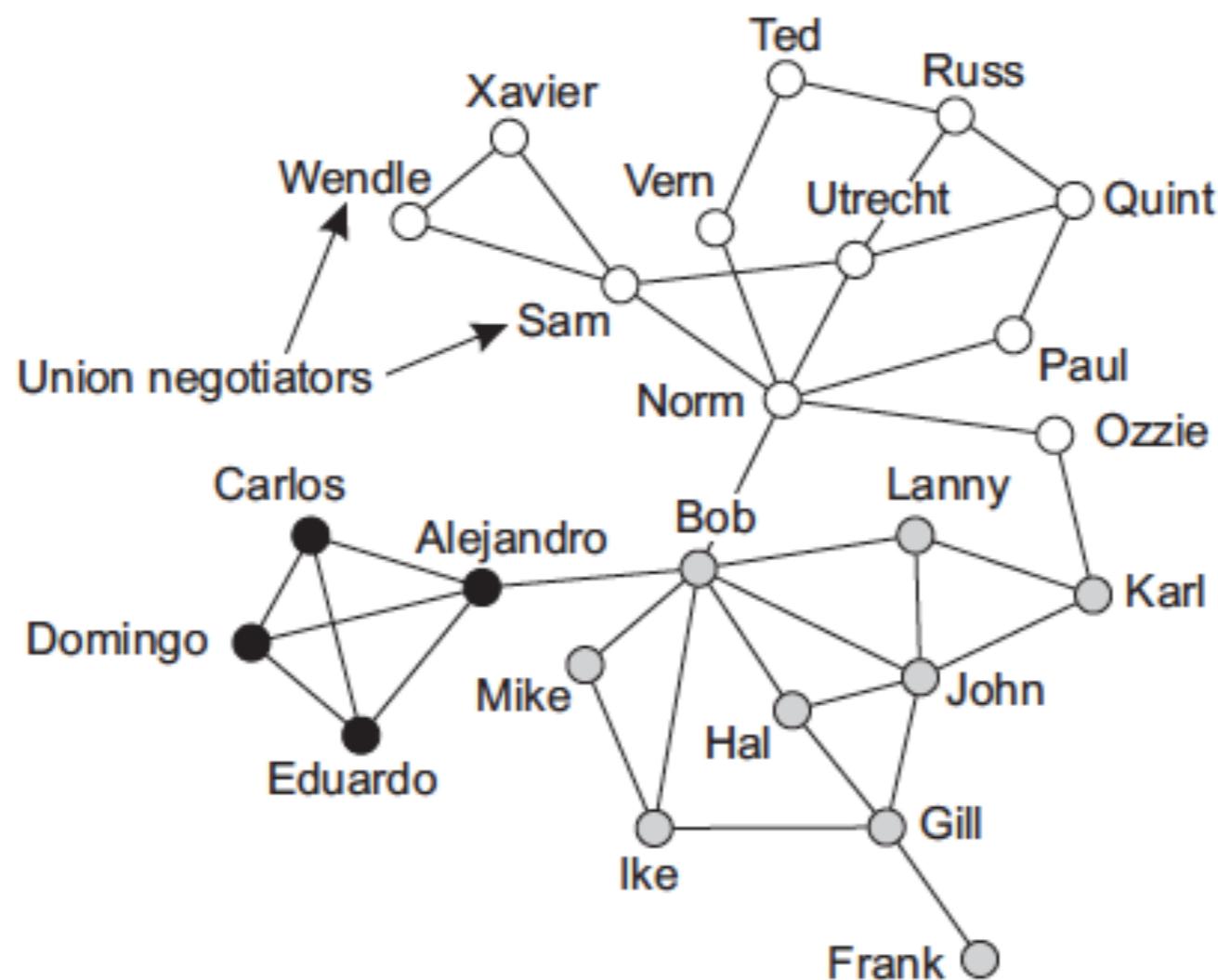


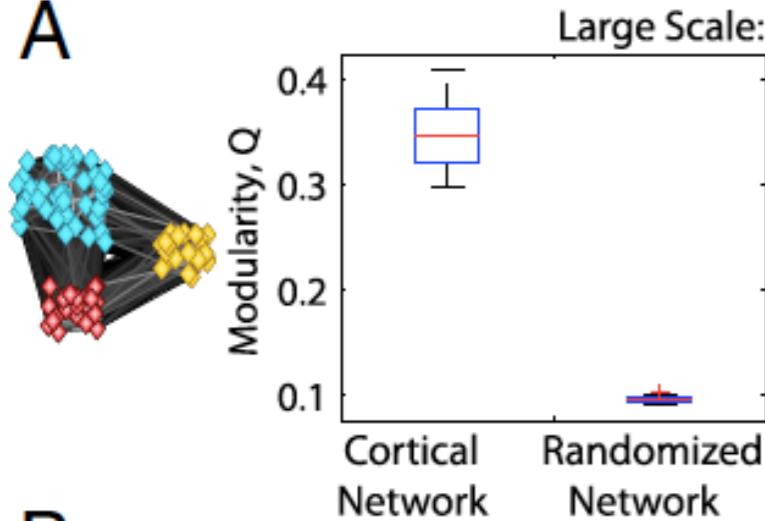
Figure 9.1: The relationship between workers on strike in a wood-processing firm.

Can complex networks provide a suitable structure?

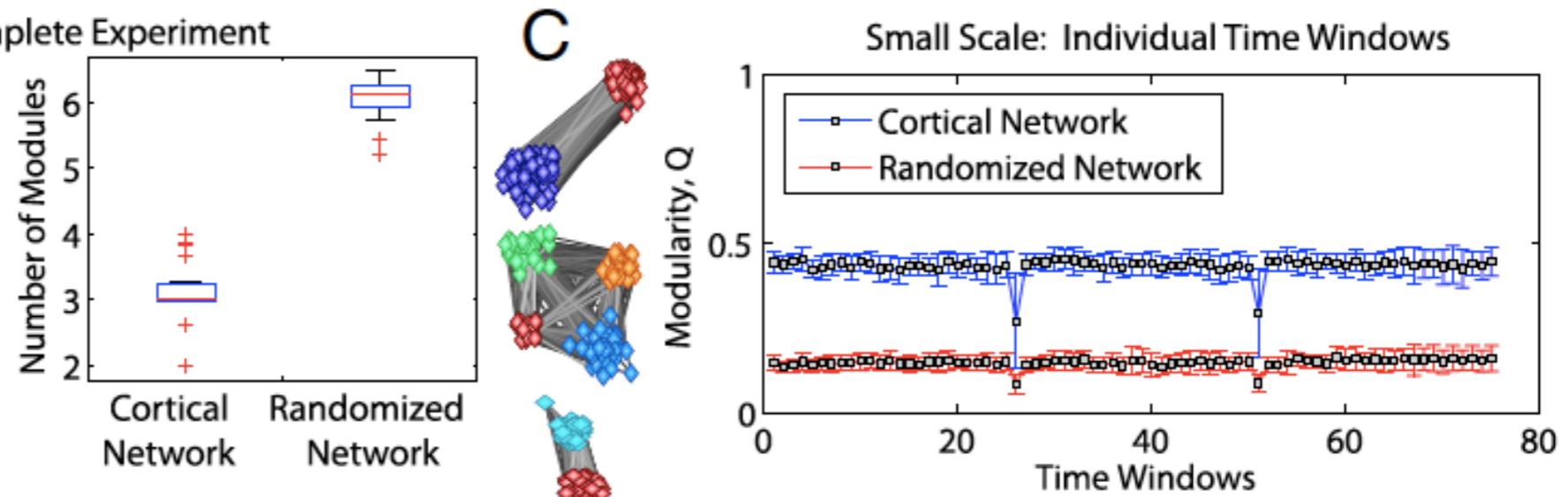
Multi-scale analysis

see also: Wijnants, M. L., Cox, R. F. A., Hasselman, F., Bosman, A. M. T., & Van Orden, G. (2012). A Trade-Off Study Revealing Nested Timescales of Constraint. *Frontiers in Fractal Physiology*, 3(May), 1-15. doi:10.3389/fphys.2012.00116

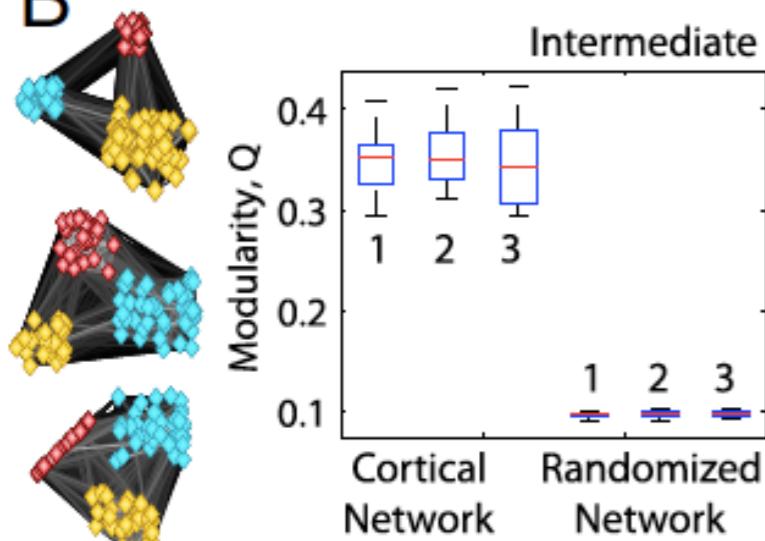
A



C

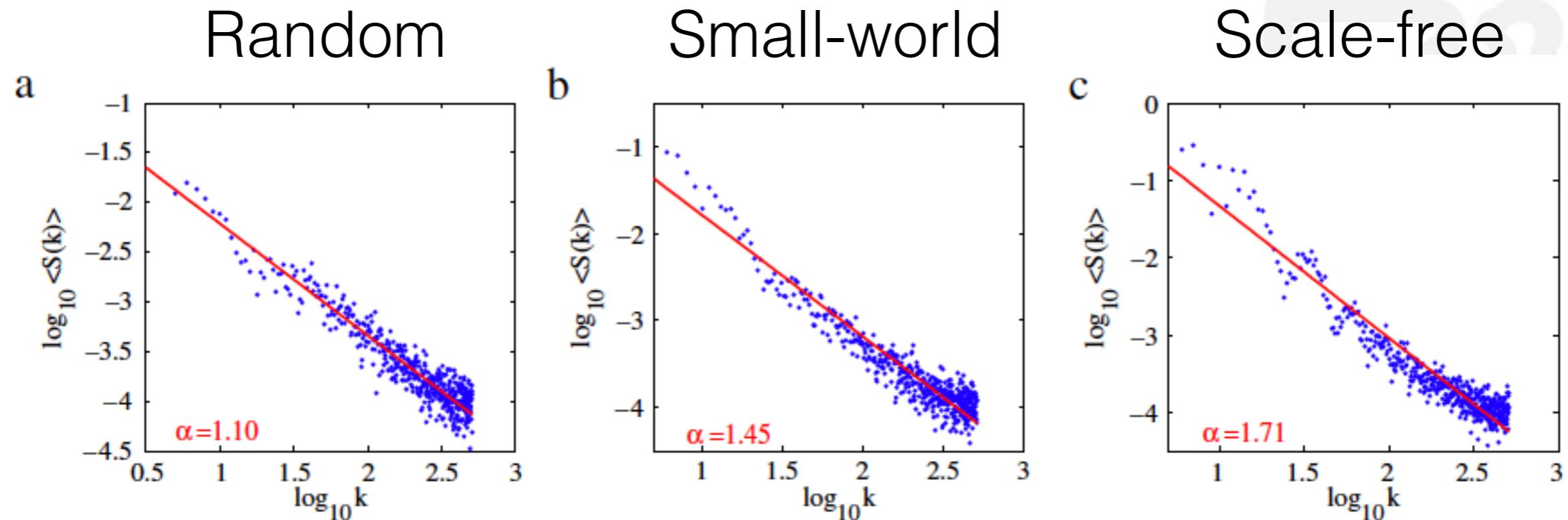


B



Network / Graph topology

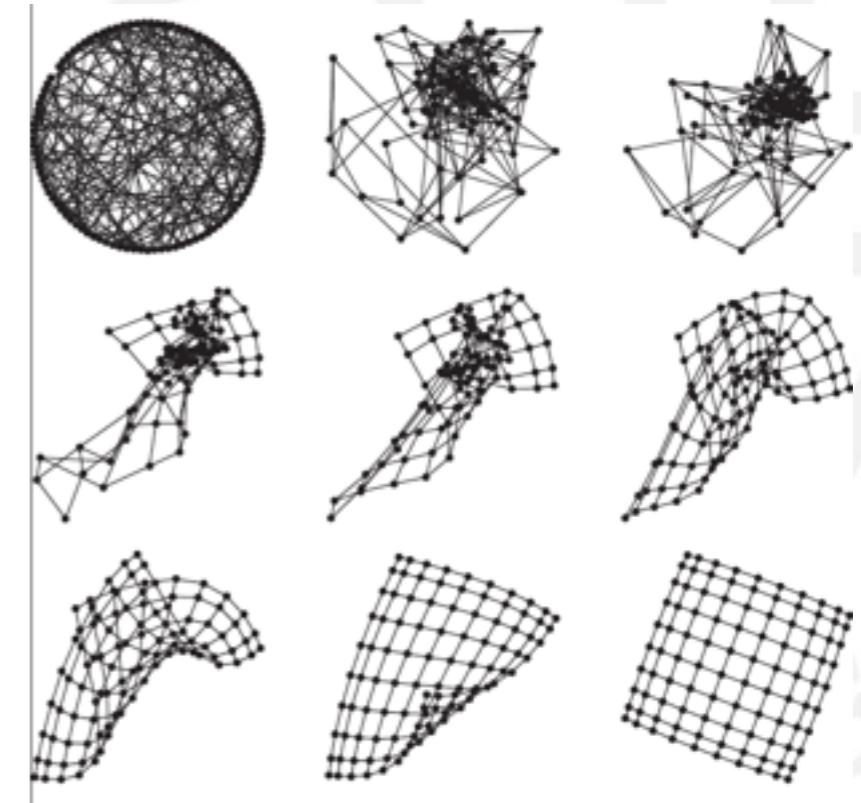
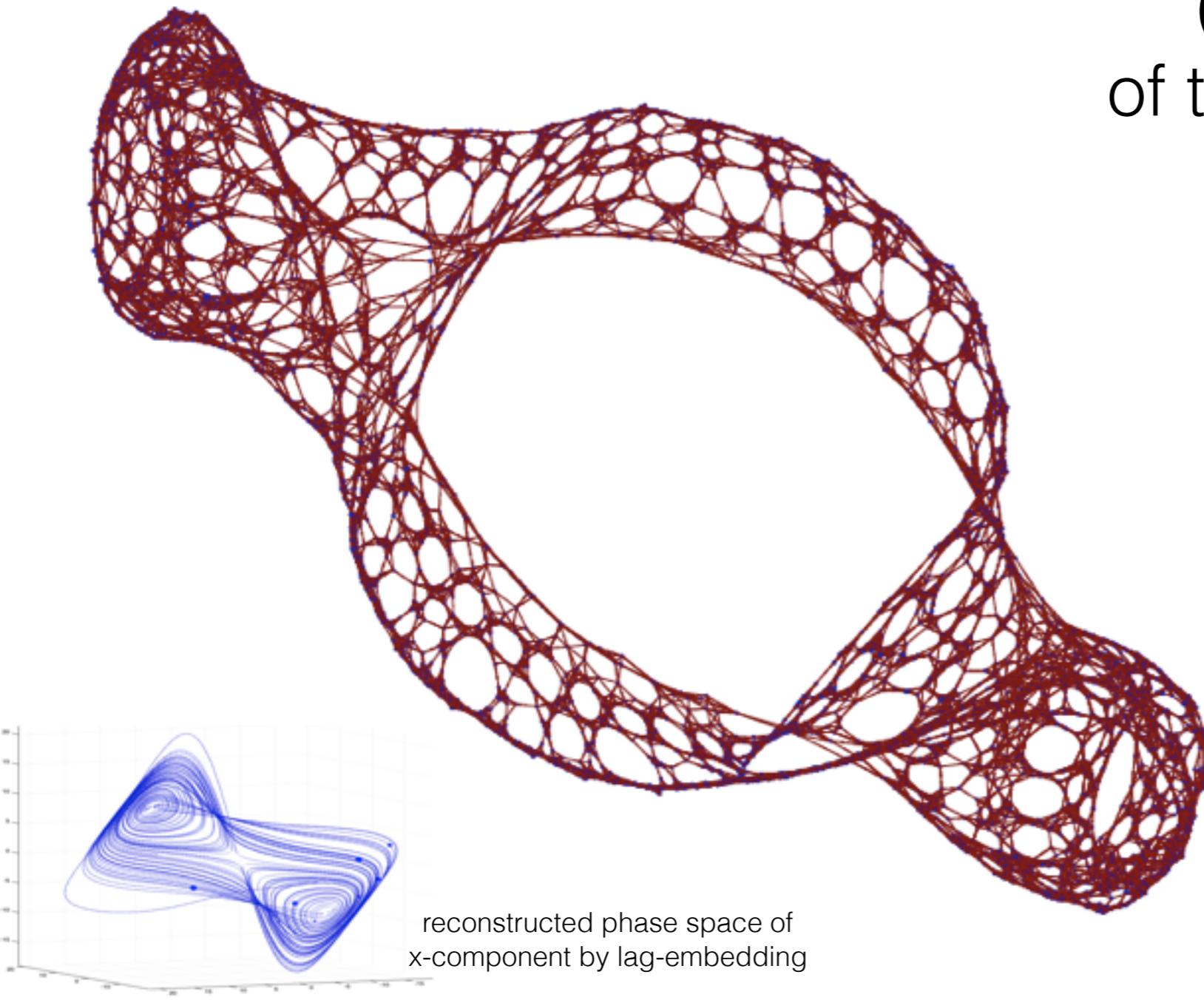
1/f^a Noise in Spectral Fluctuations of Complex Networks



Spectrum of nearest-neighbour spacing
in the adjacency matrix

Network / Graph topology

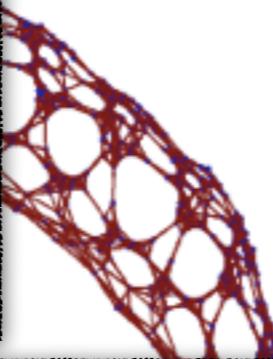
Network representation
(spring embedding)
of the x-component of the
Lorenz-system



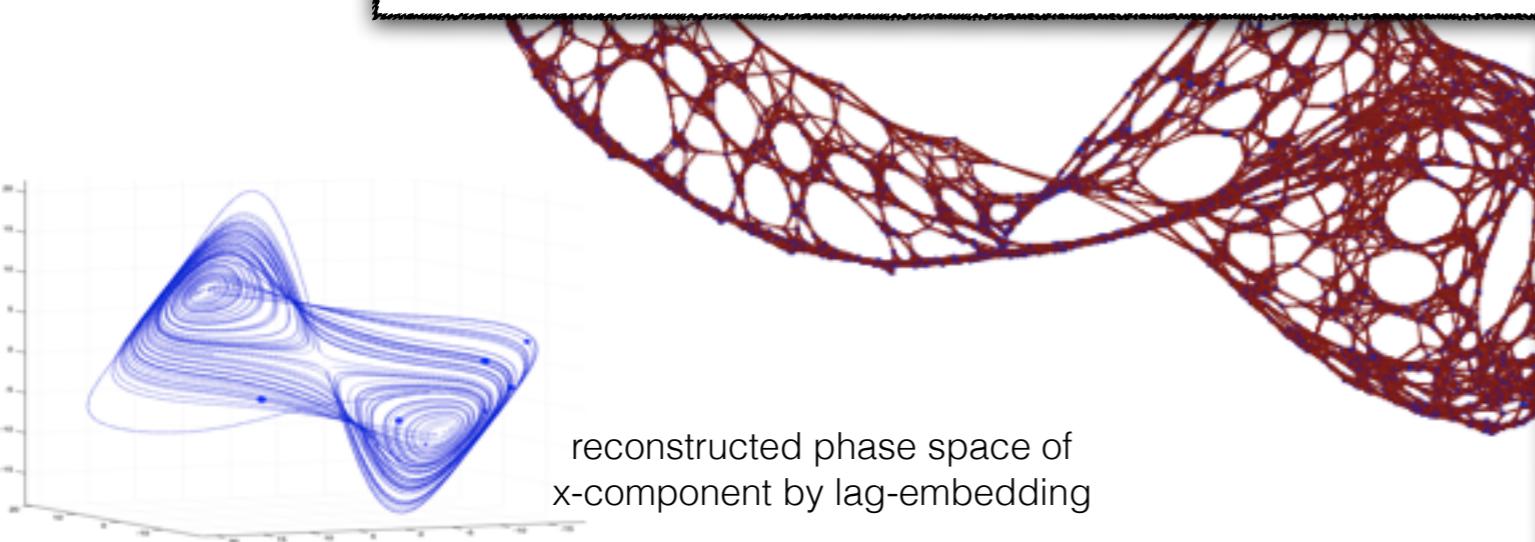
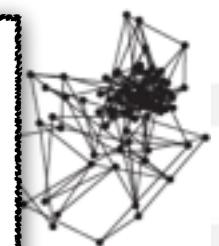
Network / Graph topology

Network representation
(spring embedding)
of the x-component of the
Lorenz-system

Data Source	Motif frequency
Chaotic Lorenz	□
Chaotic Rössler	□
Chaotic Chua's circuit	□
Hyper-chaotic Mackey-Glass	□ □ □ □ □
Periodic Rössler	□ □ □ □ □
Noisy Sine	□ □ □ □ □



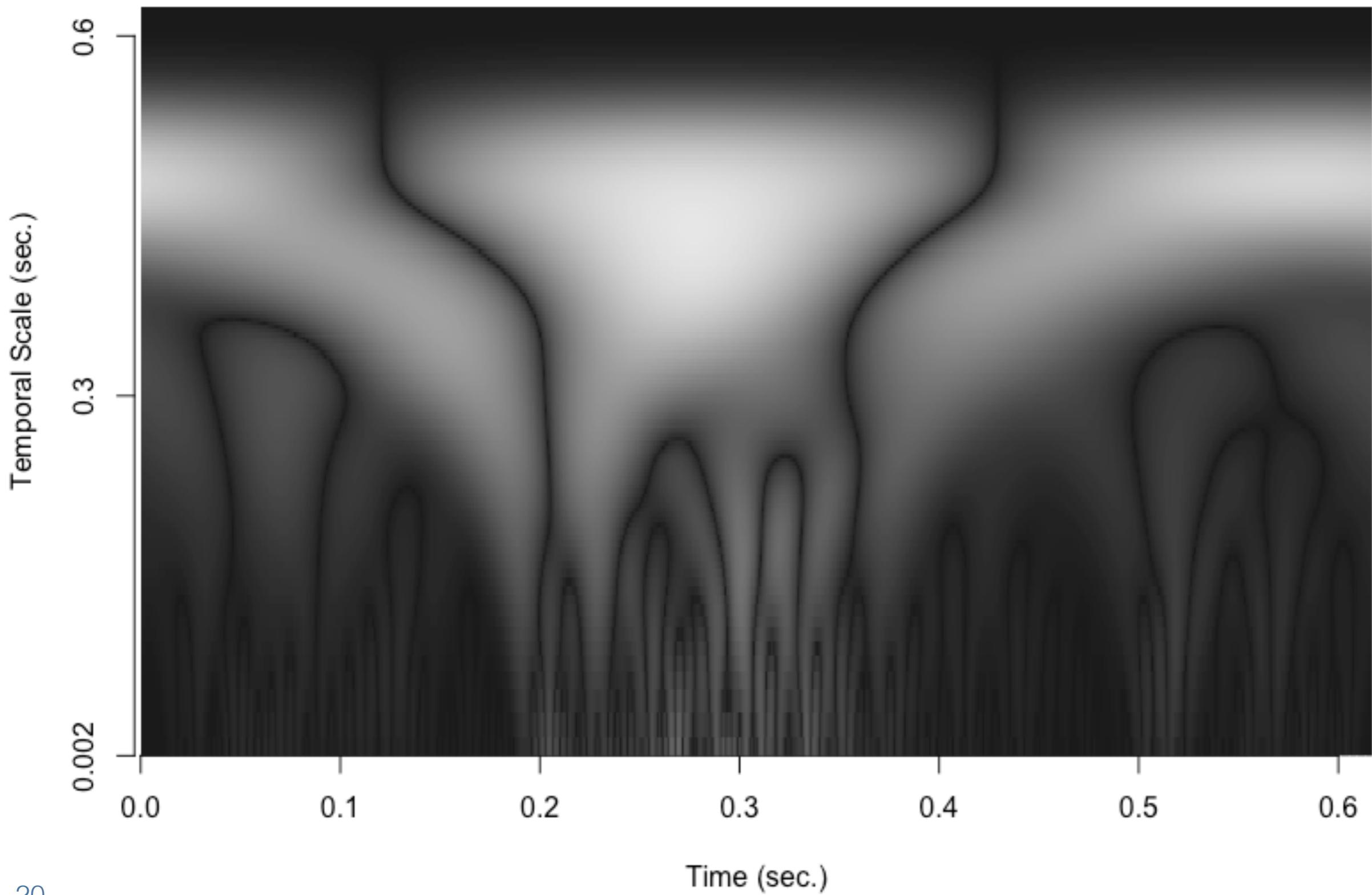
The adjacency matrix we use is not equivalent to the recurrence matrix and the properties we examine are topological features of the network rather than the temporal structure of the attractor.



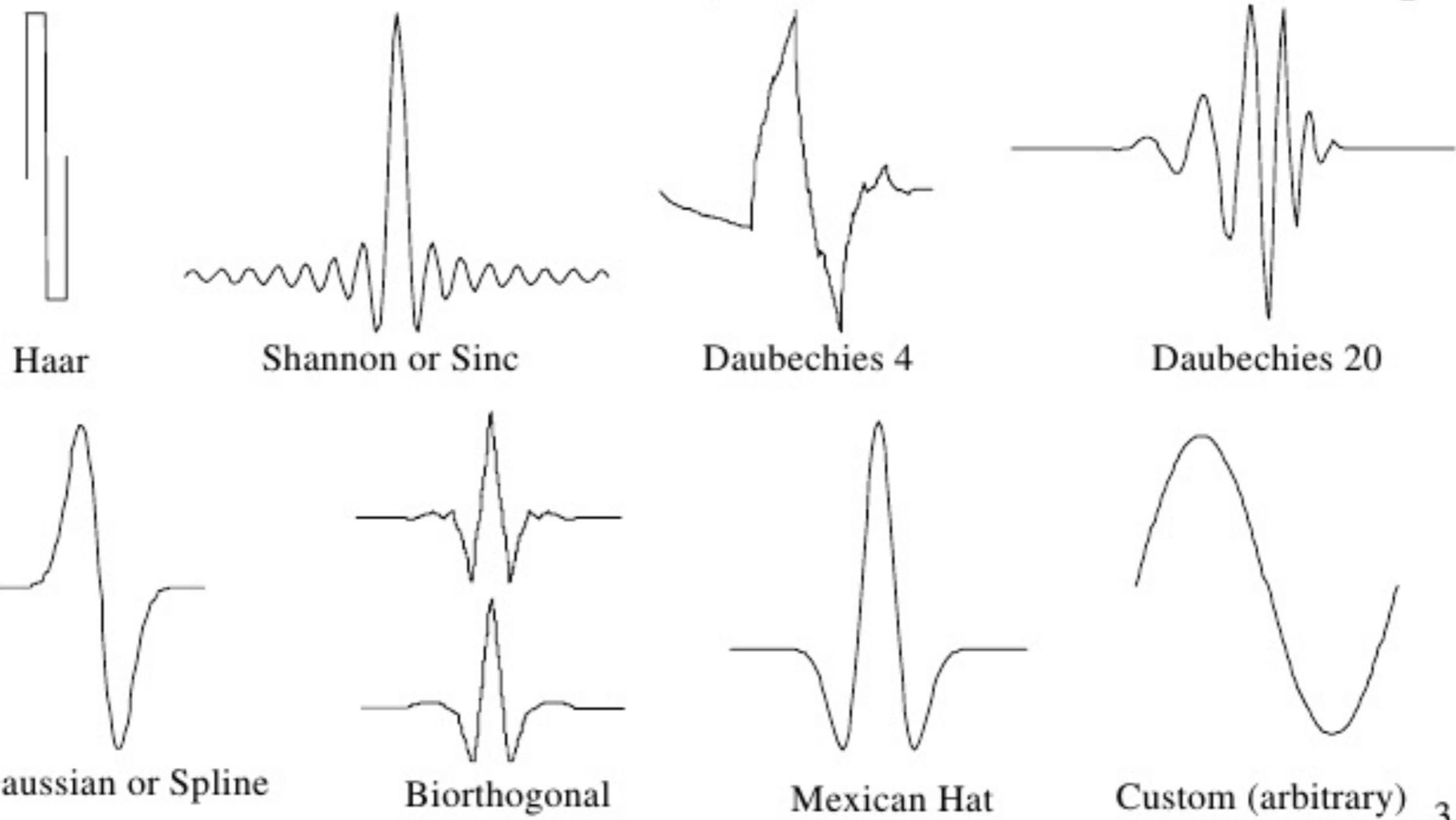
Data Source	Motif frequency
Chaotic logistic map	□
Chaotic Hénon map	□
Chaotic Ikeda map	□
Hyper-chaotic folded towel map	□
Hyper-chaotic generalised Hénon map	□
White noise	□
Fractal noise	□

Self-Affine Resonance

Scaleogram - Continuous Wavelet Transform

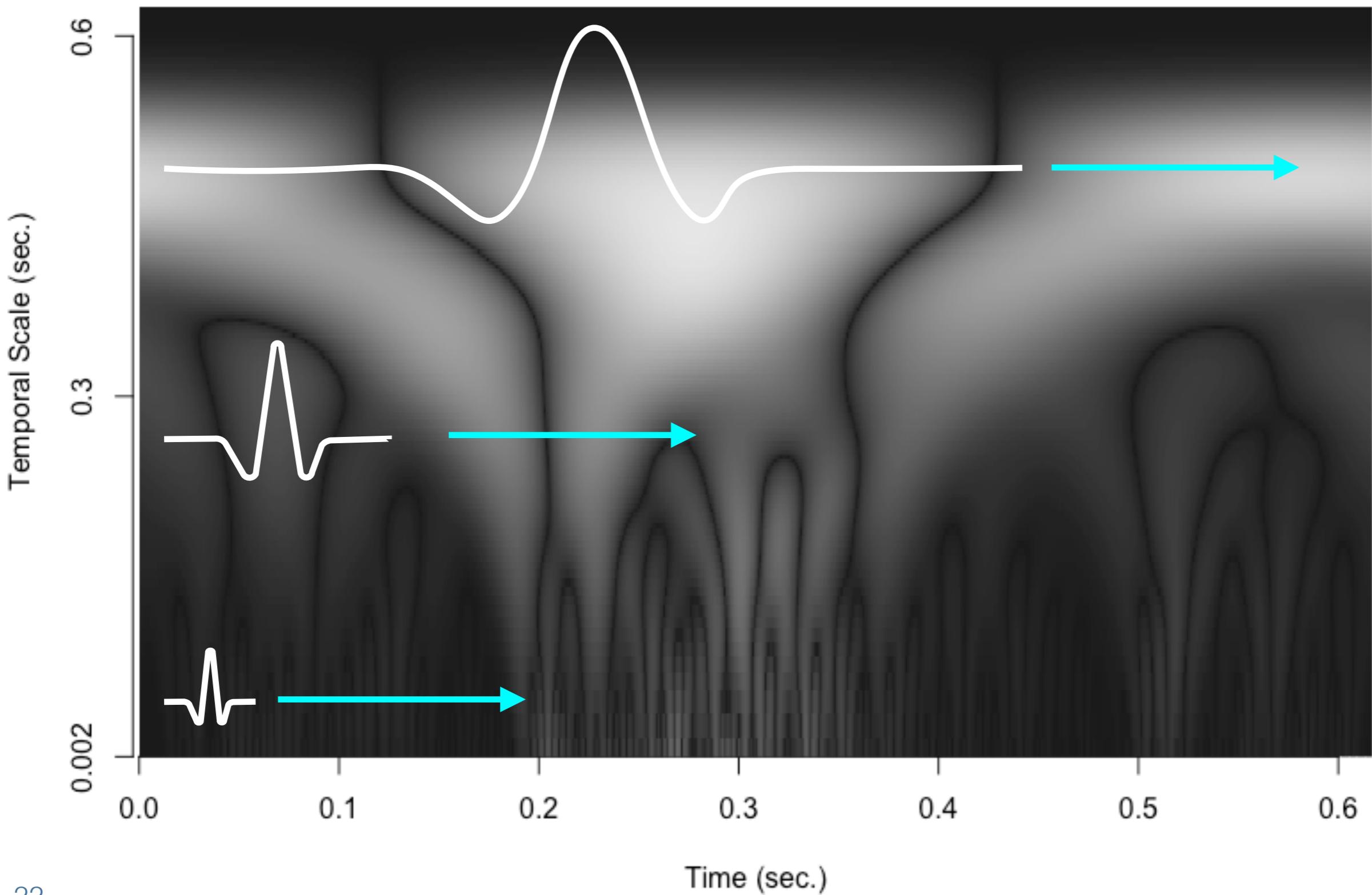


- WAVE for Frequency, LET indicates Compact Support.
- Jargon Alert*: Compact Support = having start & stop time
- Some more localized in time, some more localized in freq.



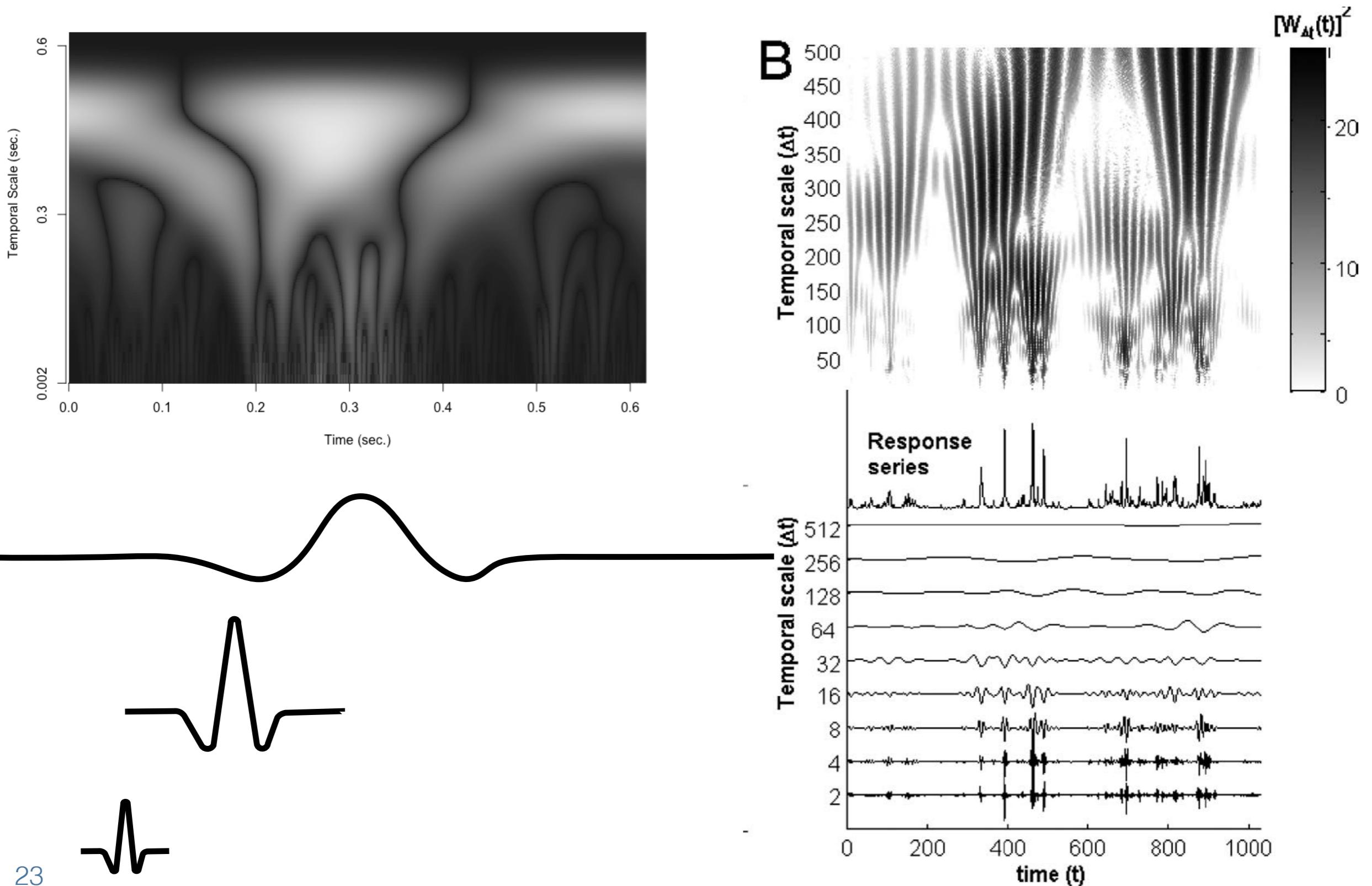
Self-Affine Resonance

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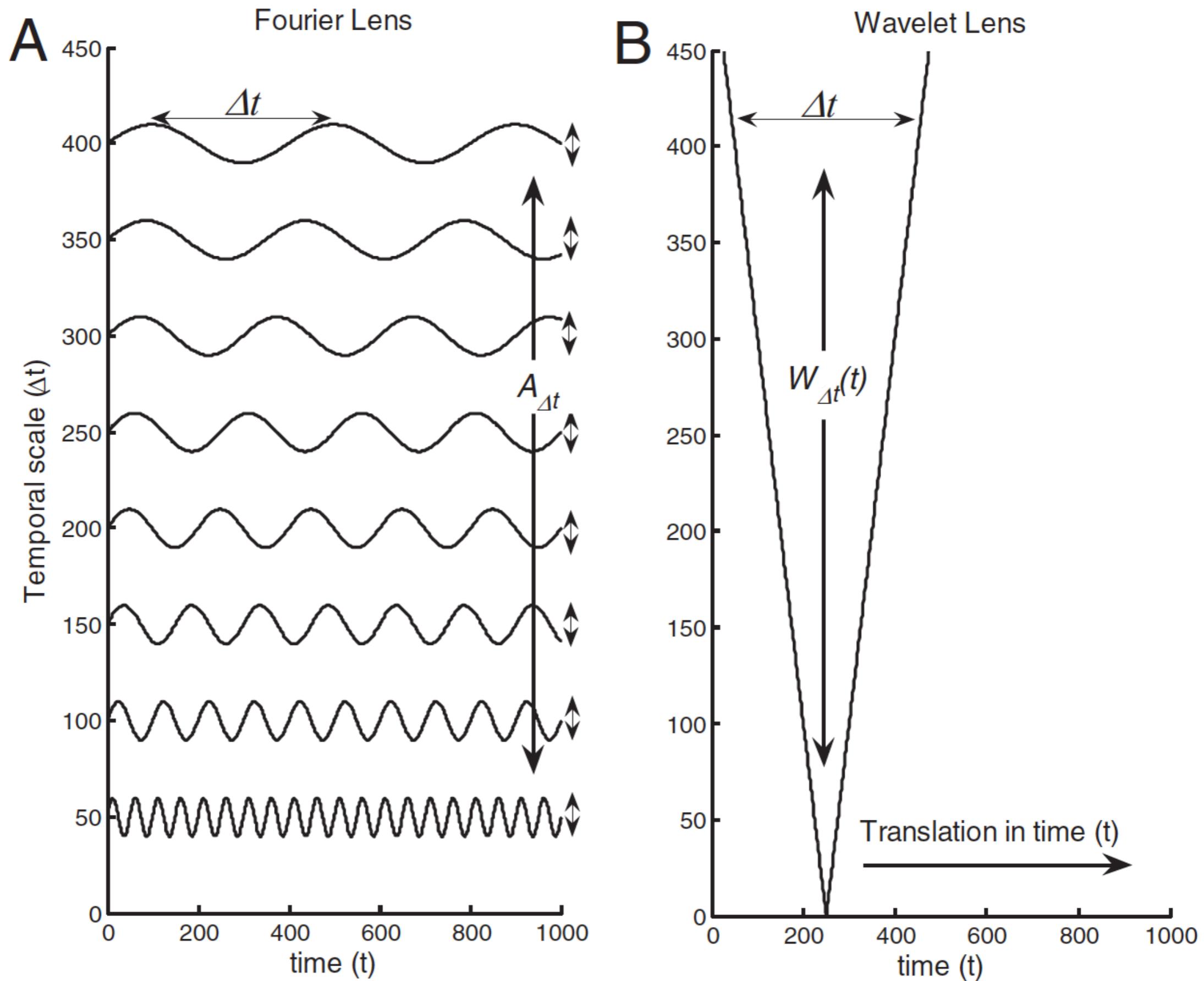


Self-Affine Resonance

Scaleogram - Continuous Wavelet Transform

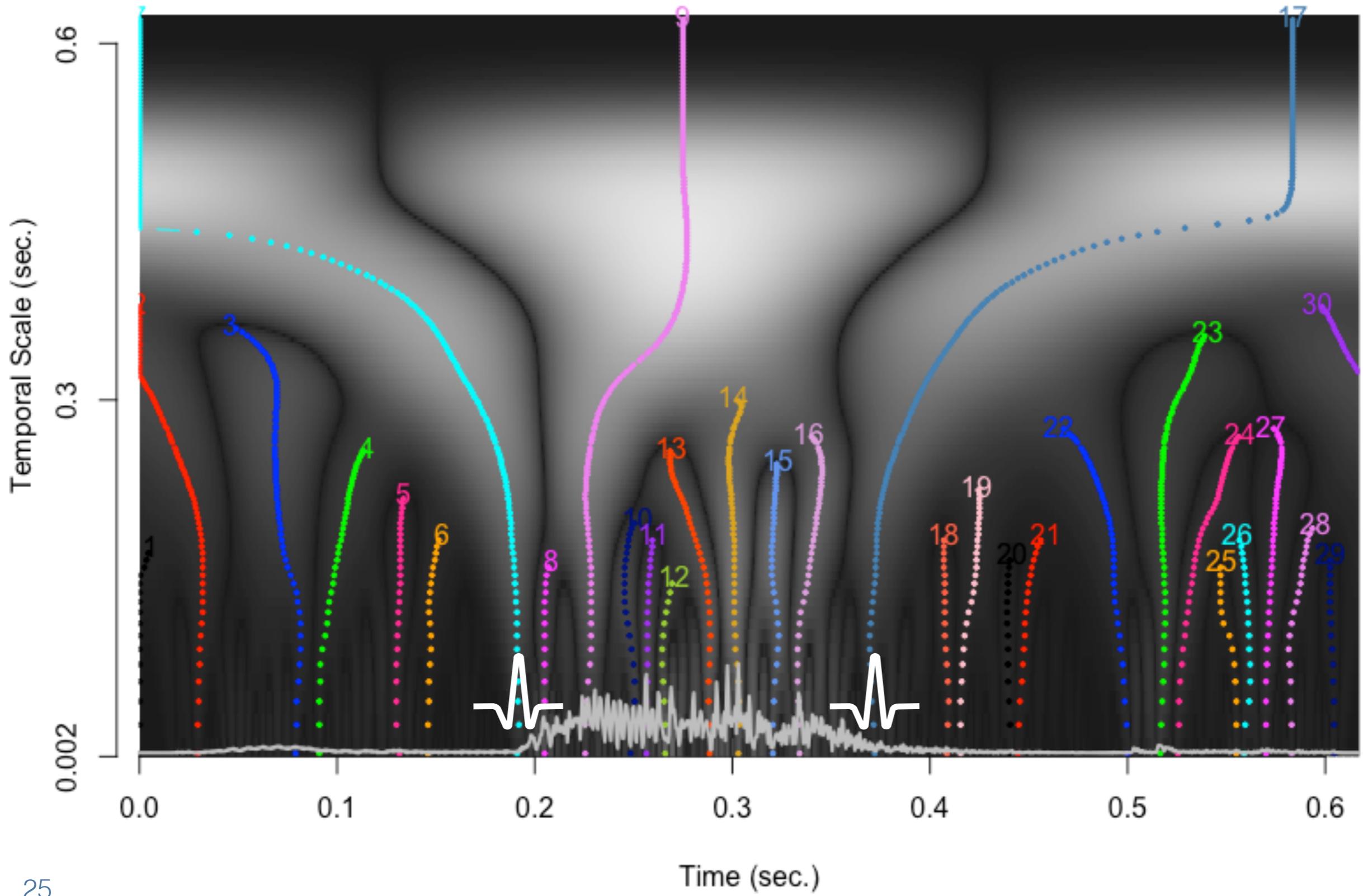


BEYOND $1/f^\alpha$ FLUCTUATION



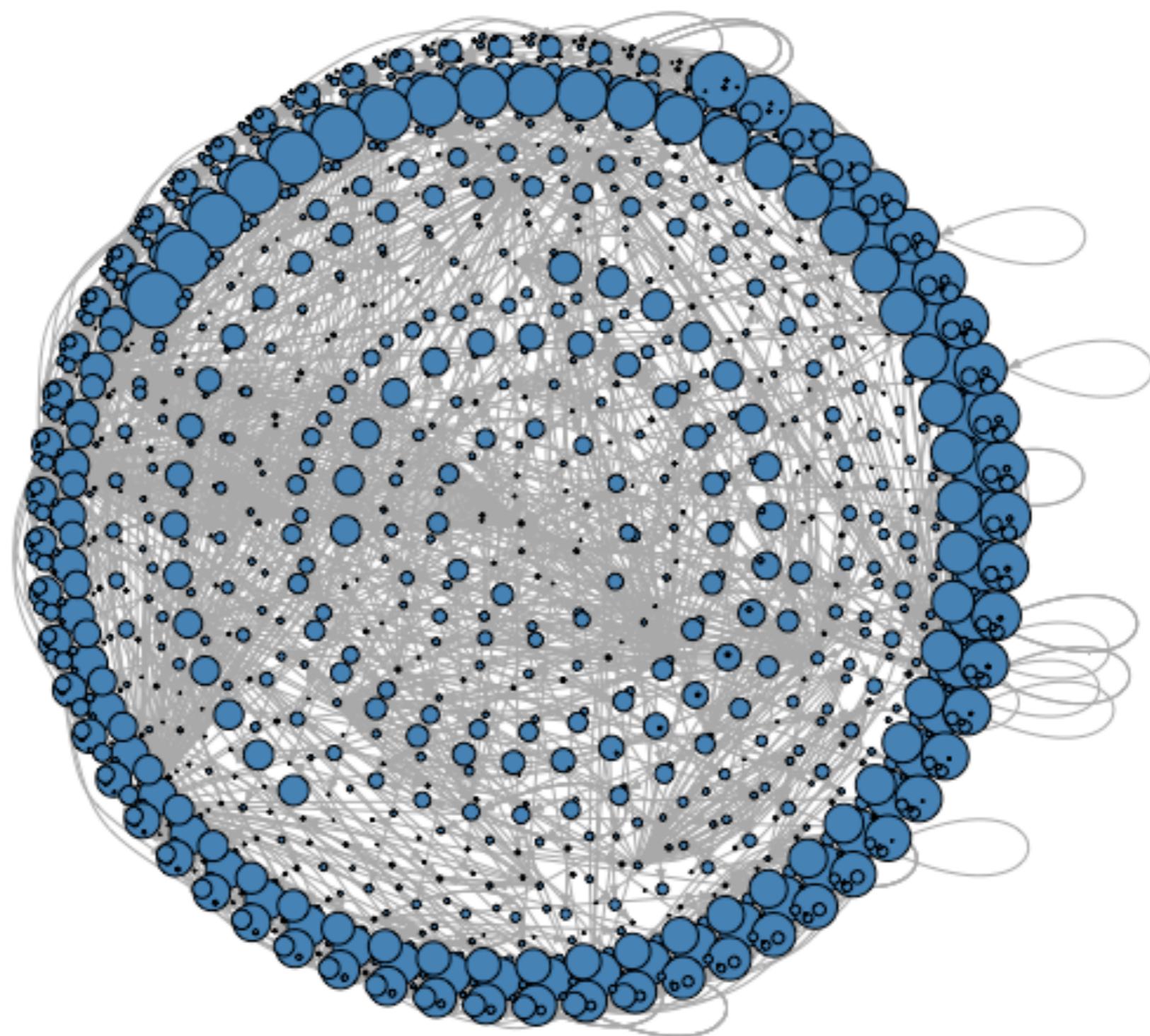
Self-Affine Resonance

Mannigfaltigkeit der unmittelbaren (Sinnes-) Erlebnisse"
-Einstein (1954)



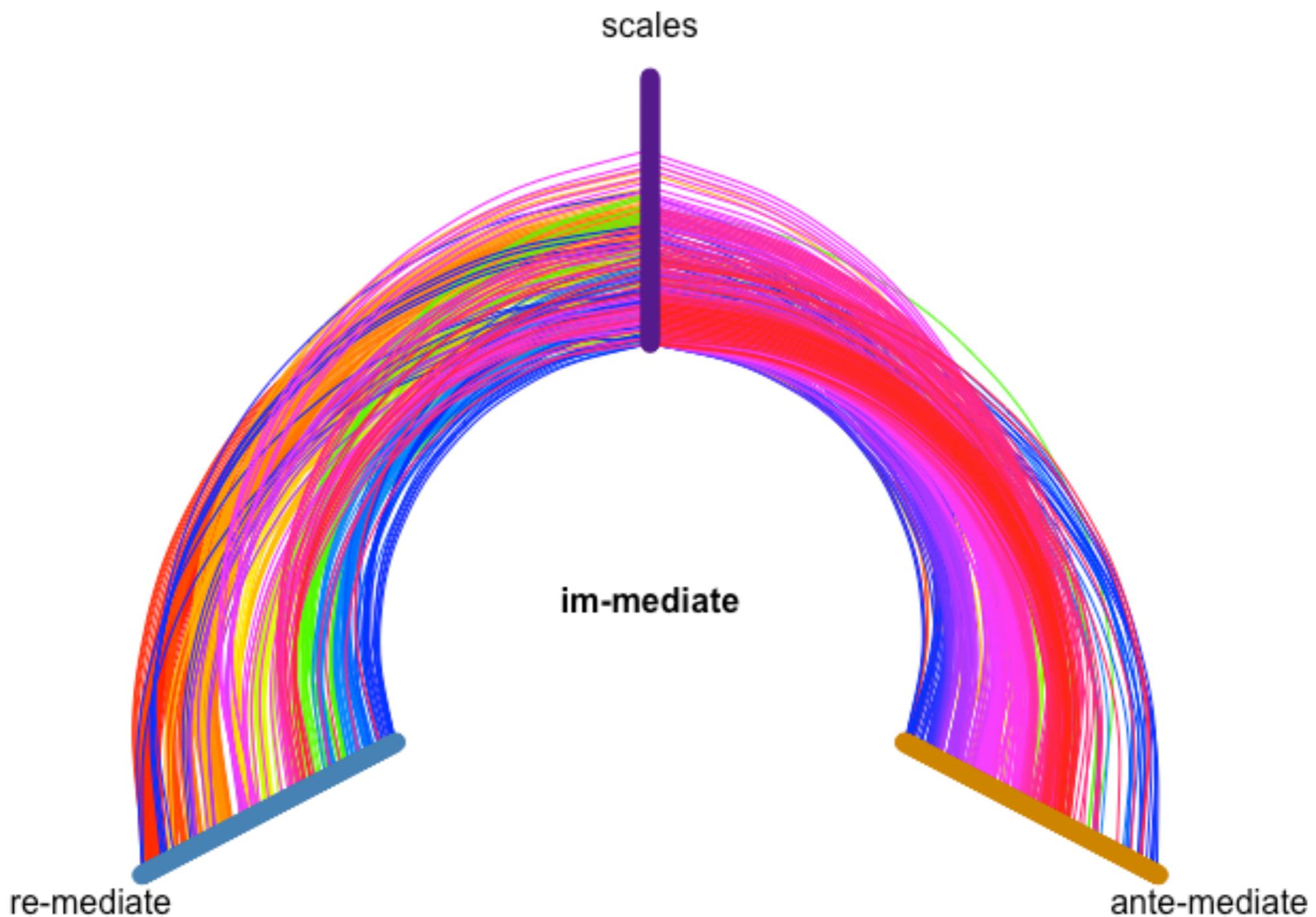
Self-Affine Resonance

Network - Singularity Skeleton



Self-Affine Resonance

Network - Singularity Skeleton

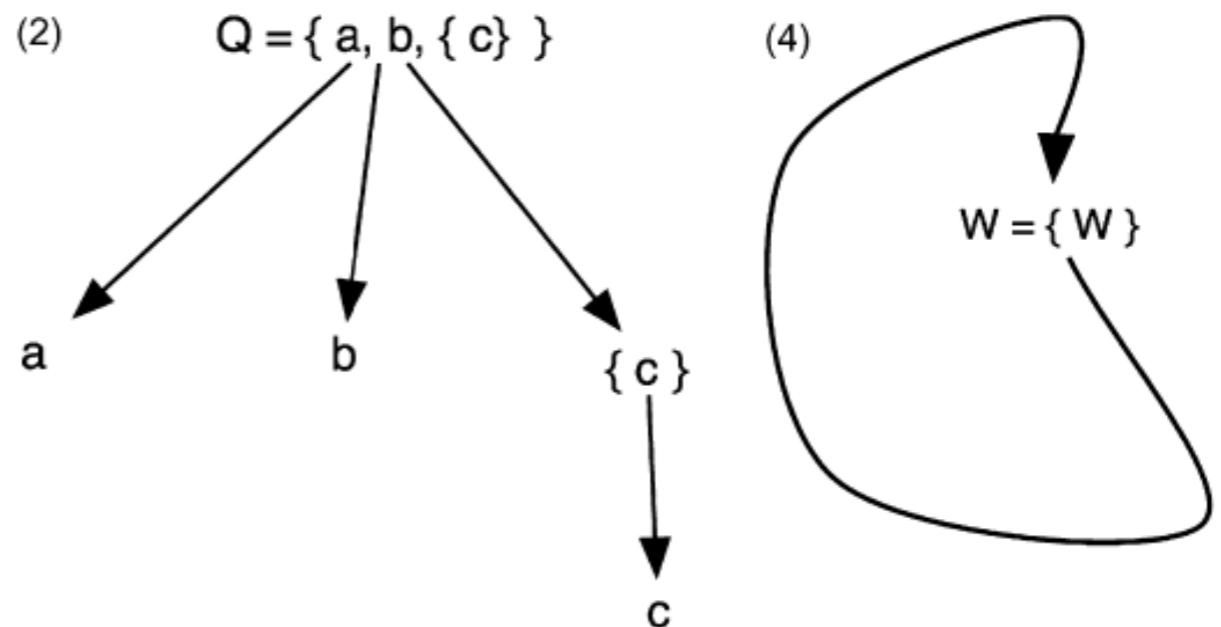
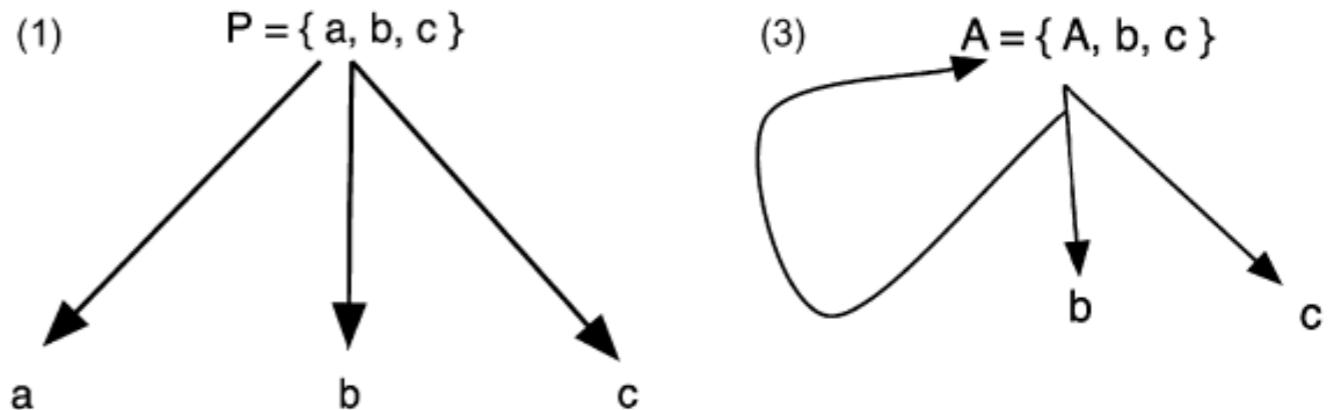


reproduction of similarity by analogy

Complex structure: Hyperset theory + Graph theory = Hyperset Graphs

A. Chemero, M.T. Turvey / BioSystems 91 (2008) 320–330

Aczel's Anti-Foundation Axiom (1988)
(hyperset theory, circular causality, complexity analysis)



Non well-founded sets:
The definition of a set
contains the set itself



Complex structure: Hyperset theory + Graph theory = Hyperset Graphs

Rosen's
definition of
a living
system

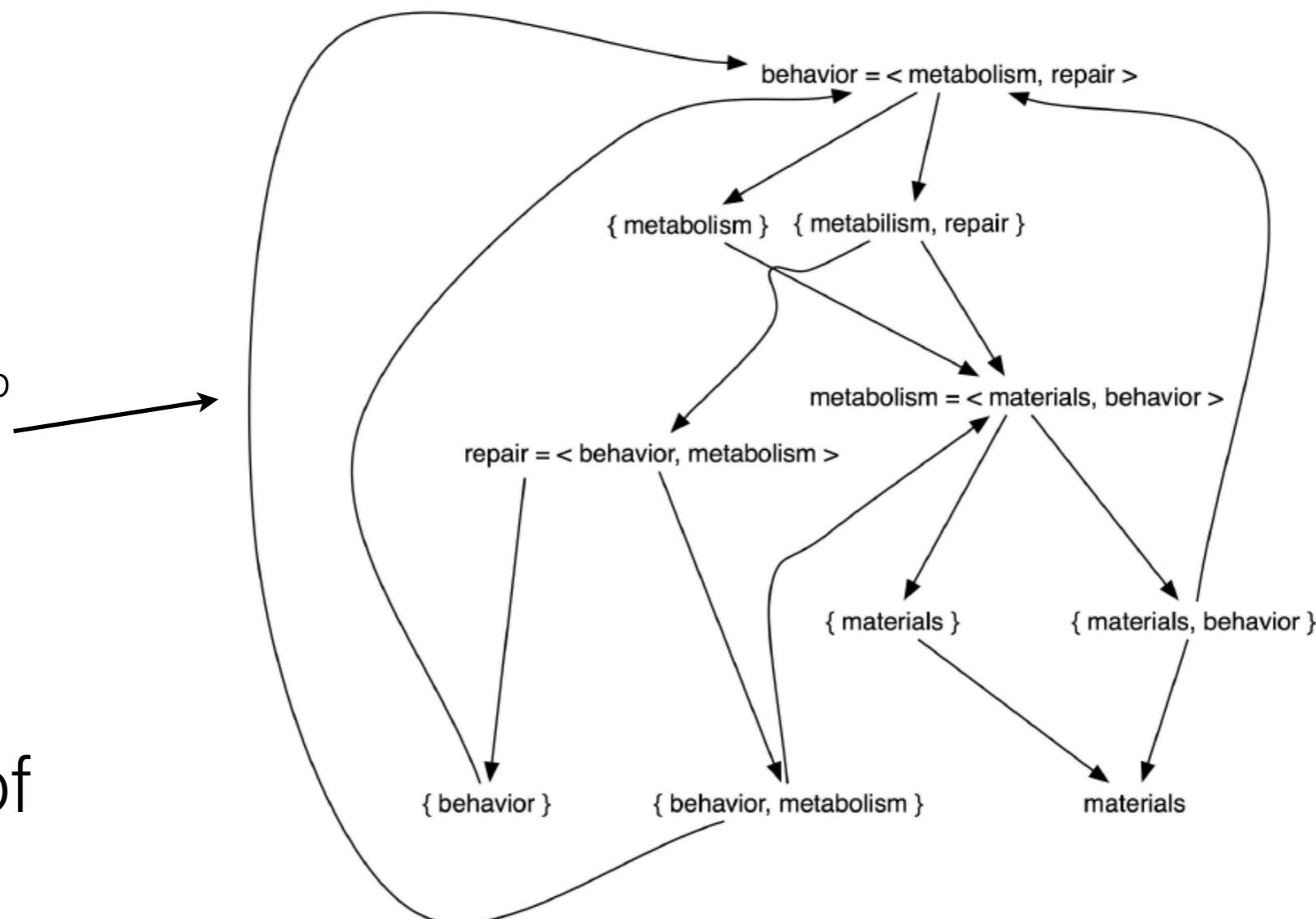


Fig. 6. Hyperset diagram of Rosen's metabolism-repair system. Functions are represented as ordered pairs containing their domain and range. So $f(a) = b$ is represented as $f = \langle a, b \rangle$.

Complex networks: Do our current models suffice?

Neural network models:

Energy/potential functions for end-states

Recurrent networks

$$\xi_i := \text{sign}(\sum_j w_{ij} \xi_j) \quad H = -\frac{1}{2} \sum_{ij} w_{ij} S_i S_j$$

$$\Rightarrow w_{ij} \propto \xi_i \xi_j$$

Self-organizing maps

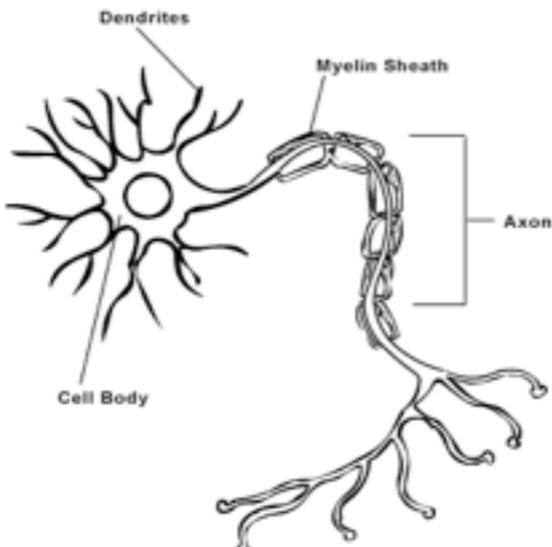
Two-neuron models:
adaptive resonance

Continuous single-neuron models:
dynamic field theory

Ising-spin models:
global, local and external
forces

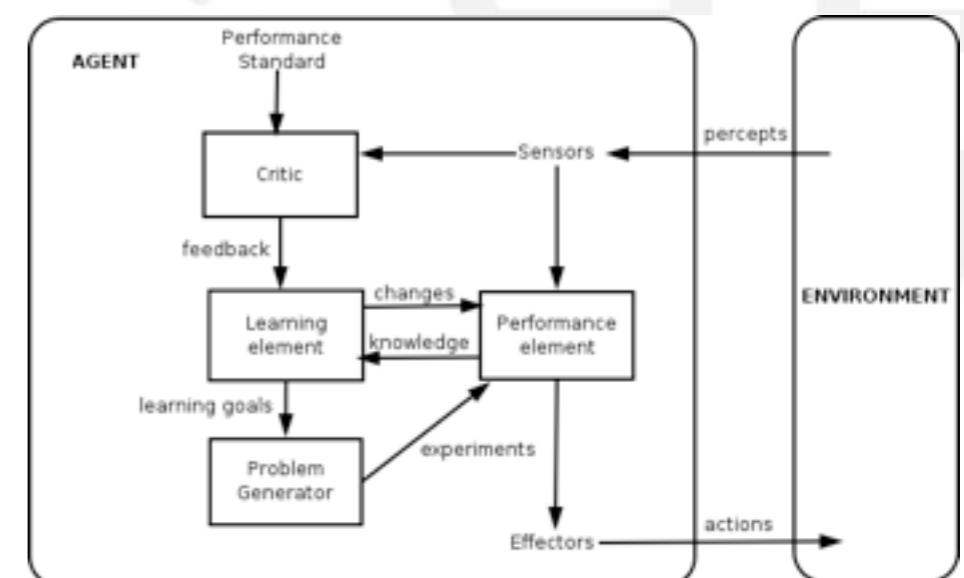
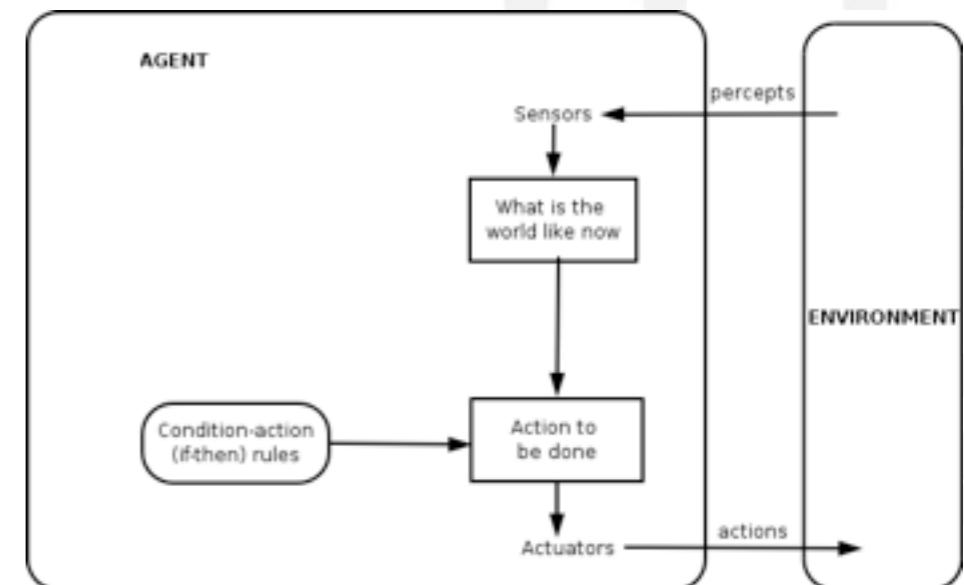
$$H_i = -\frac{J}{2} \sum_{\text{neighbor atoms}} S_i S_{\text{neighbor}}$$

$$I_i = \sqrt{\sum_j^N \left(\frac{S_j}{d_{ij}} \right)^2}$$



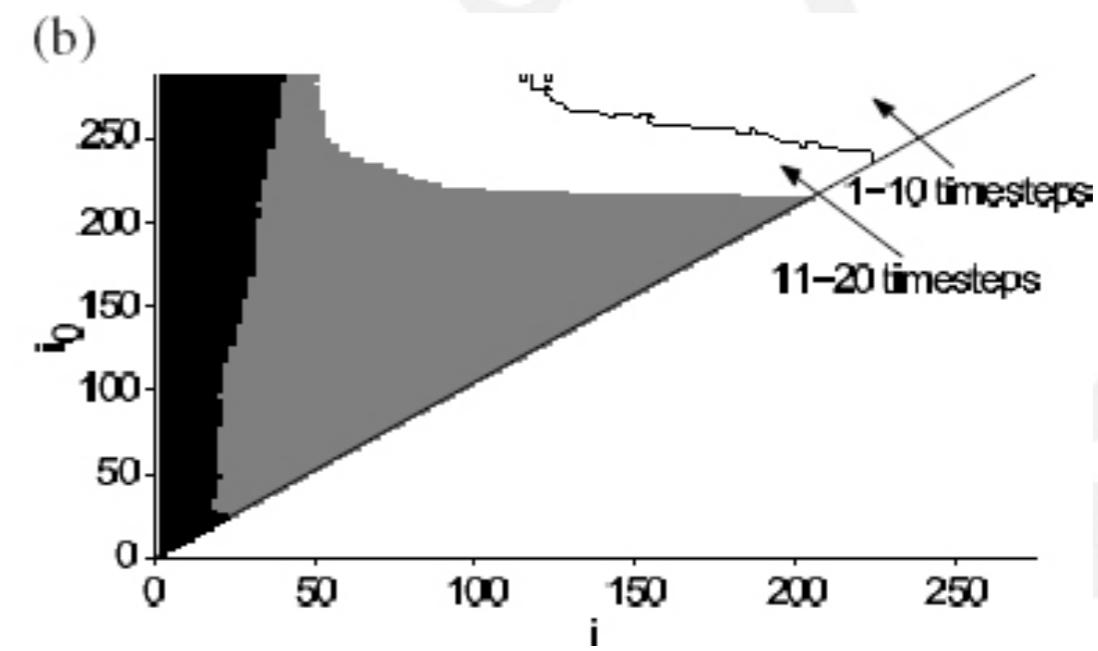
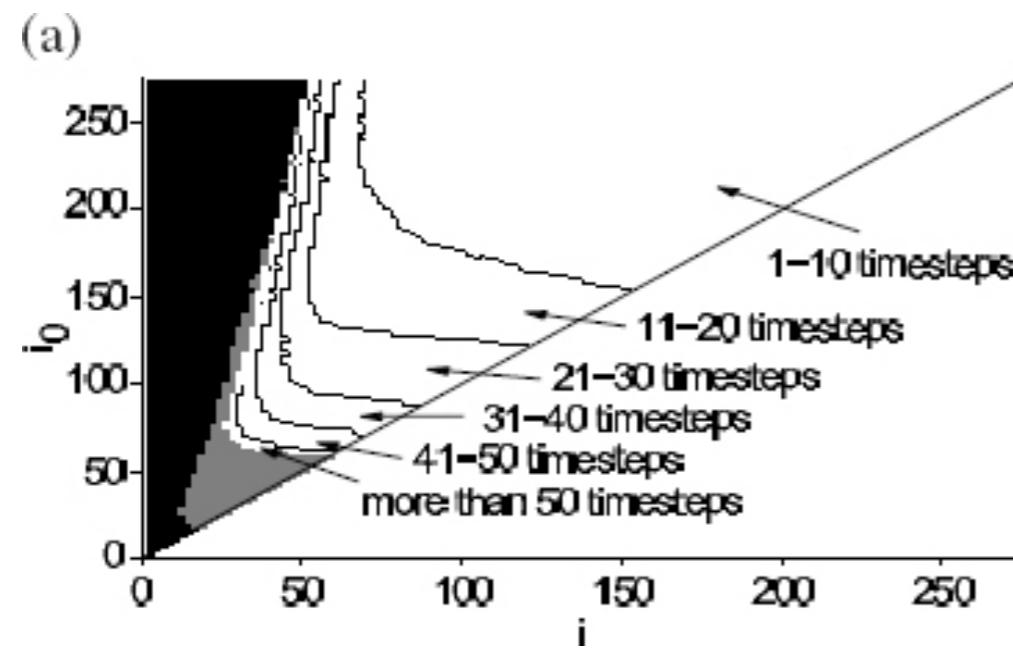
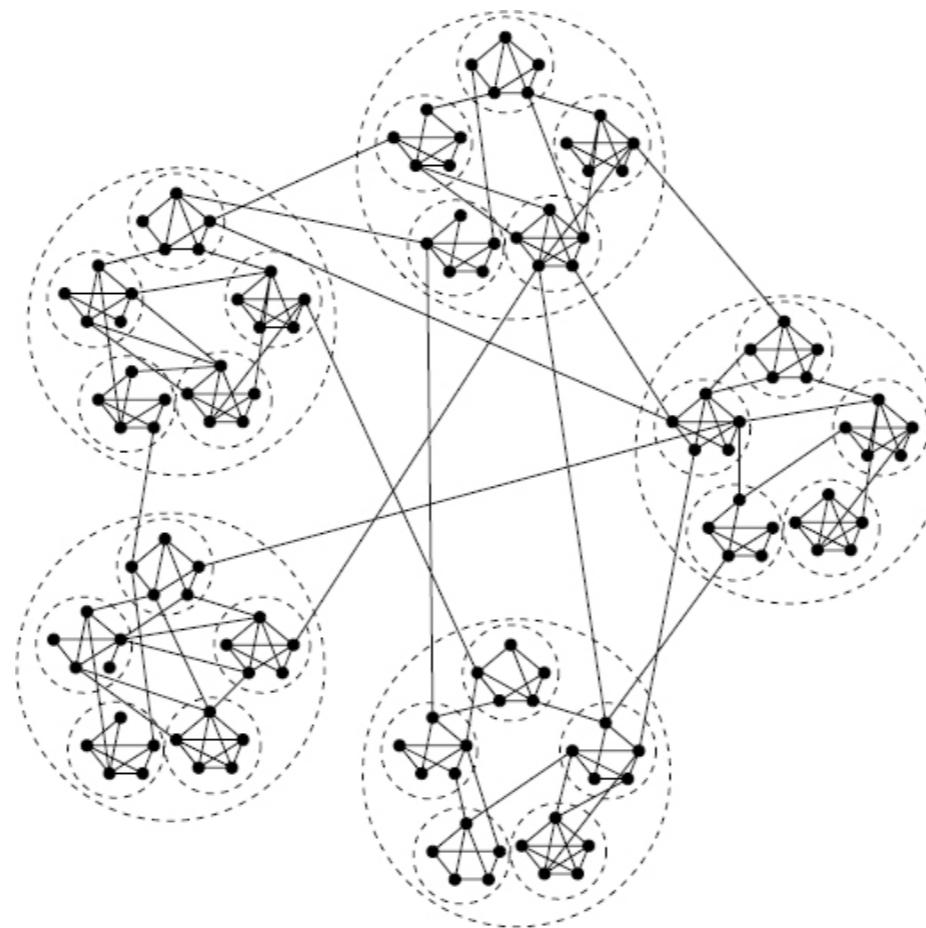
$$\tau \dot{u}(x, t) = -u(x, t) + I(x, t) + g_{\text{intra-field}}[u(x'); x'] + h + q\xi(x, t)$$

Agent-based models

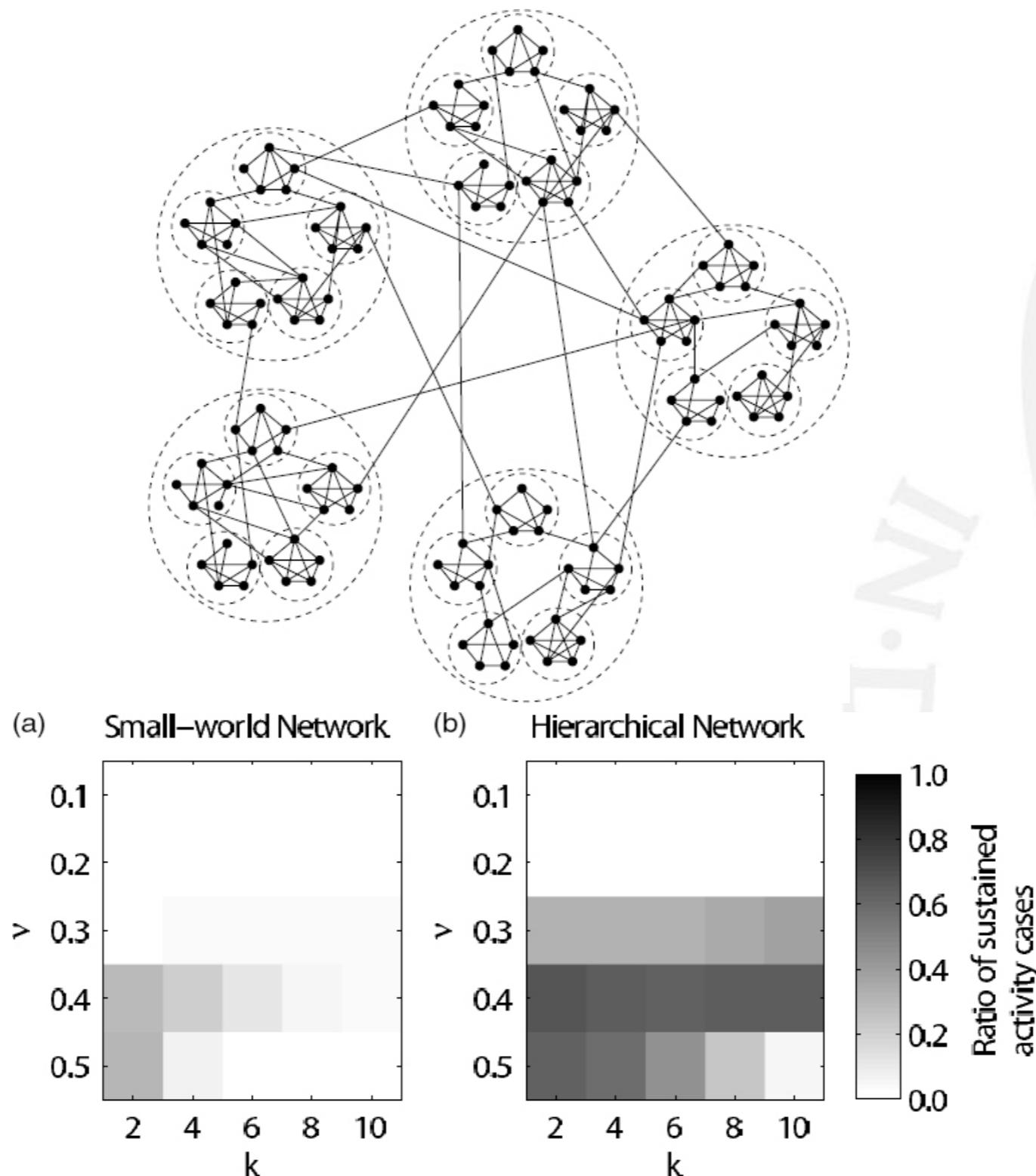


Evolving agent-based models

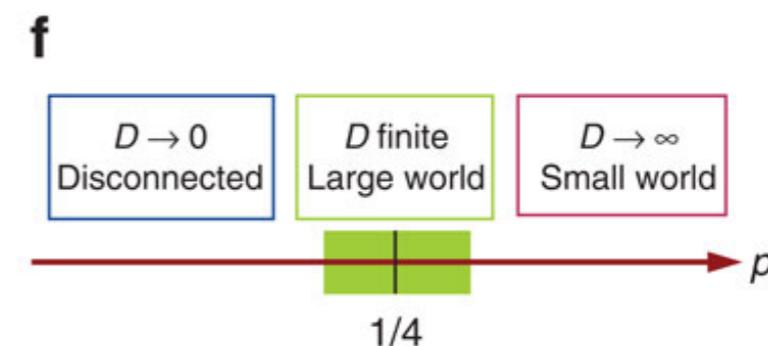
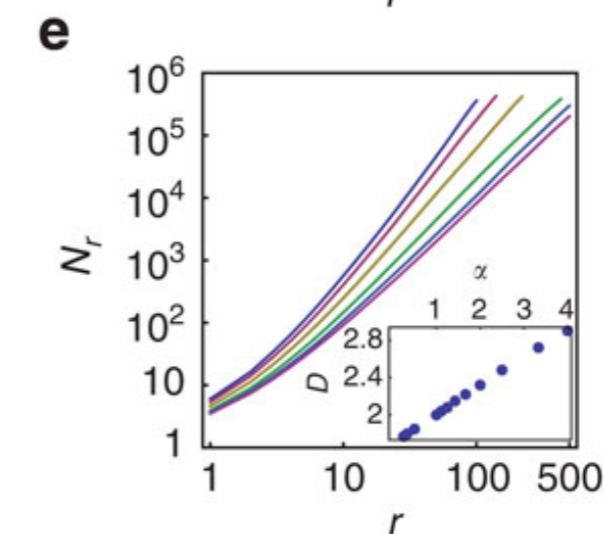
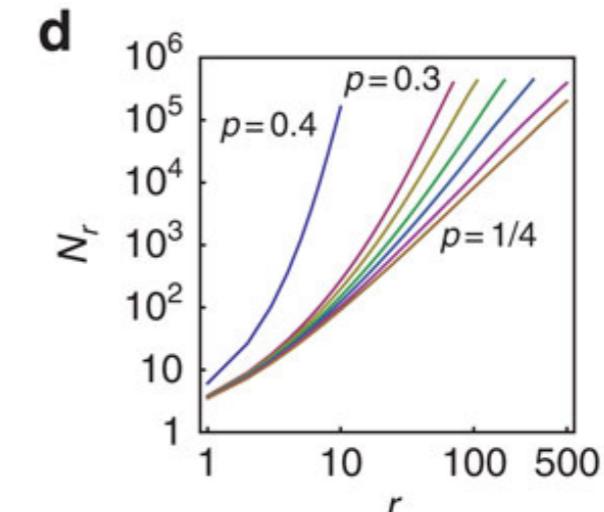
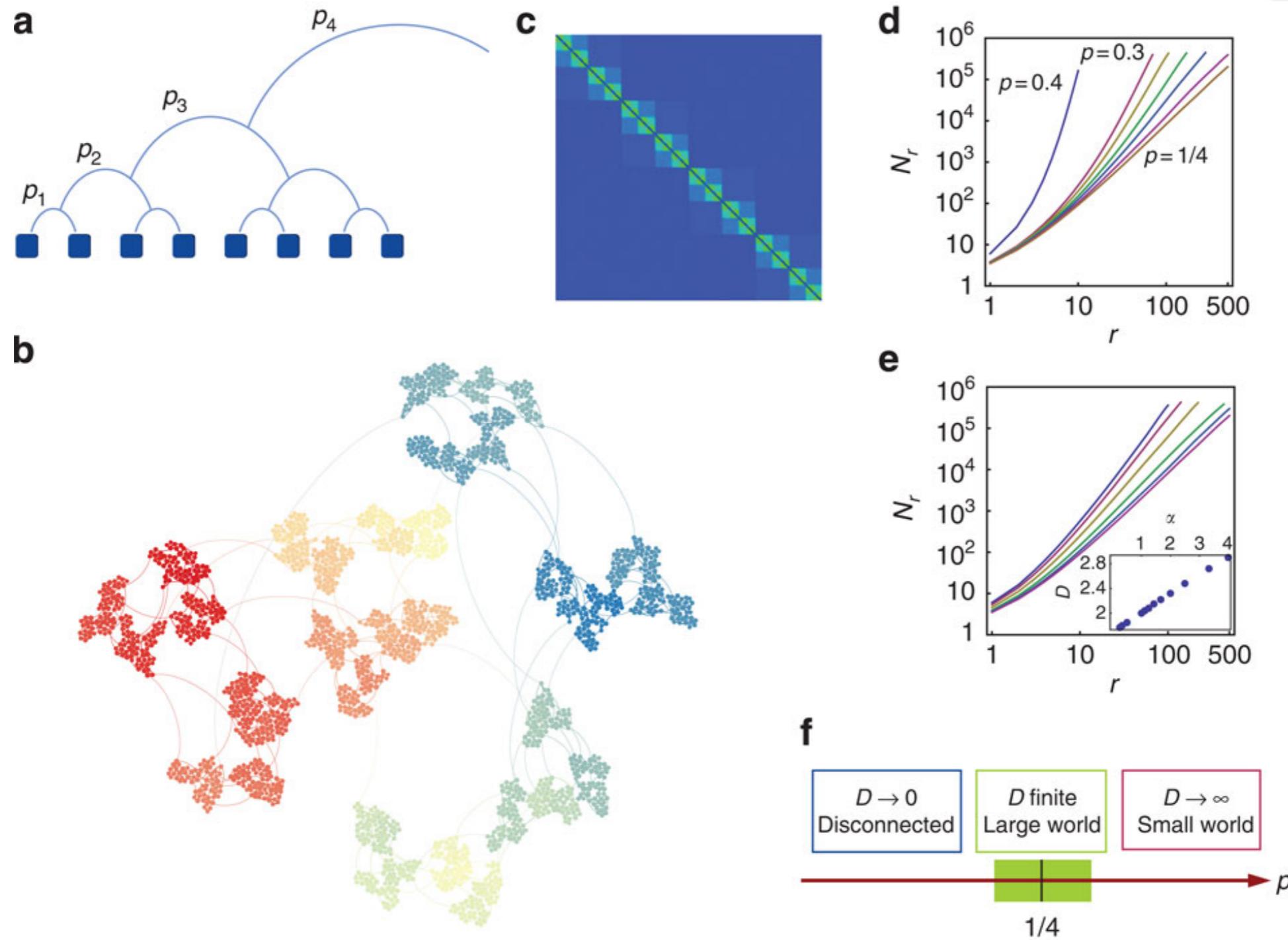
Extended (stretched) criticality = Hierarchical topology



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The wish list: Holism and Emergence

- **Composition principle:** How do parts of the system relate to wholes?

*“A physical theory is holistic if and only if it is **impossible in principle**, for a set of local agents each having access to a single subsystem only, to infer the global properties of a system as assigned in the theory (which can be inferred by global measurements), by using the resource basis available to the agents.” (Epistemological criterion - Seevinck, 2004).*

*“It was shown that all theories on a state space using a **Cartesian product** to combine subsystem state spaces, **such as classical physics and Bohmian mechanics, are not holistic** in both the supervenience and epistemological approach. The reason for this is that the Boolean algebra structure of the global properties is determined by the Boolean algebra structures of the local ones. **The orthodox interpretation of quantum mechanics, however, was found to instantiate holism.**” (Seevinck, 2004).*

- **Conjecture:** Only a holistic system can set the stage for strong emergent properties and patterns arising from dynamic interactions (e.g. time evolution of the system) - *Work in progress: same analysis for strong emergence*



Some additional evidence? No impredicative loops for the Lorenz system!

Our interpretation: system defined on a classical state space, cannot be a holistic system, hence no strong emergent patterns / properties!

(Hyper)set graphs of some physical systems and their numerical implementations

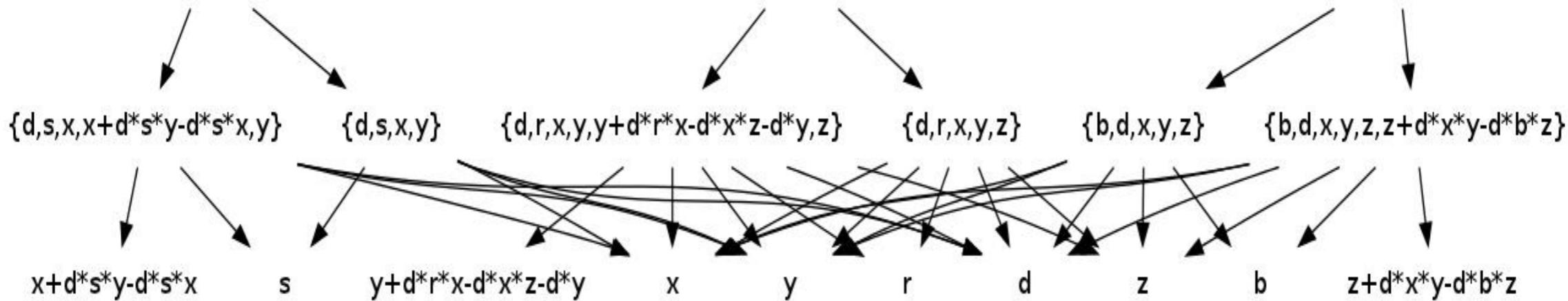
Dobromir G. Dotov, Nigel Stepp

Center for the Ecological Study of Perception and Action, University of Connecticut

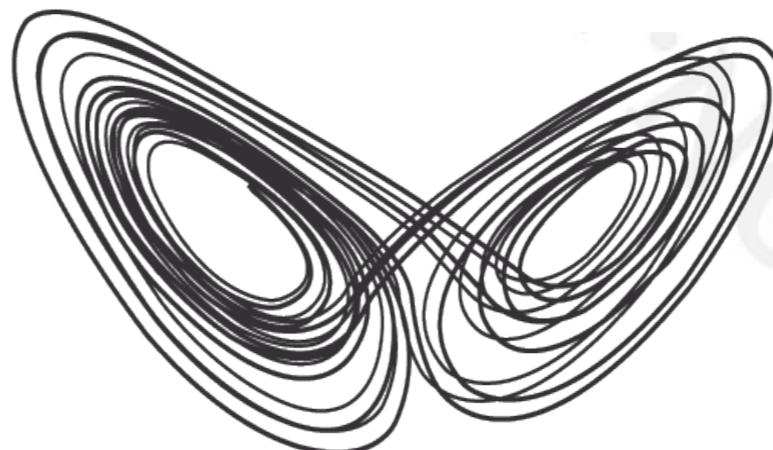
$$F_x = \{\{d, s, x, y\}, \{d, s, x, x + d*s*y - d*s*x, y\}\}$$

$$F_y = \{\{d, r, x, y, z\}, \{d, r, x, y, y + d*r*x - d*x*z - d*y, z\}\}$$

$$F_z = \{\{b, d, x, y, z\}, \{b, d, x, y, z, z + d*x*y - d*b*z\}\}$$



$$\begin{aligned} dx/dt &= \sigma(y - x) \\ dy/dt &= x(\rho - z) - y \\ dz/dt &= xy - \beta z \end{aligned}$$



“Life is a fractal in Hilbert space.”

- Rudy Rucker, 1987

Rucker, R. (1987). *Mind Tools: The Five Levels of Mathematical Reality*.
Boston : Houghton Mifflin.