Complexity Methods For Behavioural Science

Graph theory
Complex Networks
Symptom Networks

Networks of (Networks of) Complex Systems

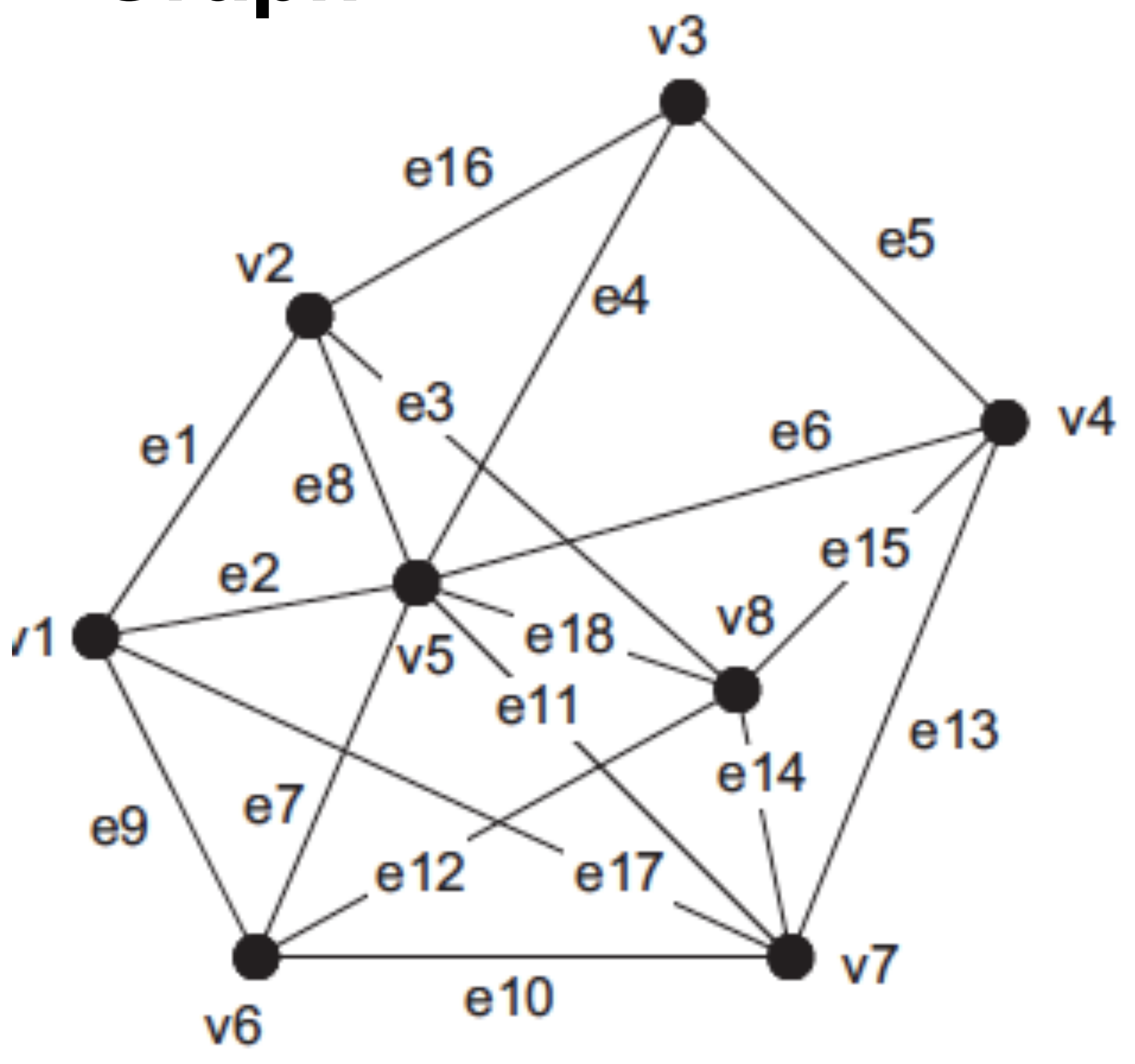
composition = topology

- Nodes (point, **vertex**)
- Connections between nodes (line, side, branch, arrow, **edge**)

Grafentheorie

- **Graph Theory:** Compositions of *edges* and *vertices*
- **Complexe network:** Many vertices and edges
- **Statistical netwerk models**

Graph



Formal

$$V(G) = \{v_1, \ldots, v_8\}$$
$$E(G) = \{e_1, \ldots, e_{18}\}$$

$$\begin{array}{ll}
e_1 = \langle v_1, v_2 \rangle & e_{10} = \langle v_6, v_7 \rangle \\
e_2 = \langle v_1, v_5 \rangle & e_{11} = \langle v_5, v_7 \rangle \\
e_3 = \langle v_2, v_8 \rangle & e_{12} = \langle v_6, v_8 \rangle \\
e_4 = \langle v_3, v_5 \rangle & e_{13} = \langle v_4, v_7 \rangle \\
e_5 = \langle v_3, v_4 \rangle & e_{14} = \langle v_7, v_8 \rangle \\
e_6 = \langle v_4, v_5 \rangle & e_{15} = \langle v_4, v_8 \rangle \\
e_7 = \langle v_5, v_6 \rangle & e_{16} = \langle v_2, v_3 \rangle \\
e_8 = \langle v_2, v_5 \rangle & e_{17} = \langle v_1, v_7 \rangle \\
e_9 = \langle v_1, v_6 \rangle & e_{18} = \langle v_5, v_8 \rangle
\end{array}$$

Figure 2.1: An example of a graph with eight vertices and 18 edges.

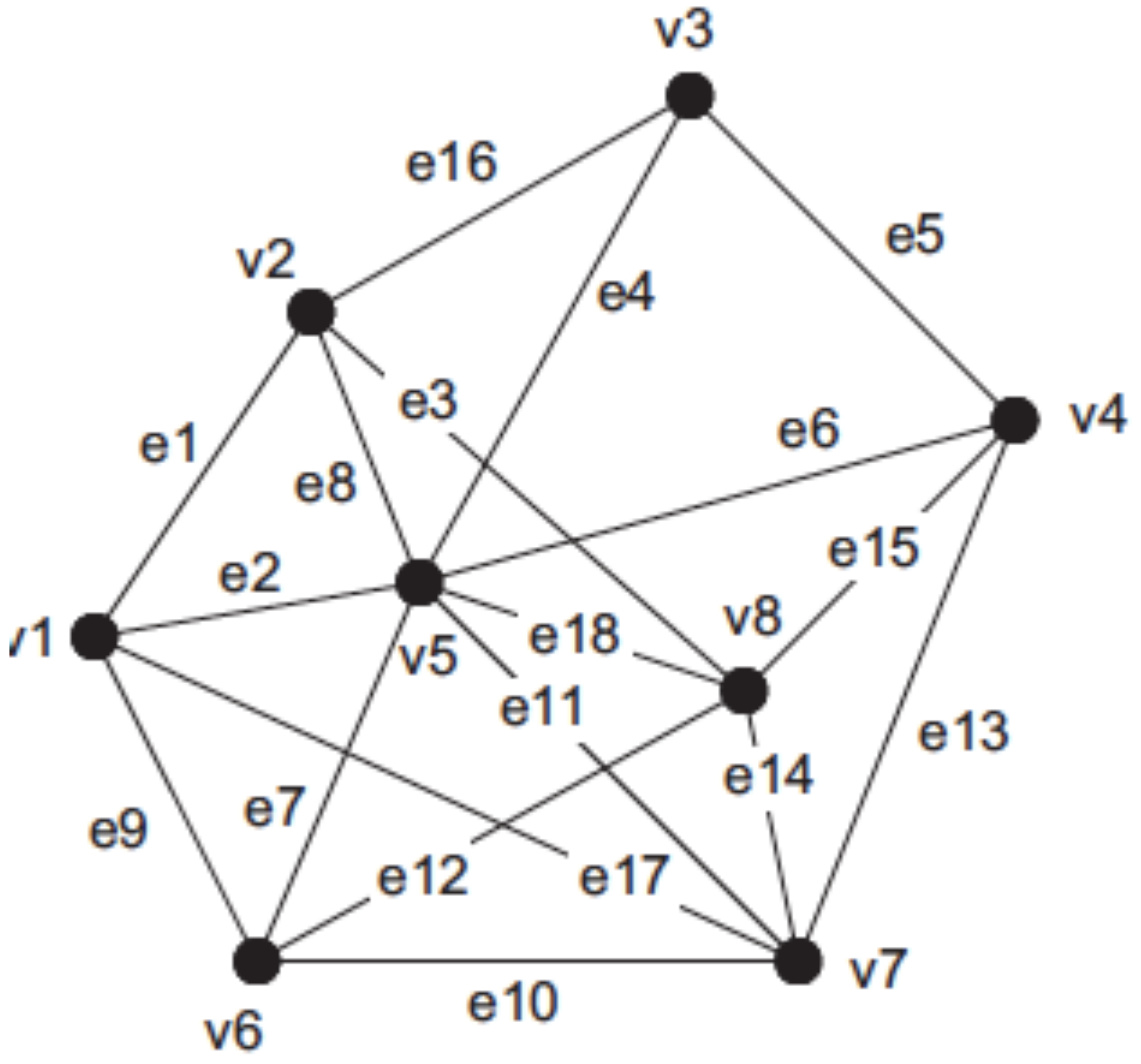
Adjacency matrix

	v1	v2	v3	v4	v5	v6	v7	v8
v1	0	1	0	0	1	1	1	0
v2	1	0	1	0	1	0	0	1
v3	0	1	0	1	1	0	0	0
v4	0	0	1	0	1	0	1	1
v5	1	1	1	1	0	1	1	1
v6	1	0	0	0	1	0	1	1
v7	1	0	0	1	1	1	0	1
v8	0	1	0	1	1	1	1	0

van Steen, M. (2010). Graph Theory and Complex Networks. An Introduction. Retrieved from: http://www.distributed-systems.net/

Graph theory

undirected graph



$$V(G) = \{v_1, \dots, v_8\}$$
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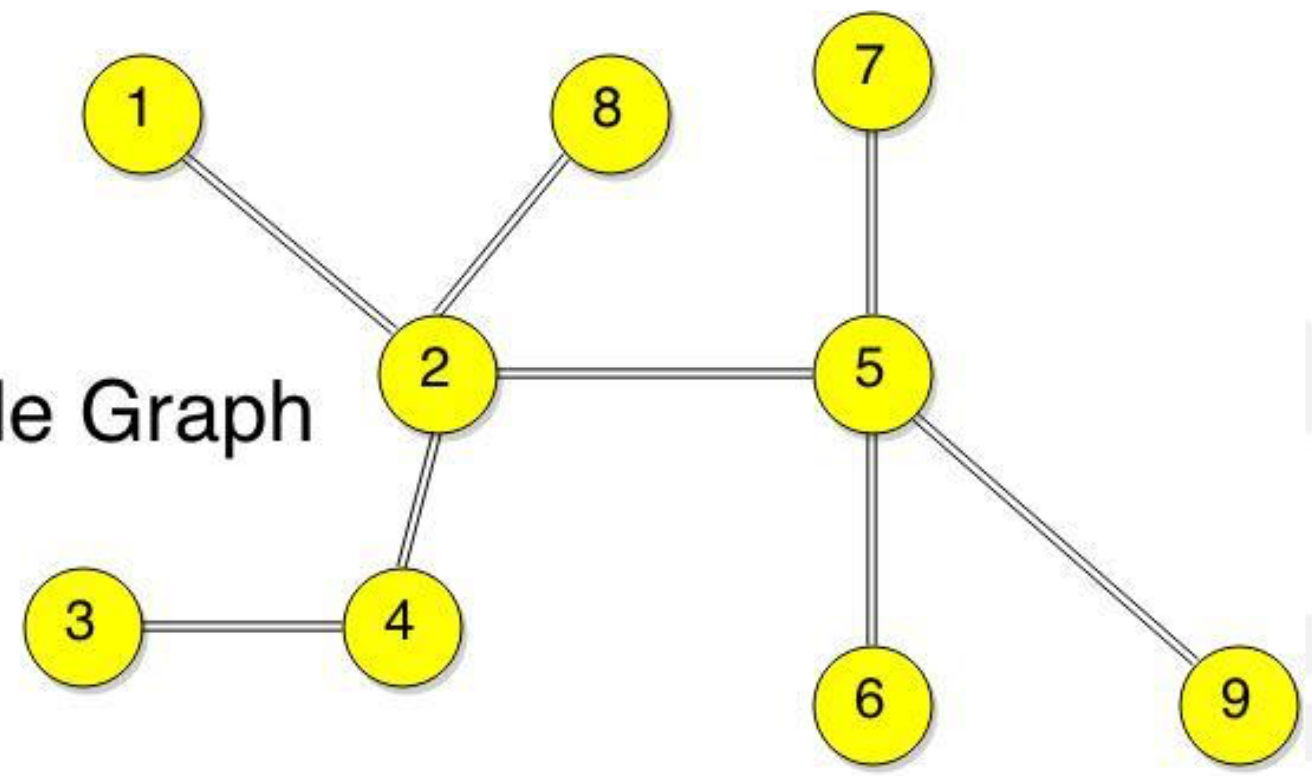
e_2 = \langle v_1, v_5 \rangle & e_{11} = \langle v_5, v_7 \rangle \\
e_3 = \langle v_2, v_8 \rangle & e_{12} = \langle v_6, v_8 \rangle \\
e_4 = \langle v_3, v_5 \rangle & e_{13} = \langle v_4, v_7 \rangle \\
e_5 = \langle v_3, v_4 \rangle & e_{14} = \langle v_7, v_8 \rangle \\
e_6 = \langle v_4, v_5 \rangle & e_{15} = \langle v_4, v_8 \rangle \\
e_7 = \langle v_5, v_6 \rangle & e_{16} = \langle v_2, v_3 \rangle \\
e_8 = \langle v_2, v_5 \rangle & e_{17} = \langle v_1, v_7 \rangle \\
e_9 = \langle v_1, v_6 \rangle & e_{18} = \langle v_5, v_8 \rangle
\end{array}$$

Figure 2.1: An example of a graph with eight vertices and 18 edges.

Simple Graph



Adjacency Matrix

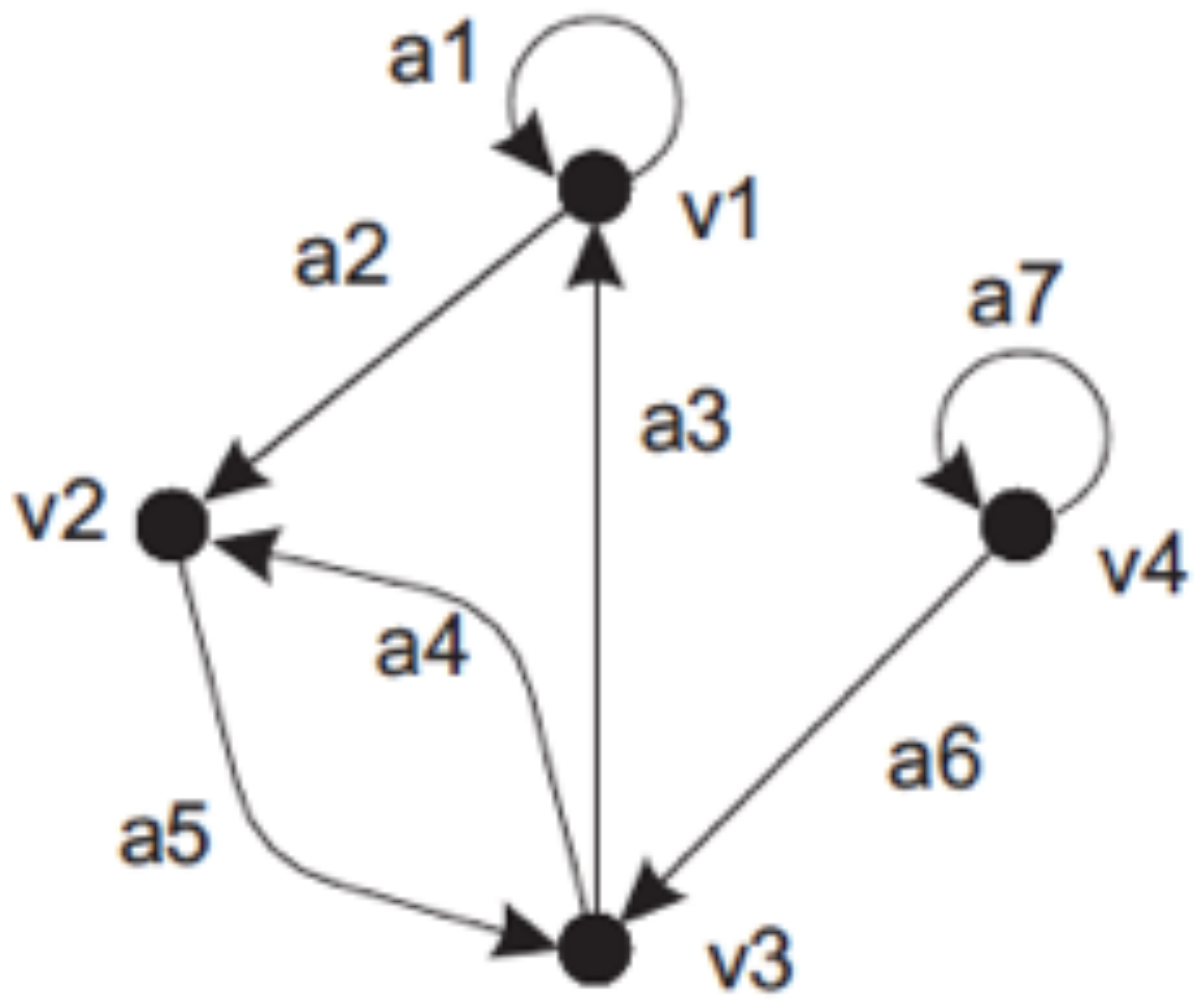
	Vertex 1	Vertex 2	Vertex 3	Vertex 4	Vertex 5	Vertex 6	Vertex 7	Vertex 8	Vertex 9
Vertex 1	0	1	0	0	0	0	0	0	0
Vertex 2	1	0	0	1	1	0	0	1	0
Vertex 3	0	0	0	1	0	0	0	0	0
Vertex 4	0	1	1	0	0	0	0	0	0
Vertex 5	0	1	0	0	0	1	1	0	1
Vertex 6	0	0	0	0	1	0	0	0	0
Vertex 7	0	0	0	0	1	0	0	0	0
Vertex 8	0	1	0	0	0	0	0	0	0
Vertex 9	0	0	0	0	1	0	0	0	0

http://theoryofprogramming.com/tag/adjacency-matrix/

van Steen, M. (2010). Graph Theory and Complex Networks. An Introduction. Retrieved from: http://www.distributed-systems.net/

Graph theory

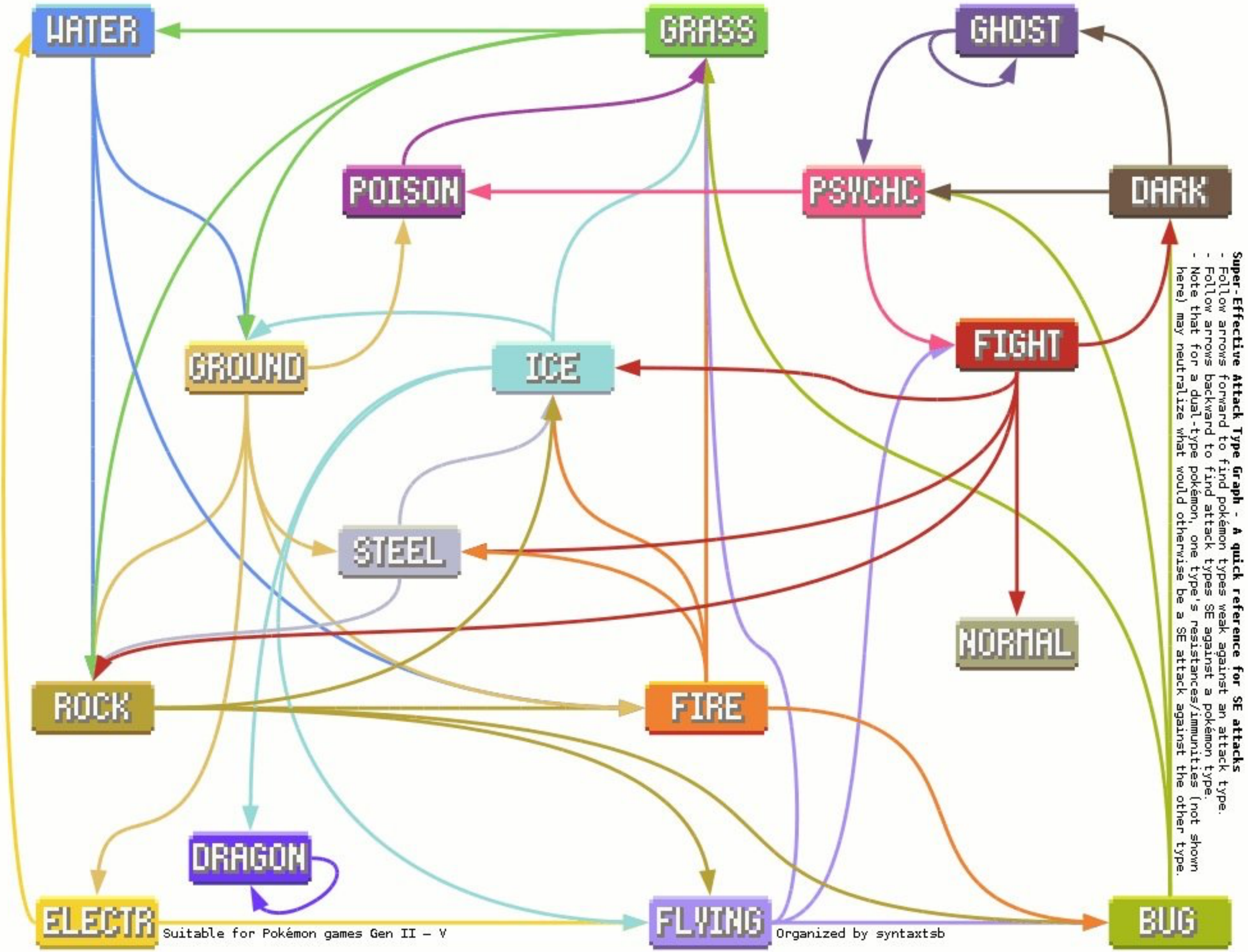
directed graph (digraph)



With *loops* en *arcs*

	v_1	v_2	v_3	v_4	OUT $\sum$
v_1	1	1	0	0	2
v_2	0	0	1	0	1
v_3	1	1	0	0	2
v_4	0	0	1	1	2
IN $\sum$	2	2	2	1	7

van Steen, M. (2010). Graph Theory and Complex Networks. An Introduction. Retrieved from: http://www.distributed-systems.net/



directed network

Effectivity of
Pokemon attacks
By species

Graph theory

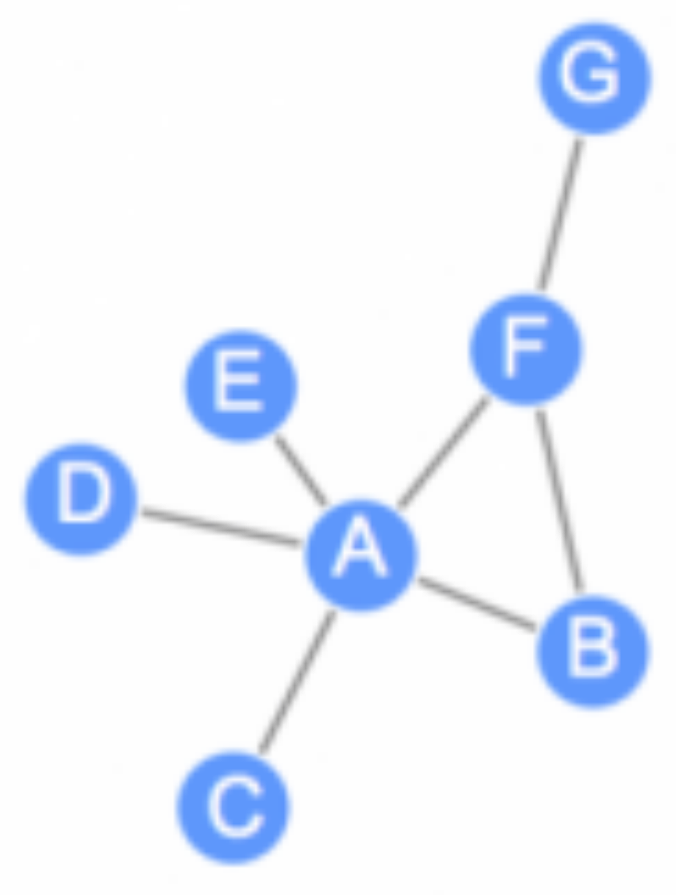
Degree:

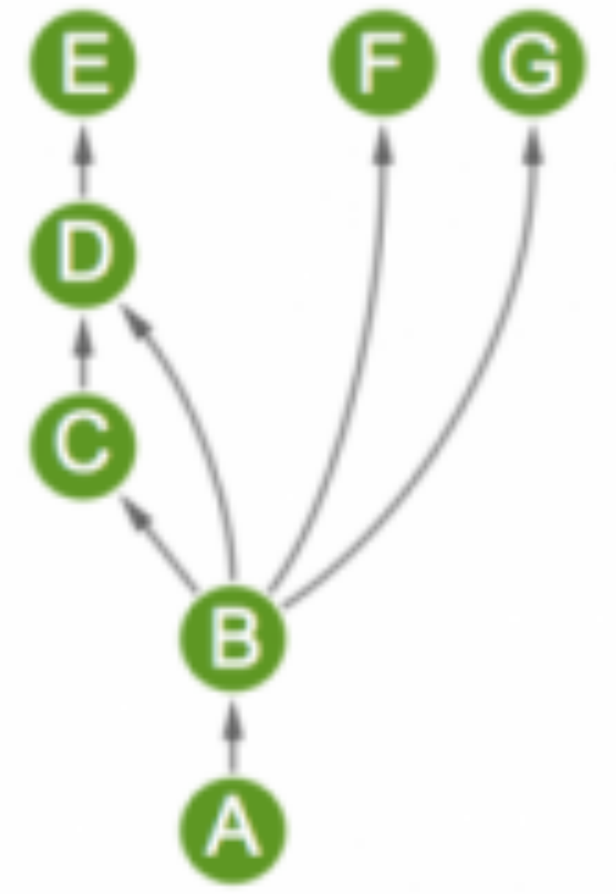
How many edges connect to a vertex/node

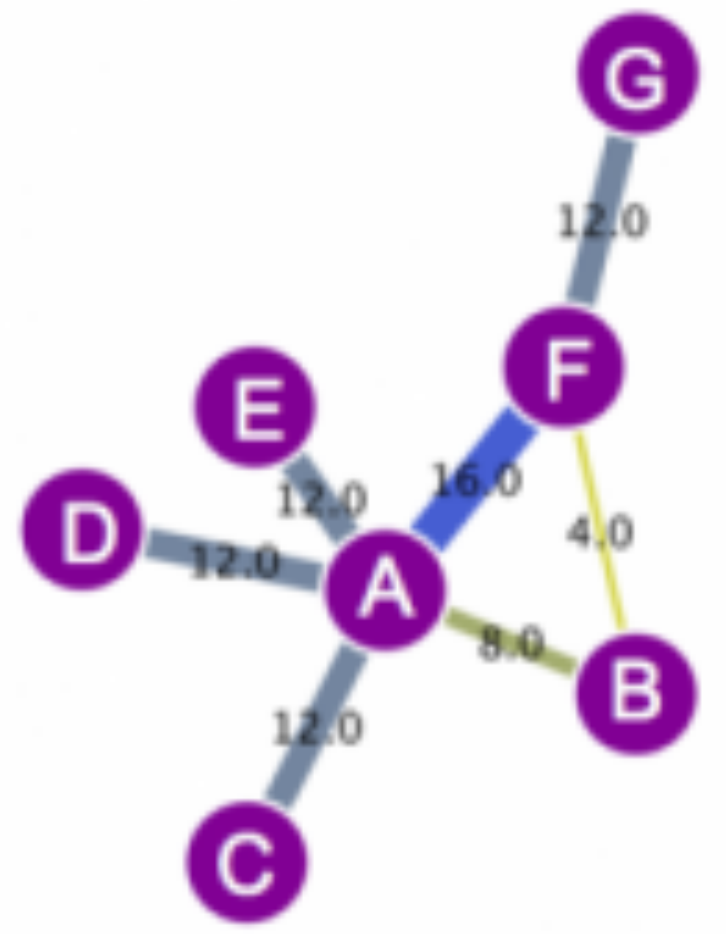
directed graphs:

in-degree, out-degree

Undirected	Directed	Weighted







	A	B	C	D	E	F	G	Degree
A	0	1	1	1	1	1	0	5
B	1	0	0	0	0	1	0	2
C	1	0	0	0	0	0	0	1
D	1	0	0	0	0	0	0	1
E	1	0	0	0	0	0	0	1
F	1	1	0	0	0	0	1	3
G	0	0	0	0	0	1	0	1

Adjacency matrices

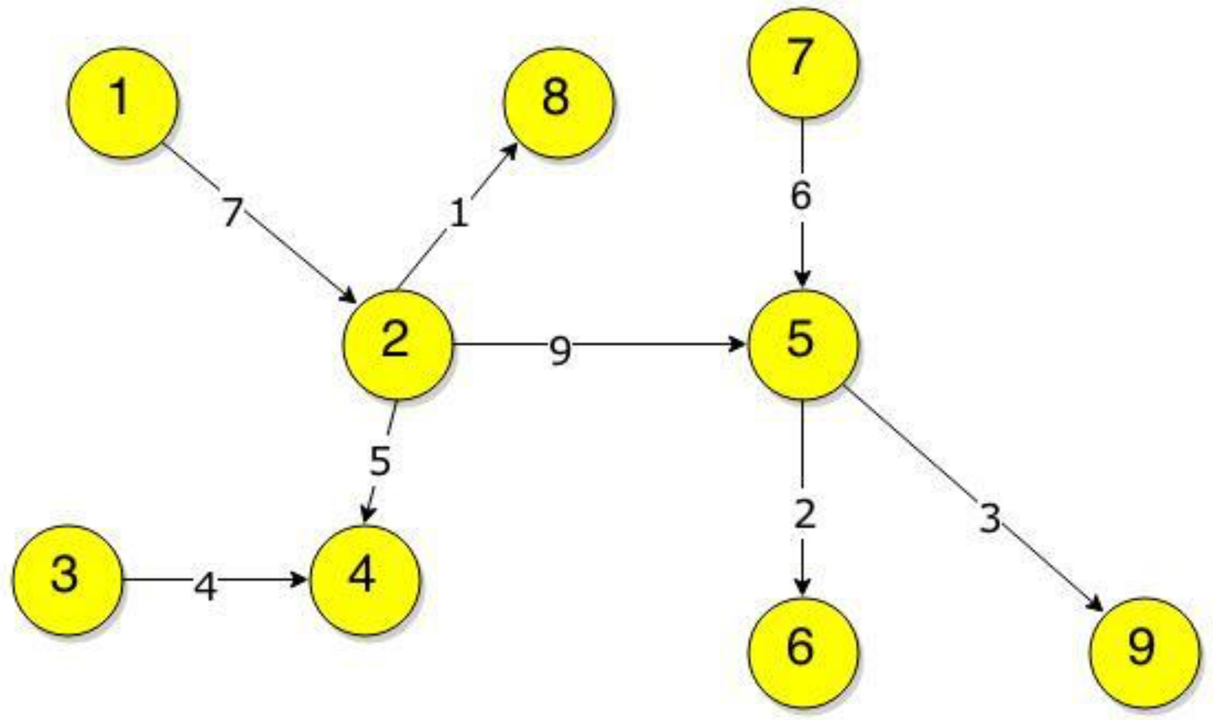
	A	B	C	D	E	F	G	Out-degree
A	0	1	0	0	0	0	0	1
B	0	0	1	1	0	1	1	4
C	0	0	0	1	0	0	0	1
D	0	0	0	0	1	0	0	1
E	0	0	0	0	0	0	0	0
F	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	0	0

	A	B	C	D	E	F	G	Degree
A	0	8	12	12	12	16	12	72
B	8	0	0	0	0	4	0	12
C	12	0	0	0	0	0	0	12
D	12	0	0	0	0	0	0	12
E	12	0	0	0	0	0	0	12
F	16	4	0	0	0	0	12	32
G	12	0	0	0	0	12	0	24

Graph theory

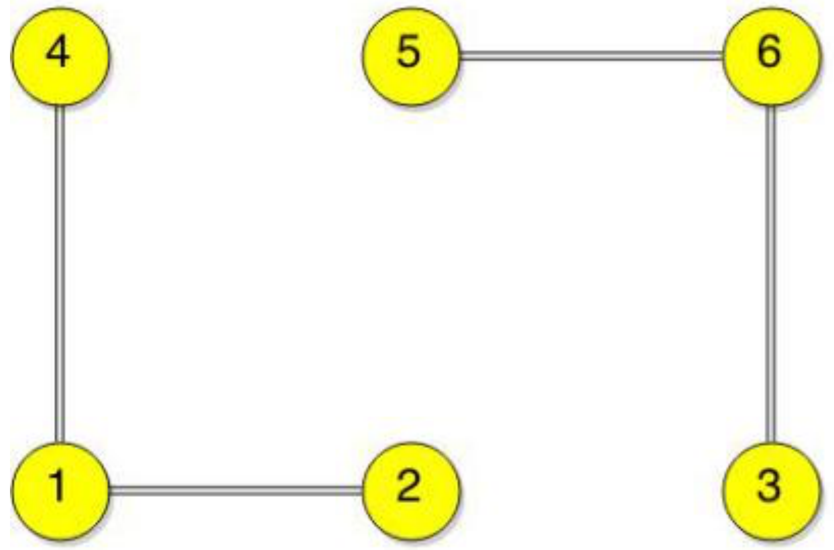
weighted directed graph

Weighted Directed Graph

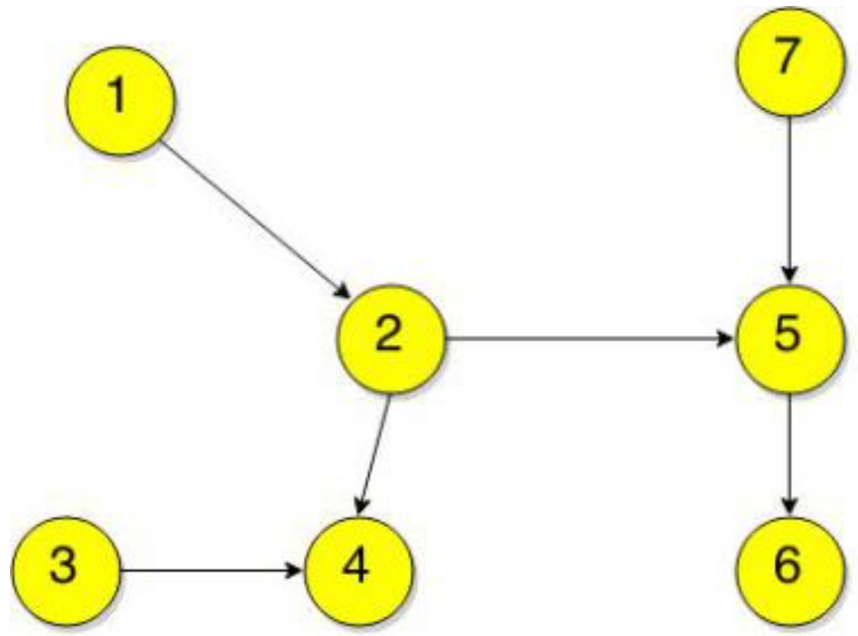


Adjacency Matrix

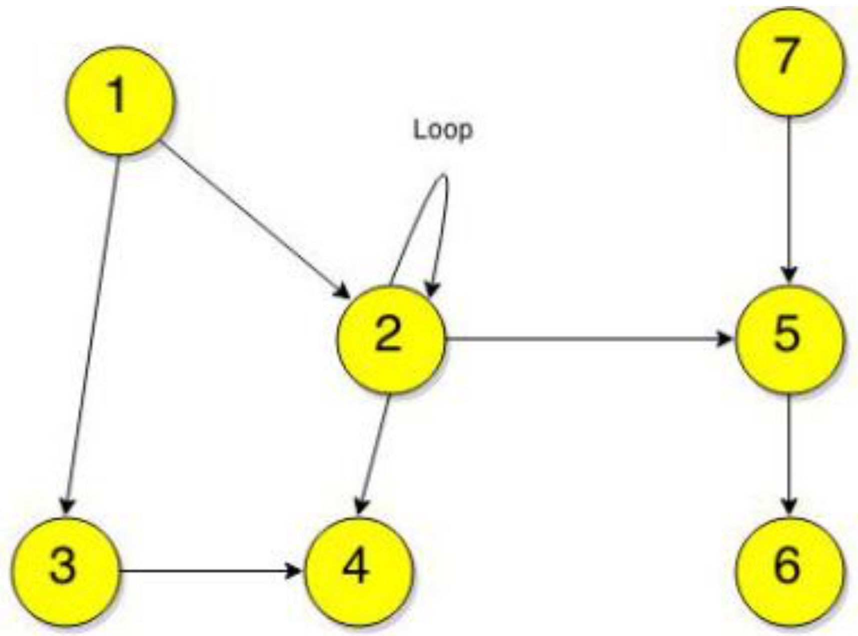
to	Vertex 1	Vertex 2	Vertex 3	Vertex 4	Vertex 5	Vertex 6	Vertex 7	Vertex 8	Vertex 9
Vertex 1	0	7	0	0	0	0	0	0	0
Vertex 2	0	0	0	5	9	0	0	1	0
Vertex 3	0	0	0	4	0	0	0	0	0
Vertex 4	0	0	0	0	0	0	0	0	0
Vertex 5	0	0	0	0	0	2	0	0	3
Vertex 6	0	0	0	0	0	0	0	0	0
Vertex 7	0	0	0	0	6	0	0	0	0
Vertex 8	0	0	0	0	0	0	0	0	0
Vertex 9	0	0	0	0	0	0	0	0	0



Disconnected Graph

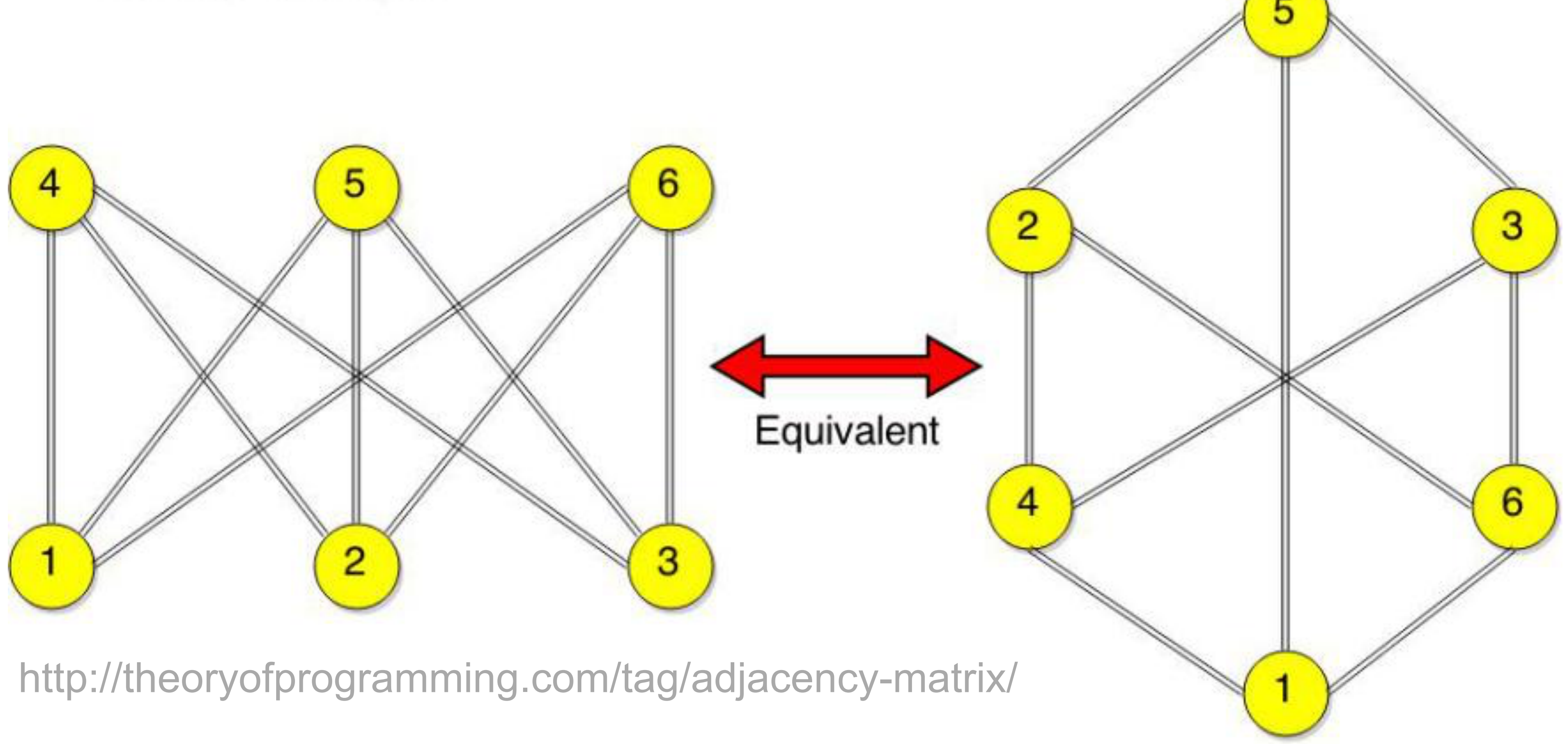


Simple Graph



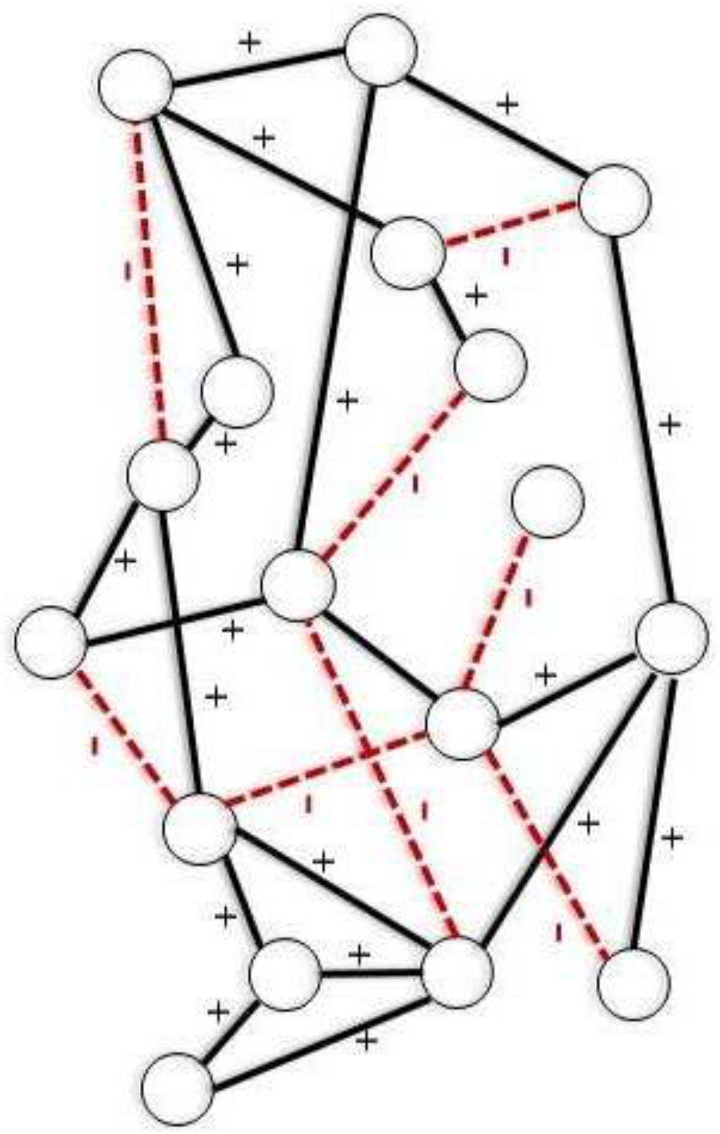
Non - Simple Graph

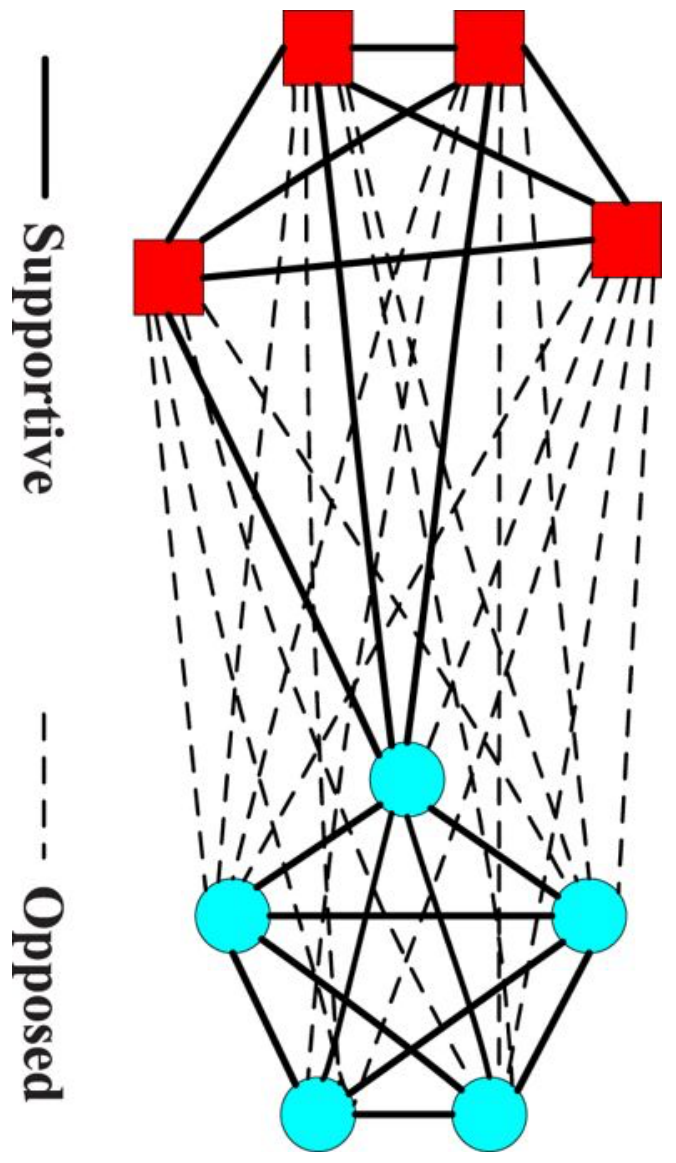
Isomorphic Graphs -



http://theoryofprogramming.com/tag/adjacency-matrix/

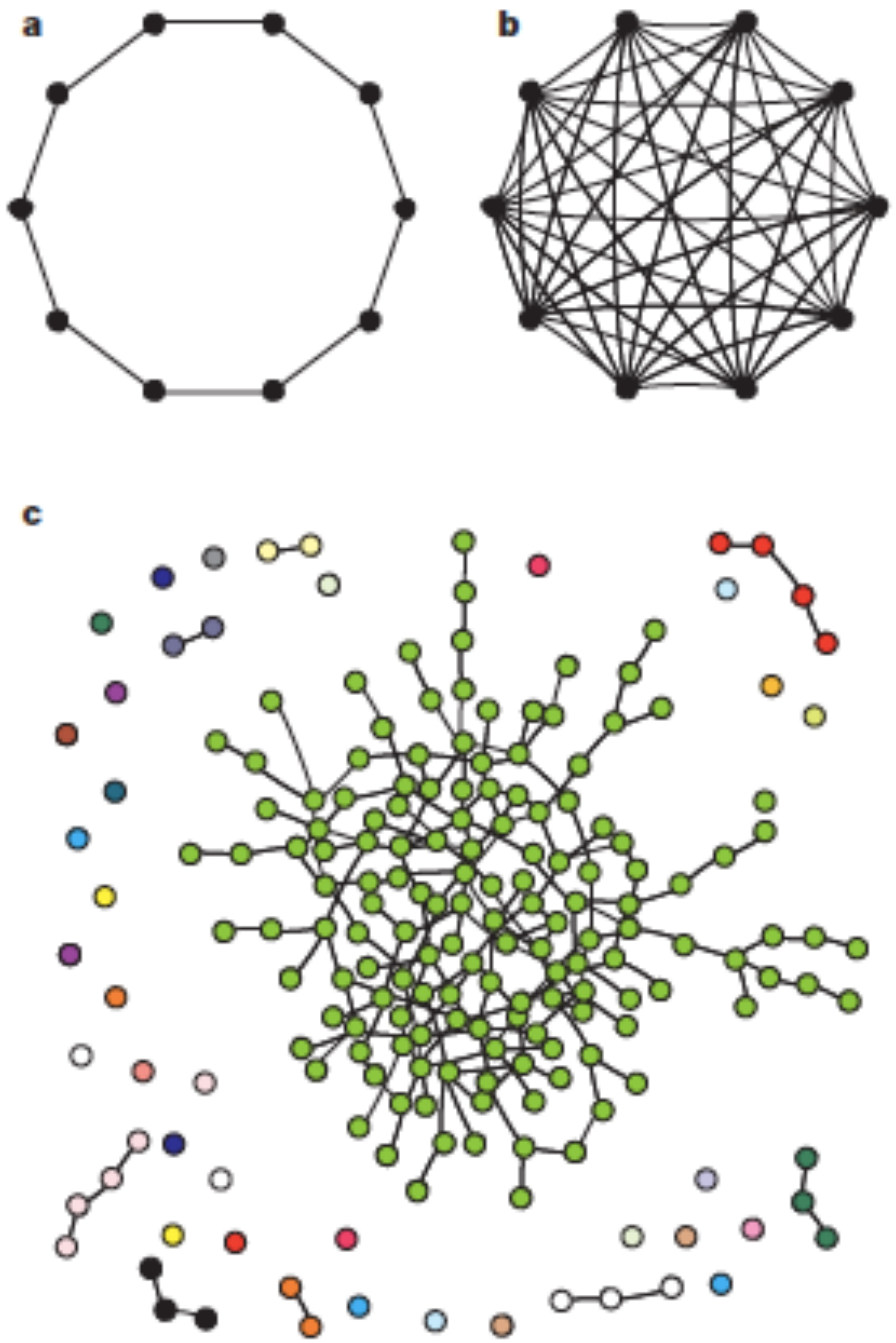
signed graphs





nearest neighbour ring

complete network



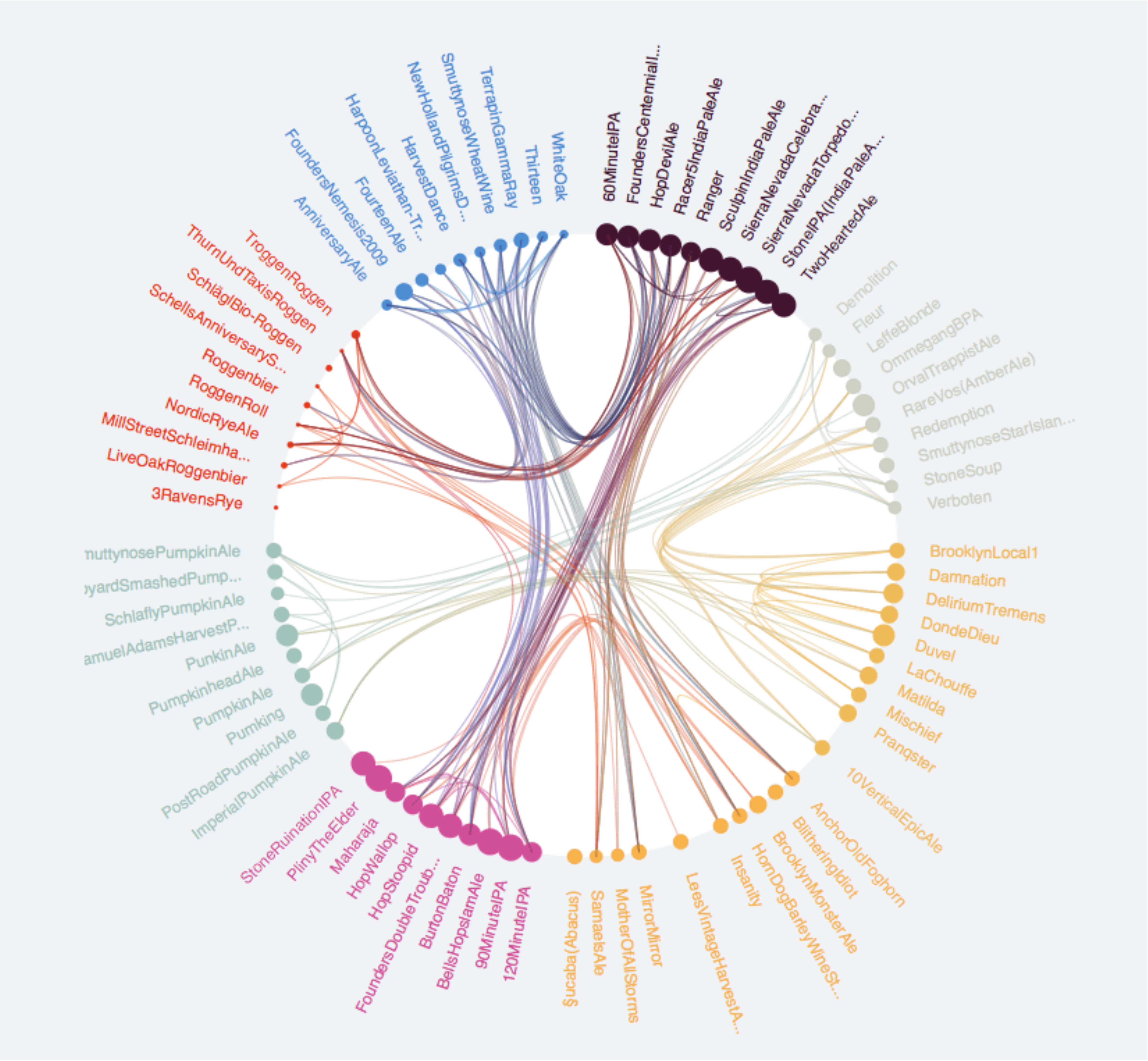
random network

(random edges)

Strogatz, S. H. (2001). Exploring complex networks. Nature, 410(6825), 268-76. doi: 10.1038/35065725.

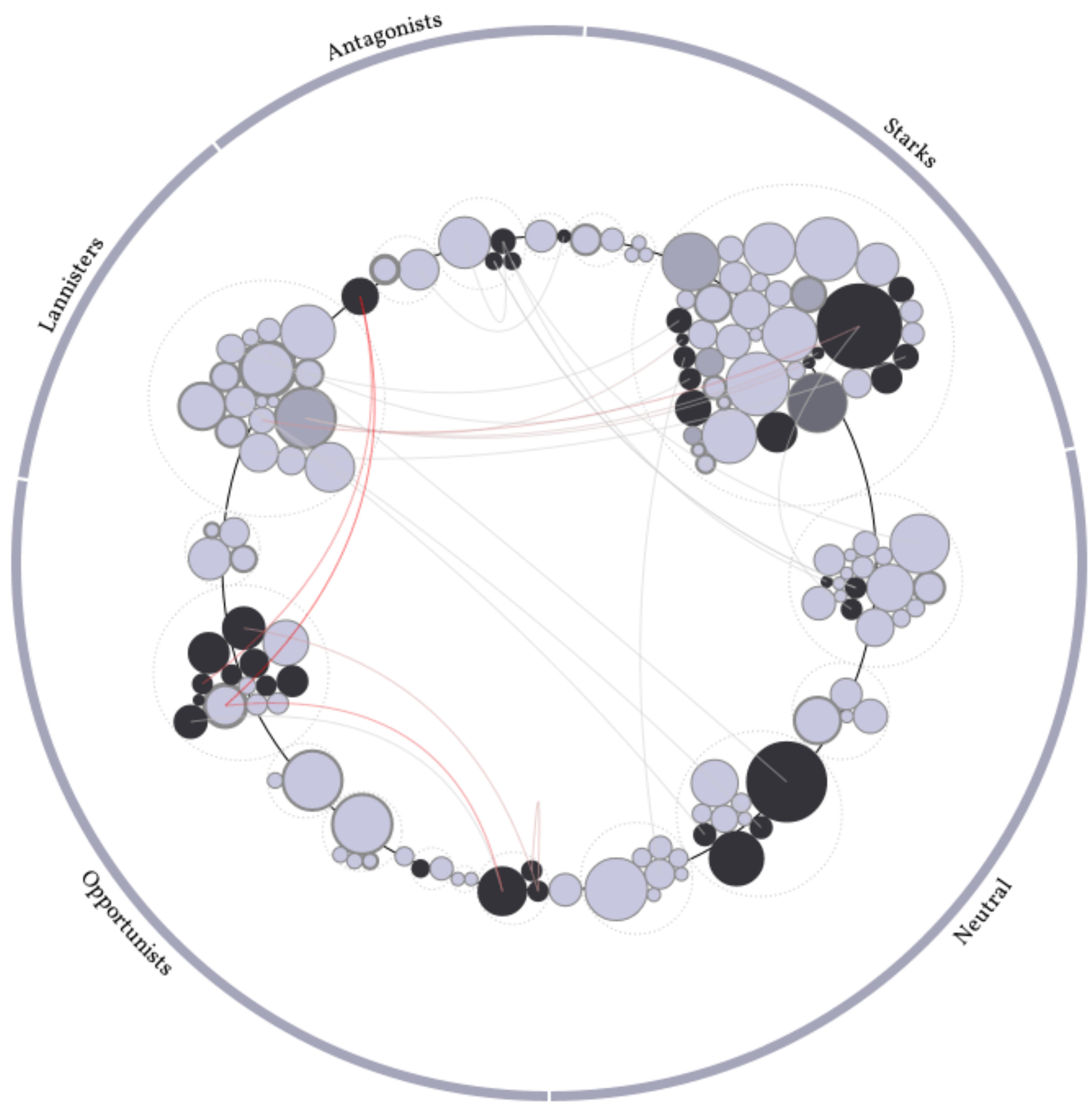
Graph theory

Netwerk that helps you find new beers based on your taste preference



"Relation" between Game of Thrones characters

http://www.jeromecukier.net/projects/agot/events.html

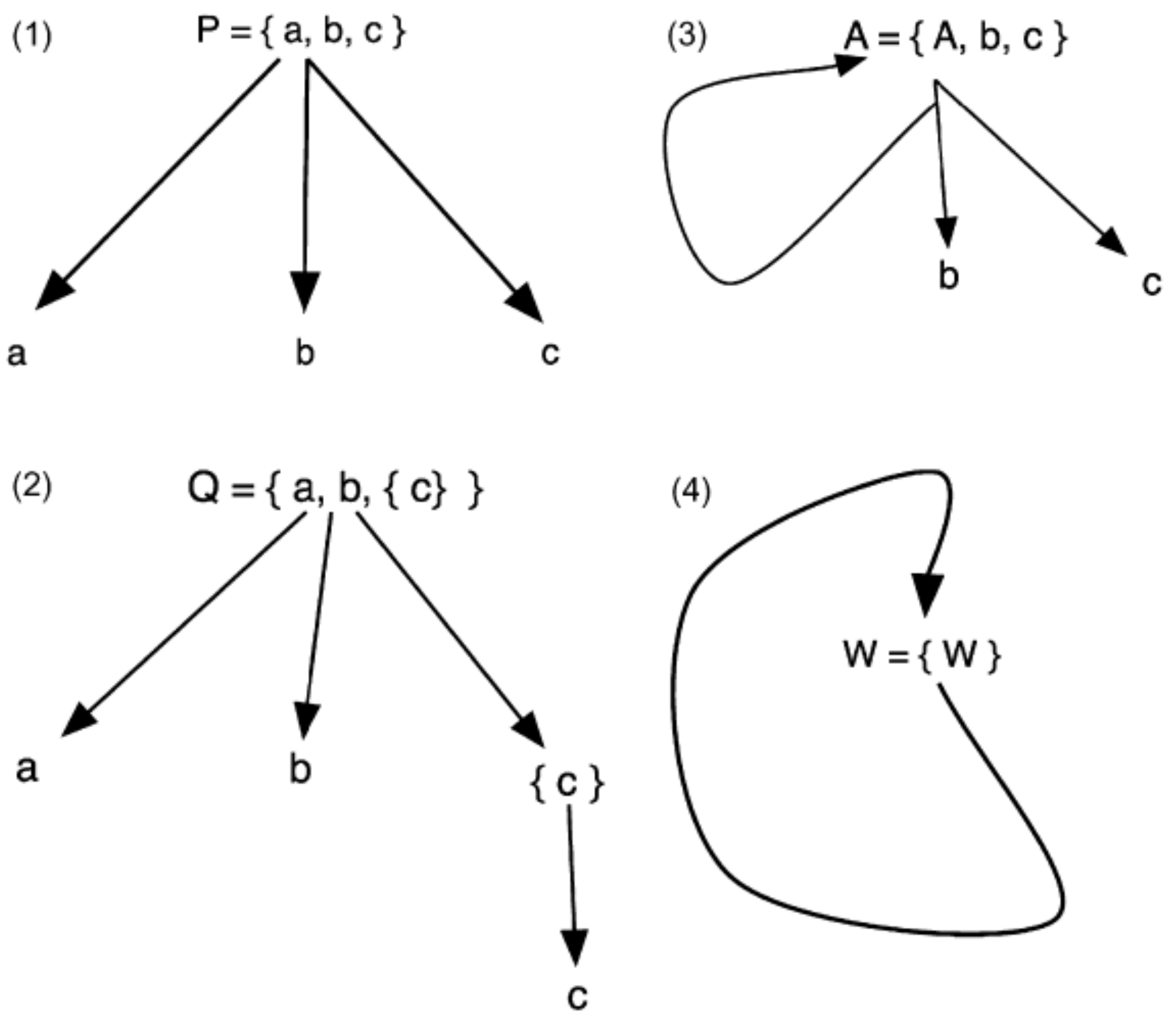


Hyperset theory + Graph theory = Hyperset Graphs (Impredicative Logic)

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

Non well-founded sets:

Definition of a set can contain itself



Aczel, P. (1988). *Non-well-founded sets. Foreword by Jon Barwise*. CSLI Lecture Notes, 14.

Hyperset theory + Graph theory = Hyperset Graphs (Impredicative Logic)

Impredicative loop

Hyperset loop

Rosen's definition of a living system

(metabolism-repair-system)

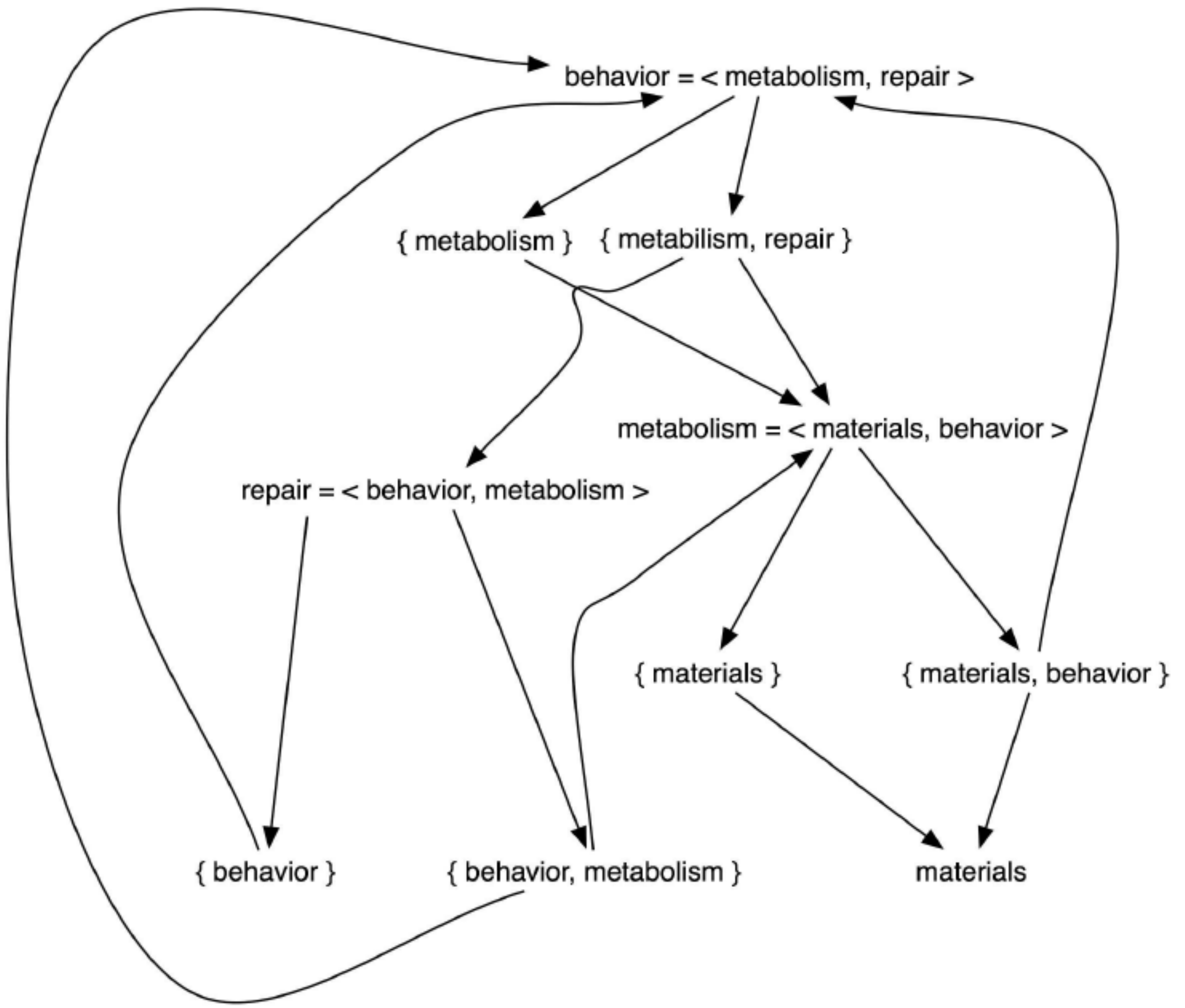


Fig. 6. Hyperset diagram of Rosen's metabolism-repair system. Functions are represented as ordered pairs containing their domain and range. So f (a) = b is represented as f = < a, b >.

Chemero, A., & Turvey, M. T. (2010). Is Life Computable? *Advances in modeling adaptive and cognitive systems*, 29-37.

Social networks

Moreno, 1930

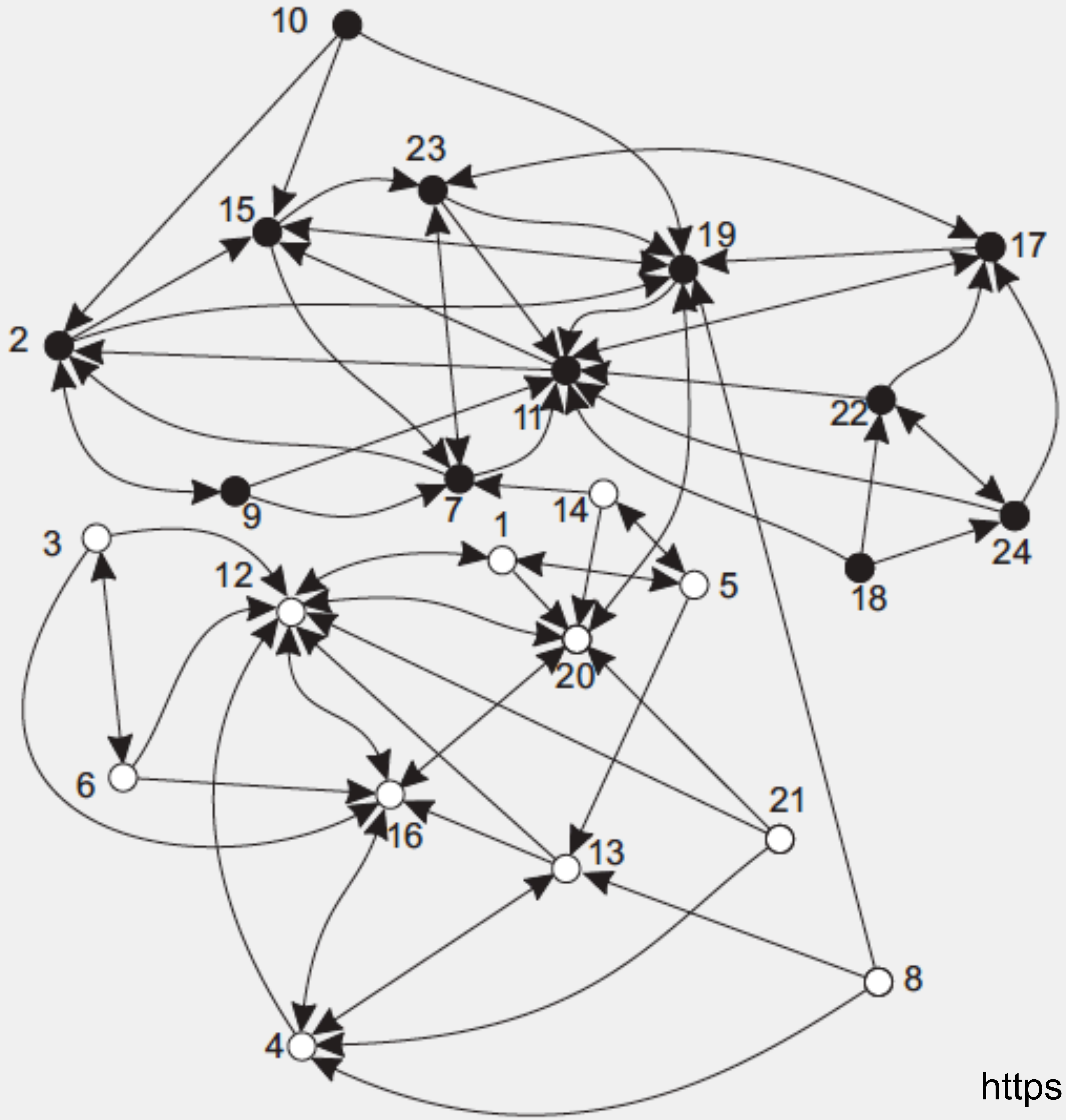
sociogram

3 “most liked”
3 “most disliked”

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	■				+				−	−		+								+	−			
M	2	−	■							+						+				+			−	−	
F	3			■			+	−			−		+				+					−			
F	4				■						−		+	+			+			−	−				
F	5	+				■					−			+	+					−	−				
F	6	−		+			■						+			−	+						−		
M	7		+					■			−	+								−		−		+	
F	8				+		−		■					+				−		+					−
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											+						+			−	−	+	−	■
	+	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

https://www.distributed-systems.net/index.php/books/gtcn/

Classroom example - positive nominations



- Clear distinction between boys ("•") and girls ("○")
- Relation between 19 and 20 is important
- There are a few "isolated" children (8 & 10)

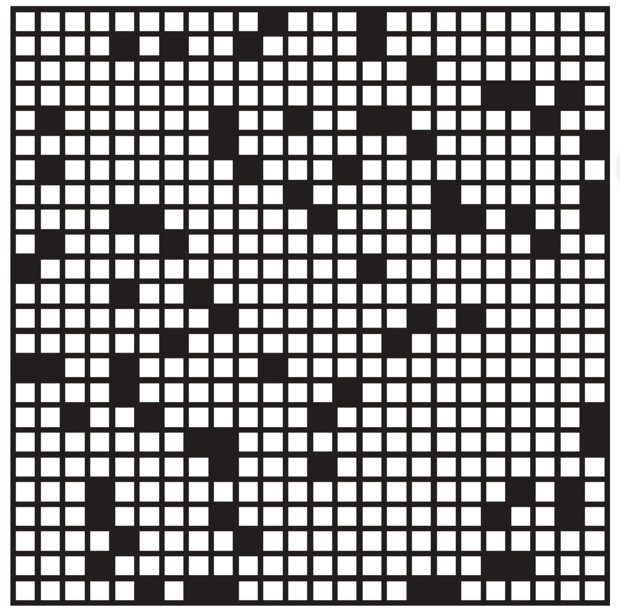
Issue

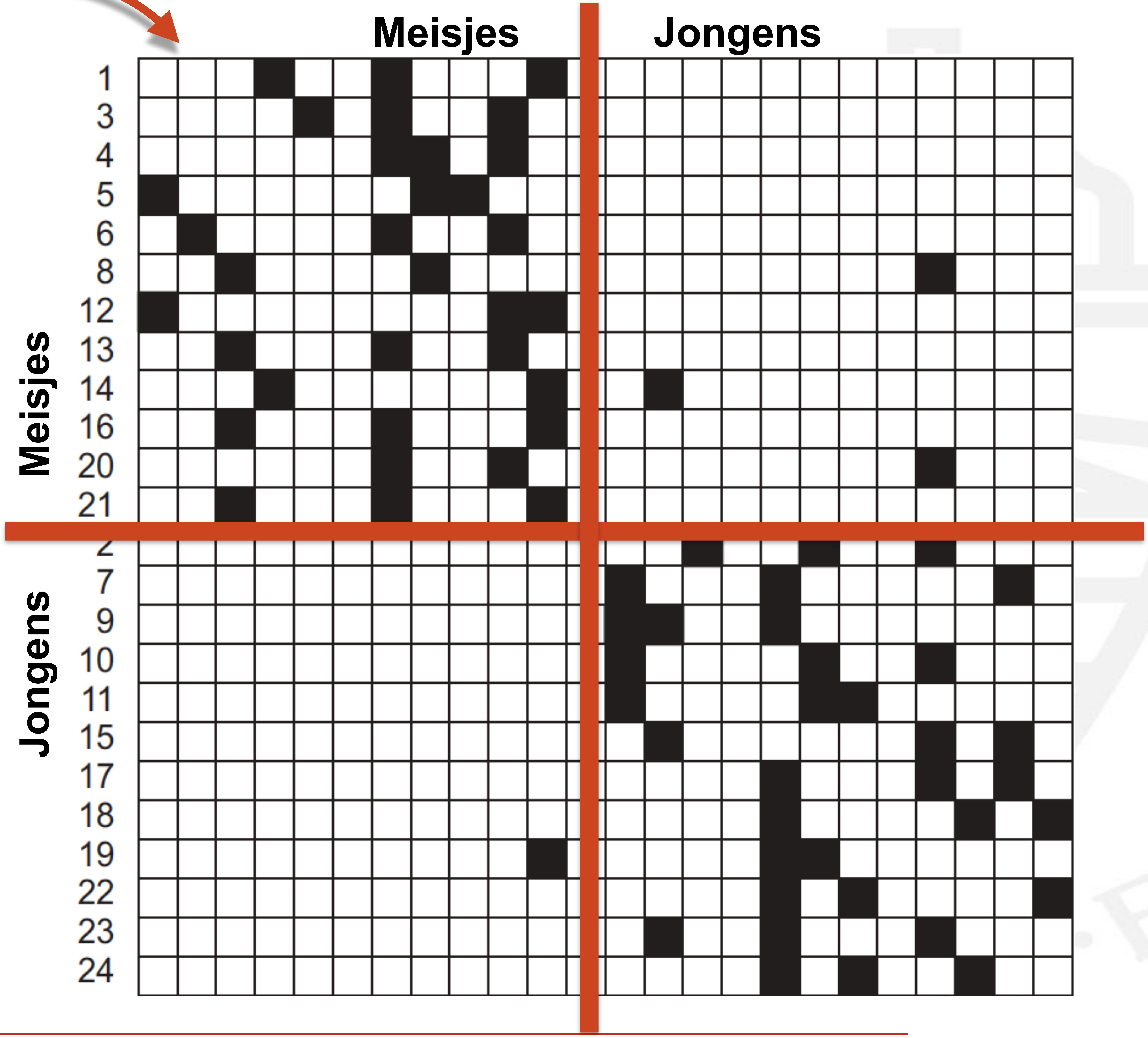
Can we discover these properties **mathematically**?

Degree, Centrality, Closeness, Eccentricity, Betweenness,

https://www.distributed-systems.net/index.php/books/gtcn/

Sociale networks





Clusters (communities, subgraphs, modules)

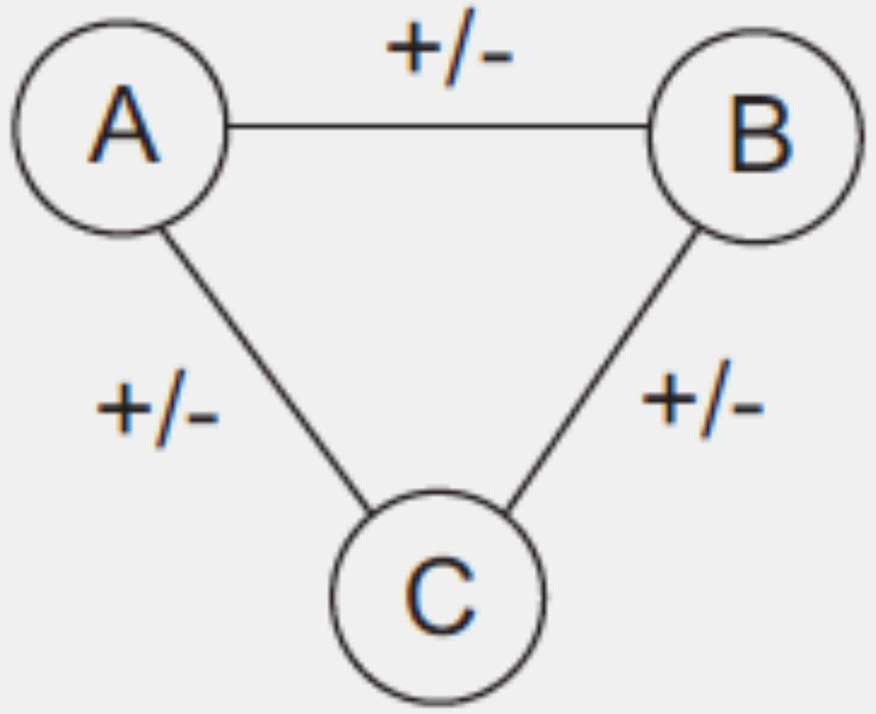
"hubs"

https://www.distributed-systems.net/index.php/books/gtcn/

Structural balance

https://www.distributed-systems.net/index.php/books/gtcn/

Motifs (signed)
Motieven

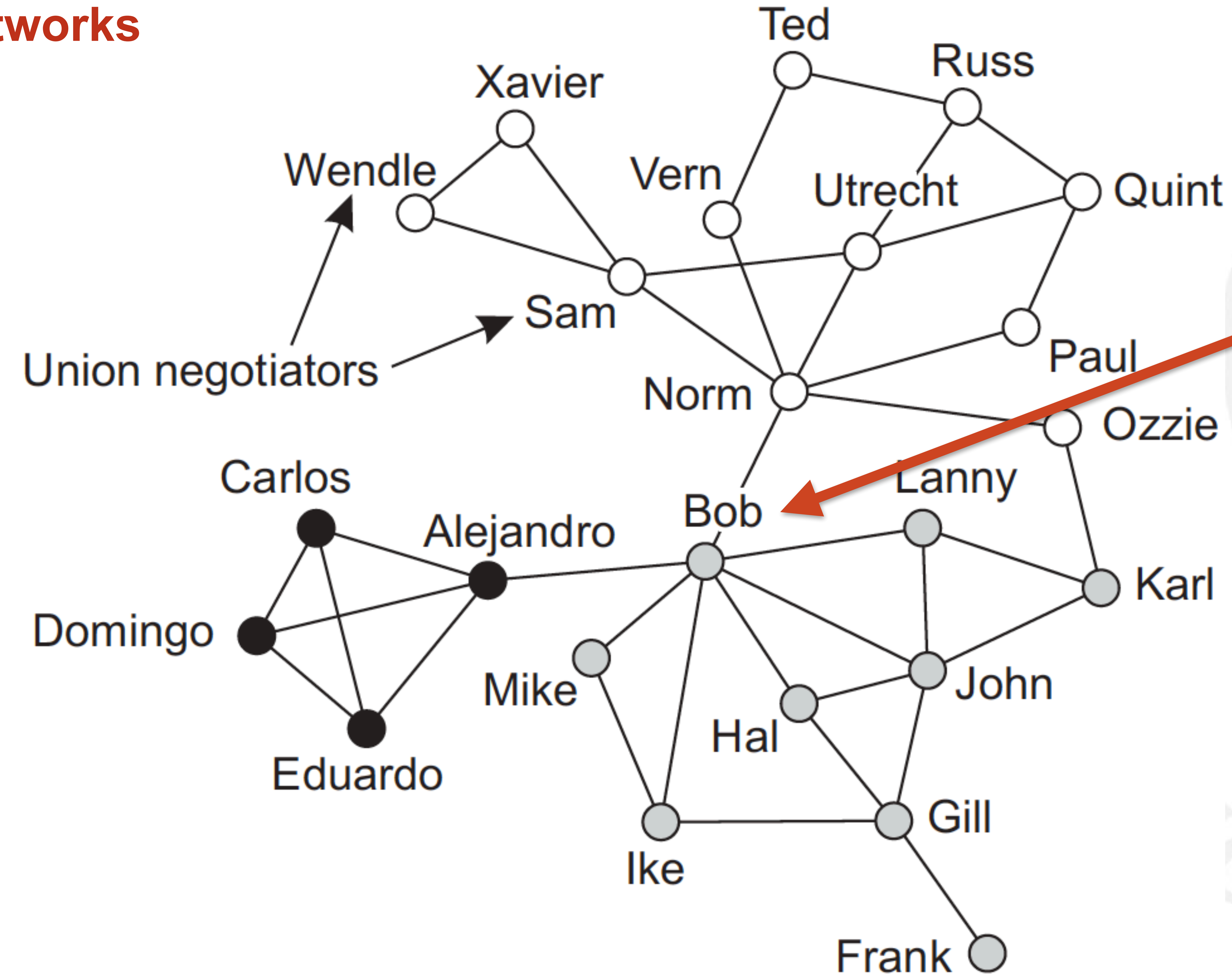


Basic idea

Consider **triads**: potential relationships between triples of social entities, and label every relationship as positive or negative. We then consider **balanced** triads.

A–B	B–C	A–C	B/I	Description
+	+	+	B	Everyone likes each other
+	+	–	I	Dislike A–C stresses relation B has with either of them
+	–	+	I	Dislike B–C stresses relation A has with either of them
+	–	–	B	A and B like each other, and both dislike C
–	+	+	I	Dislike A–B stresses relation C has with either of them
–	+	–	B	B and C like each other, and both dislike A
–	–	+	B	A and C like each other, and both dislike B
–	–	–	I	Nobody likes each other

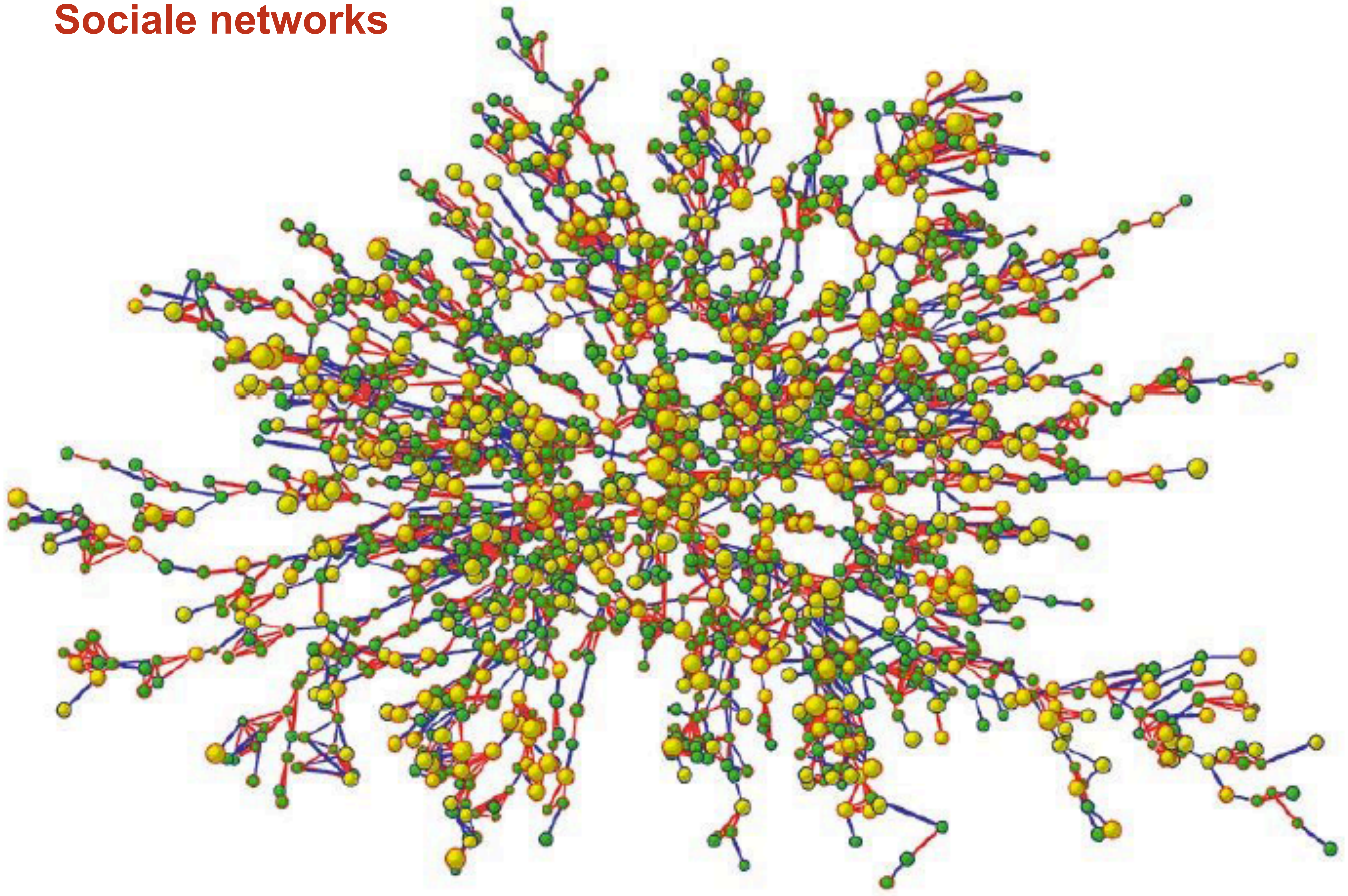
Sociale networks



Bob is a ‘connector hub’
For 3 clusters

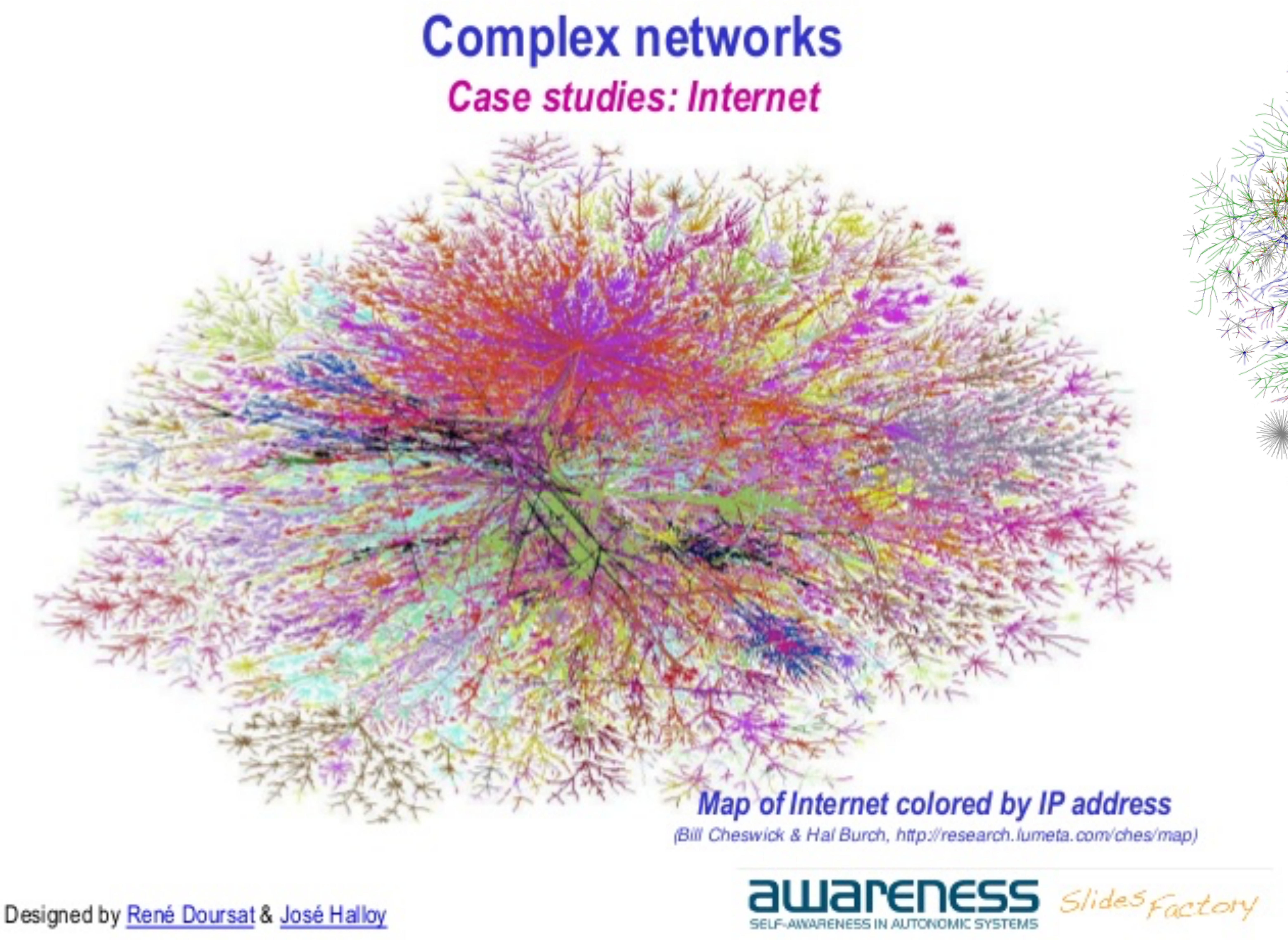
http://www.distributed-systems.net/gtcn/

Sociale networks

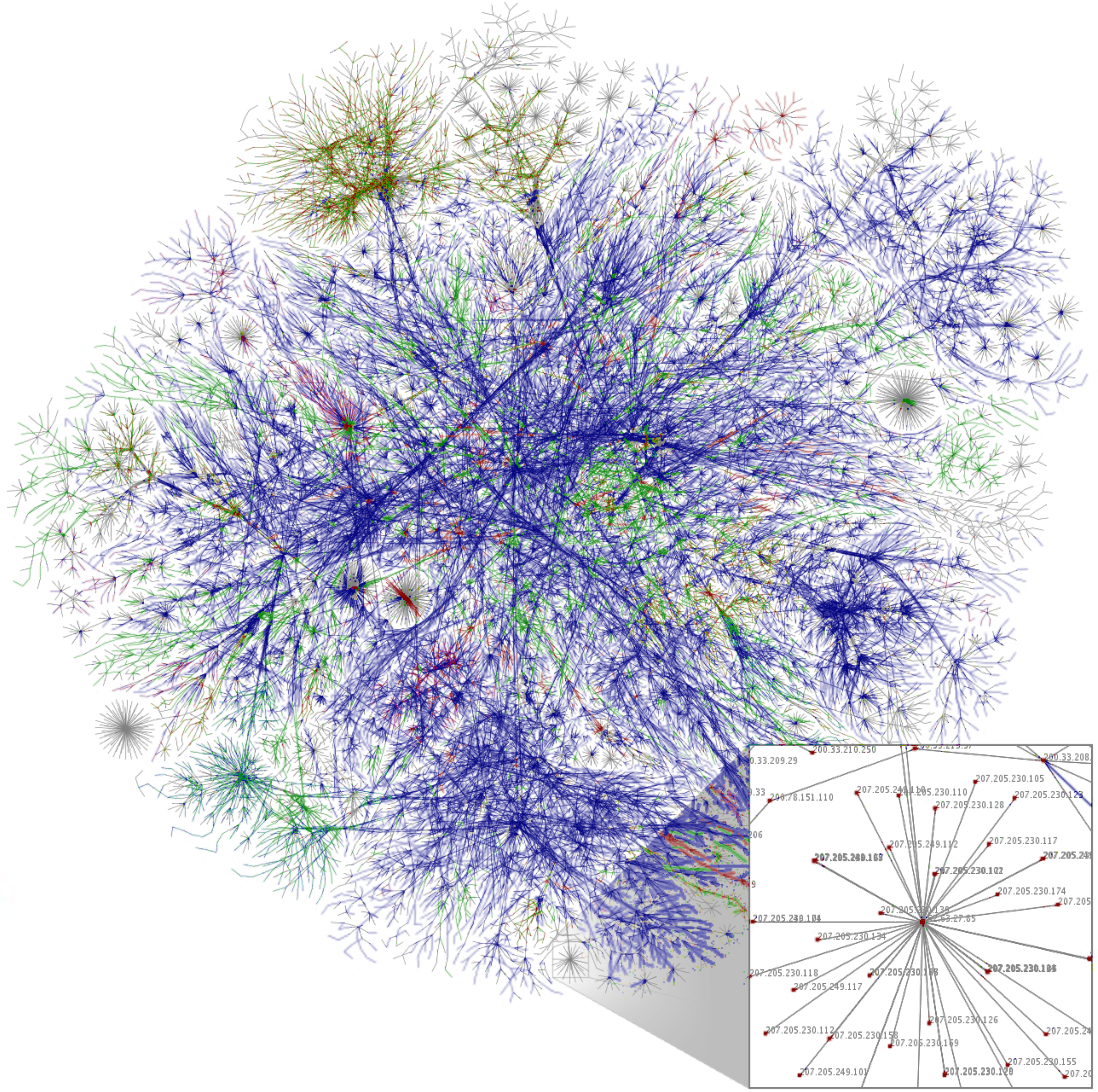


Yellow: obese | Green: nonobese | Purple: friend/marriage | Red: family

Complexe ‘sociale’ networks

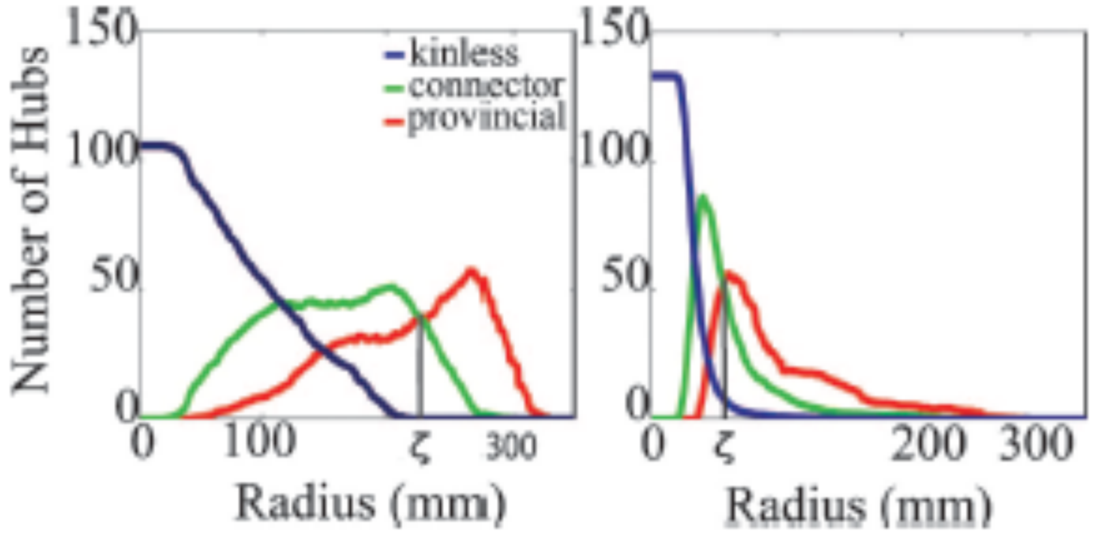


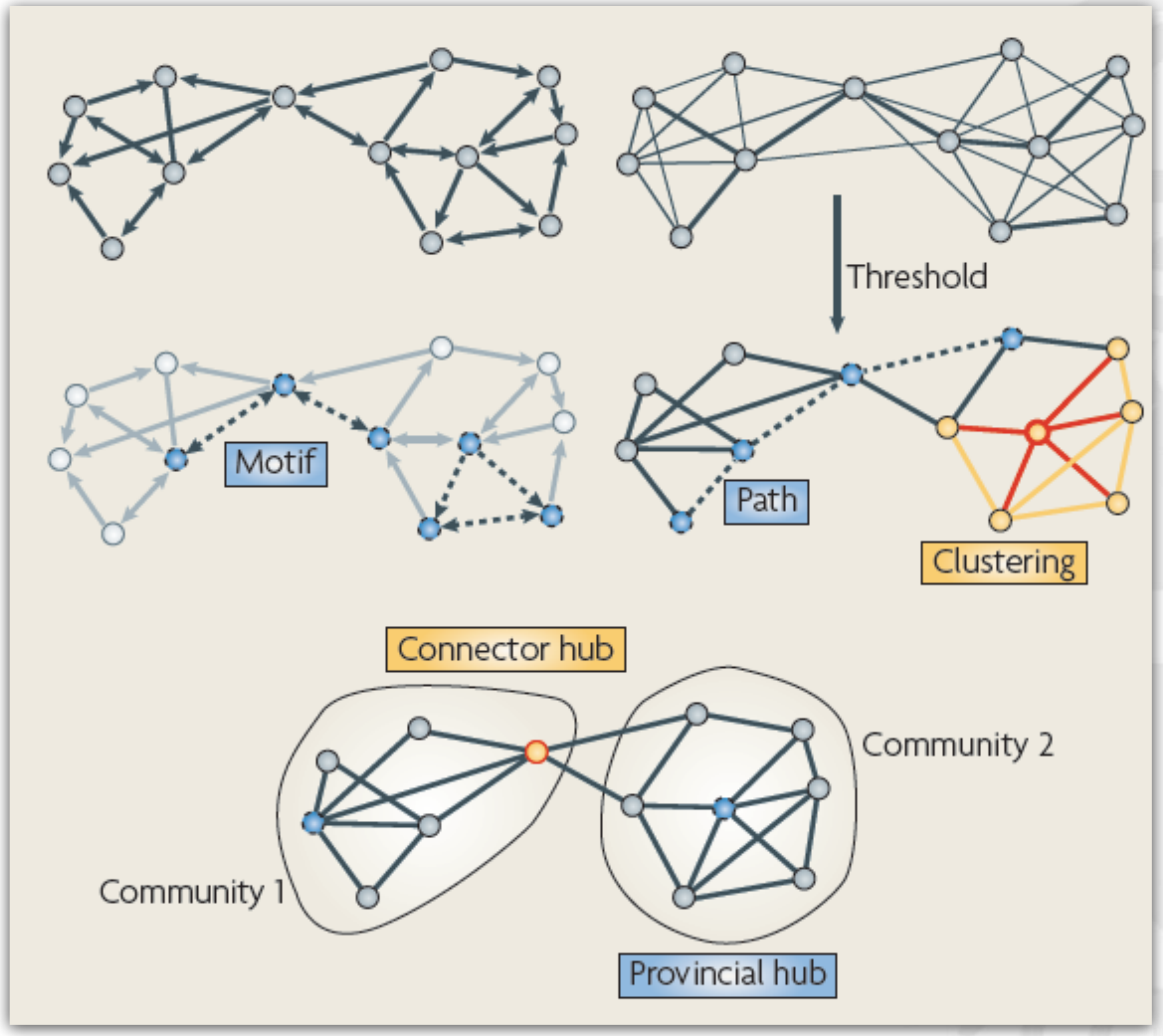
An Opte Project visualization of routing paths through a portion of the Internet



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





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.

Table A1 (*continued*)

Measure	Binary and undirected definitions	Weighted and directed definitions
Modularity	Modularity of the network (Newman, 2004b), $$Q = \sum_{u \in M} \left[e_{uu} - \left(\sum_{v \in M} e_{uv} \right)^2 \right],$$ where the network is fully subdivided into a set of nonoverlapping modules M, and e_{uv} is the proportion of all links that connect nodes in module u with nodes in module v. An equivalent alternative formulation of the modularity (Newman, 2006) is given by $Q = \frac{1}{l} \sum_{i,j \in N} \left(a_{ij} - \frac{k_i k_j}{l} \right) \delta_{m_i, m_j}$, where m_i is the module containing node i, and $\delta_{m_i m_j} = 1$ if $m_i = m_j$, and 0 otherwise.	Weighted modularity (Newman, 2004), $Q^w = \frac{1}{l^w} \sum_{i,j \in N} \left[w_{ij} - \frac{k_i^w k_j^w}{l^w} \right] \delta_{m_i, m_j}$. Directed modularity (Leicht and Newman, 2008), $Q^{\rightarrow} = \frac{1}{l} \sum_{i,j \in N} \left[a_{ij} - \frac{k_i^{out} k_j^{in}}{l} \right] \delta_{m_i, m_j}$.
Measures of centrality		
Closeness centrality	Closeness centrality of node i (e.g. Freeman, 1978), $$L_i^{-1} = \frac{n-1}{\sum_{j \in N, j \neq i} d_{ij}}.$$	Weighted closeness centrality, $\left(L_i^w\right)^{-1} = \frac{n-1}{\sum_{j \in N, j \neq i} d_{ij}^w}$. Directed closeness centrality, $\left(L_i^{\rightarrow}\right)^{-1} = \frac{n-1}{\sum_{j \in N, j \neq i} d_{ij}^{\rightarrow}}$.
Betweenness centrality	Betweenness centrality of node i (e.g., Freeman, 1978), $$b_i = \frac{1}{(n-1)(n-2)} \sum_{\substack{h,j \in N \\ h \neq j, h \neq i, j \neq i}} \frac{\rho_{hj}(i)}{\rho_{hj}},$$ where ρ_{hj} is the number of shortest paths between h and j, and $\rho_{hj}(i)$ is the number of shortest paths between h and j that pass through i.	Betweenness centrality is computed equivalently on weighted and directed networks, provided that path lengths are computed on respective weighted or directed paths.
Within-module degree z-score	Within-module degree z-score of node i (Guimera and Amaral, 2005), $$z_i = \frac{k_i(m_i) - \bar{k}(m_i)}{\sigma^{k(m_i)}},$$ where m_i is the module containing node i, $k_i(m_i)$ is the within-module degree of i (the number of links between i and all other nodes in m_i), and $\bar{k}(m_i)$ and $\sigma^{k(m_i)}$ are the respective mean and standard deviation of the within-module m_i degree distribution.	Weighted within-module degree z-score, $z_i^w = \frac{k_i^w(m_i) - \bar{k}^w(m_i)}{\sigma^{k^w(m_i)}}$. Within-module out-degree z-score, $z_i^{out} = \frac{k_i^{out}(m_i) - \bar{k}^{out}(m_i)}{\sigma^{k^{out}(m_i)}}$. Within-module in-degree z-score, $z_i^{in} = \frac{k_i^{in}(m_i) - \bar{k}^{in}(m_i)}{\sigma^{k^{in}(m_i)}}$.

Rubinov, M., & Sporns, O. (2010). Complex network measures of brain connectivity: uses and interpretations. *NeuroImage*, *52*(3), 1059-69. Elsevier Inc. doi:10.1016/j.neuroimage.2009.10.003

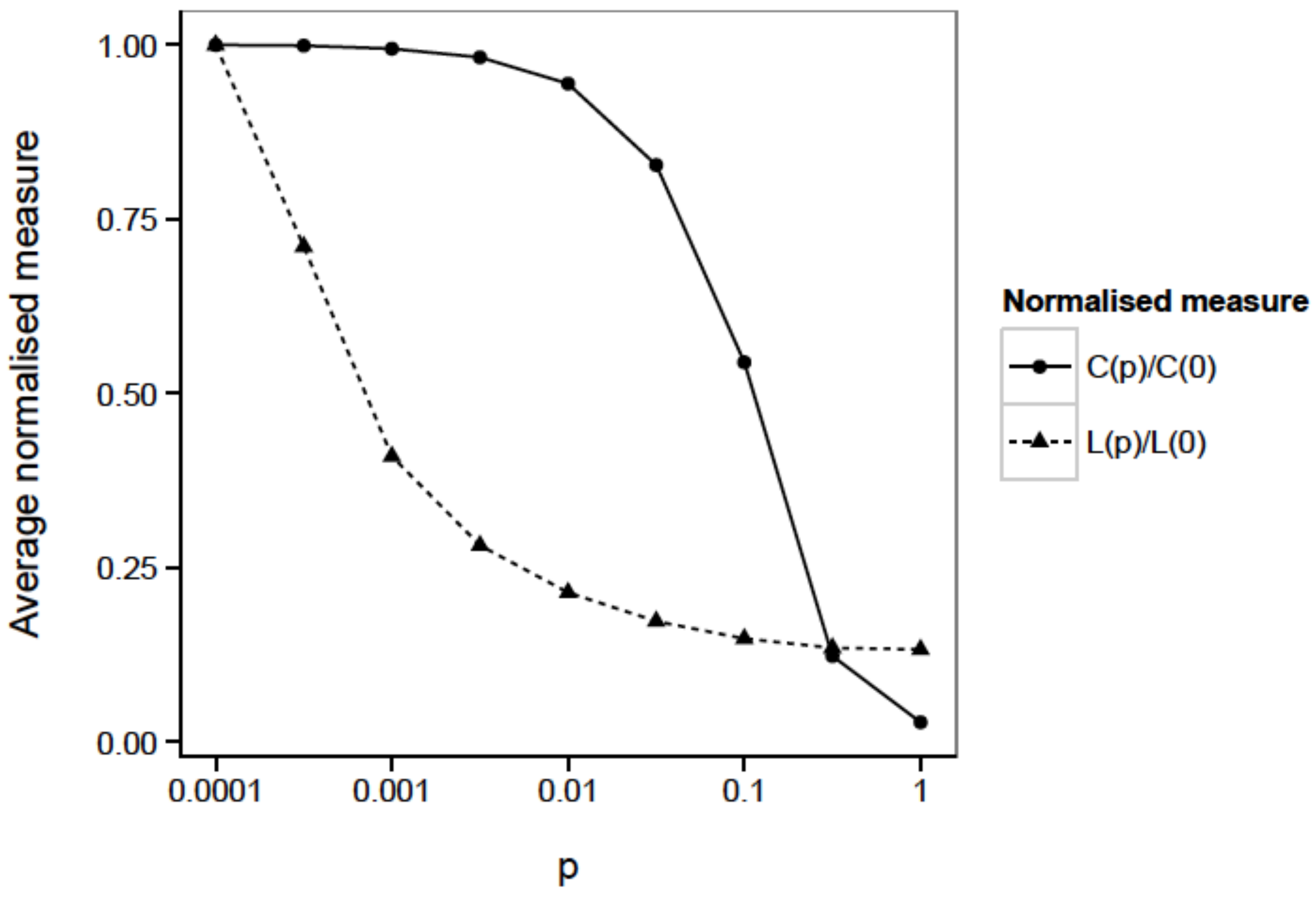
Network / Graph topology: It's a Small World After All

"small-world" test:

Average path length (L)

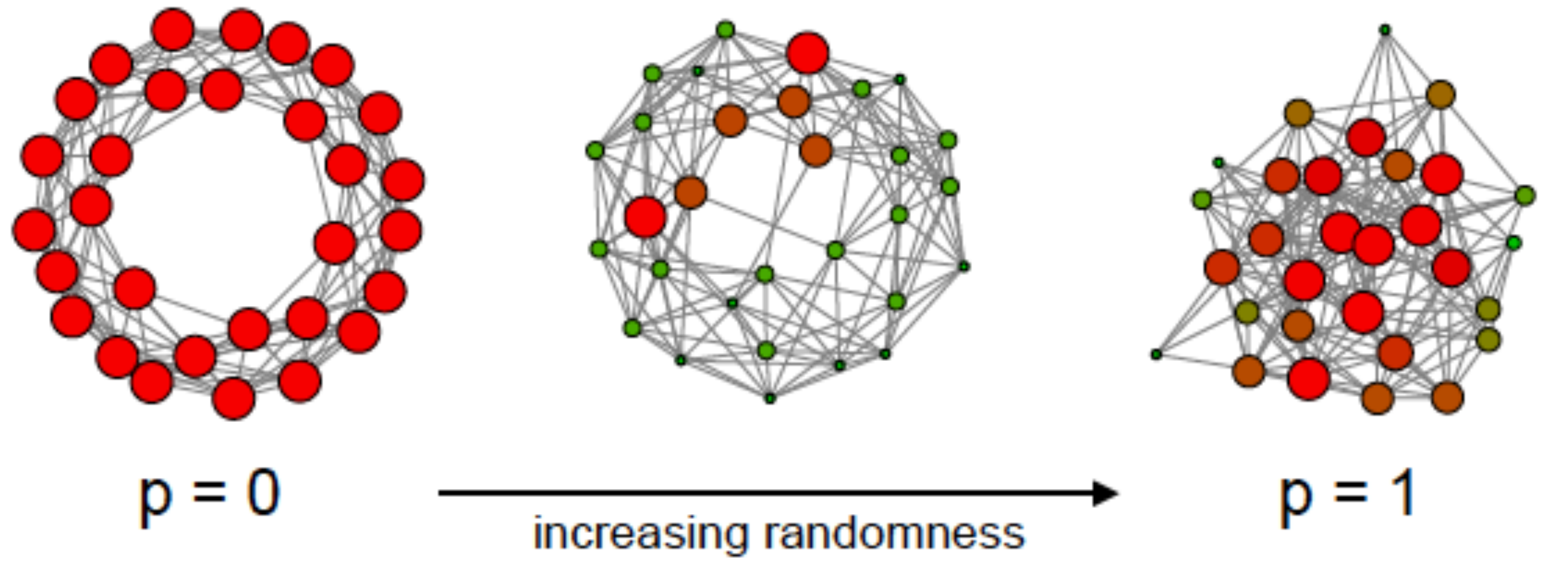
Clustering coefficient (C)

Compare to randomly rewired version



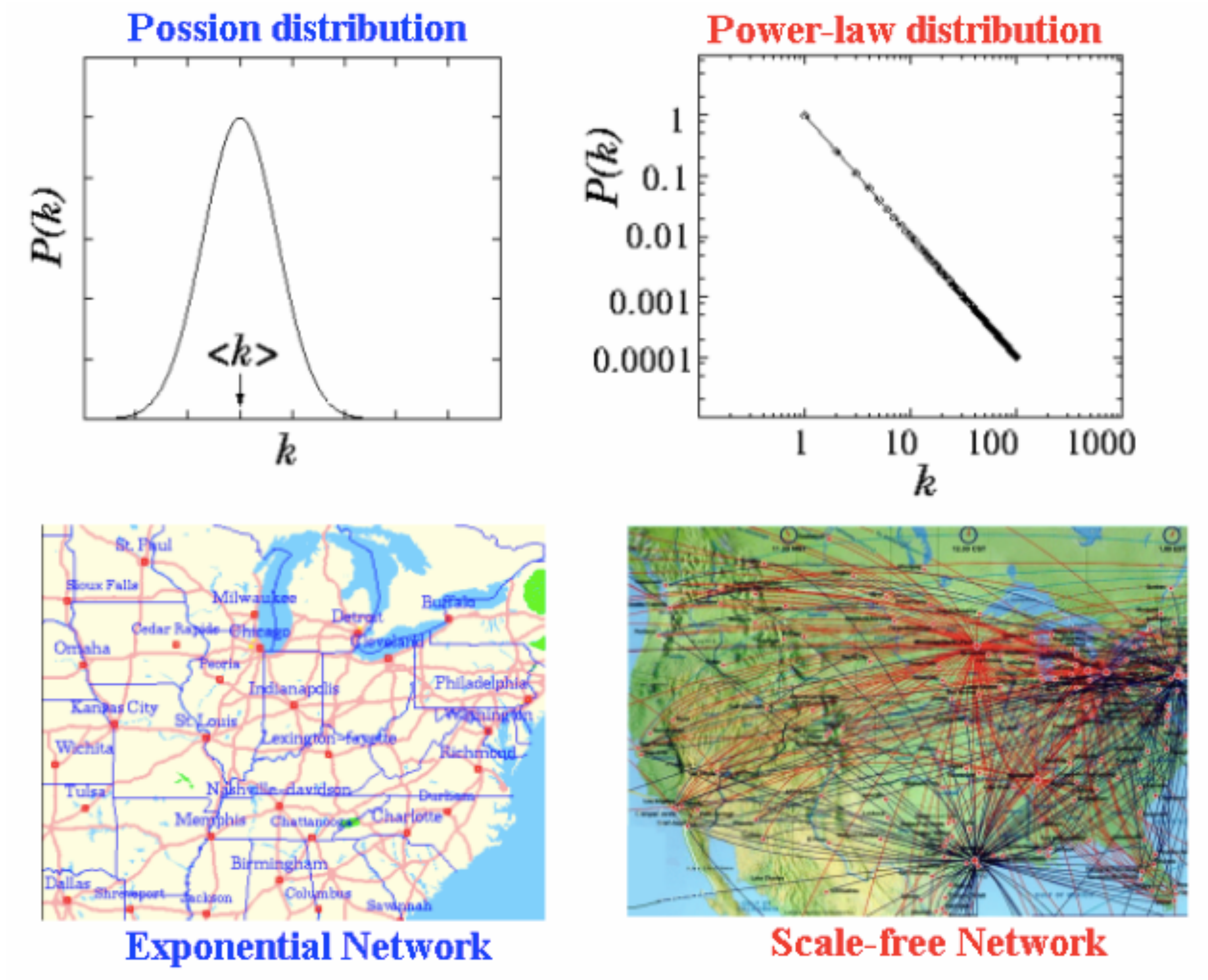
Sound familiar?

In between
fully ordered
&
completely random
=
optimal



Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world'networks. N*ature*, *393*(6684), 440-442.

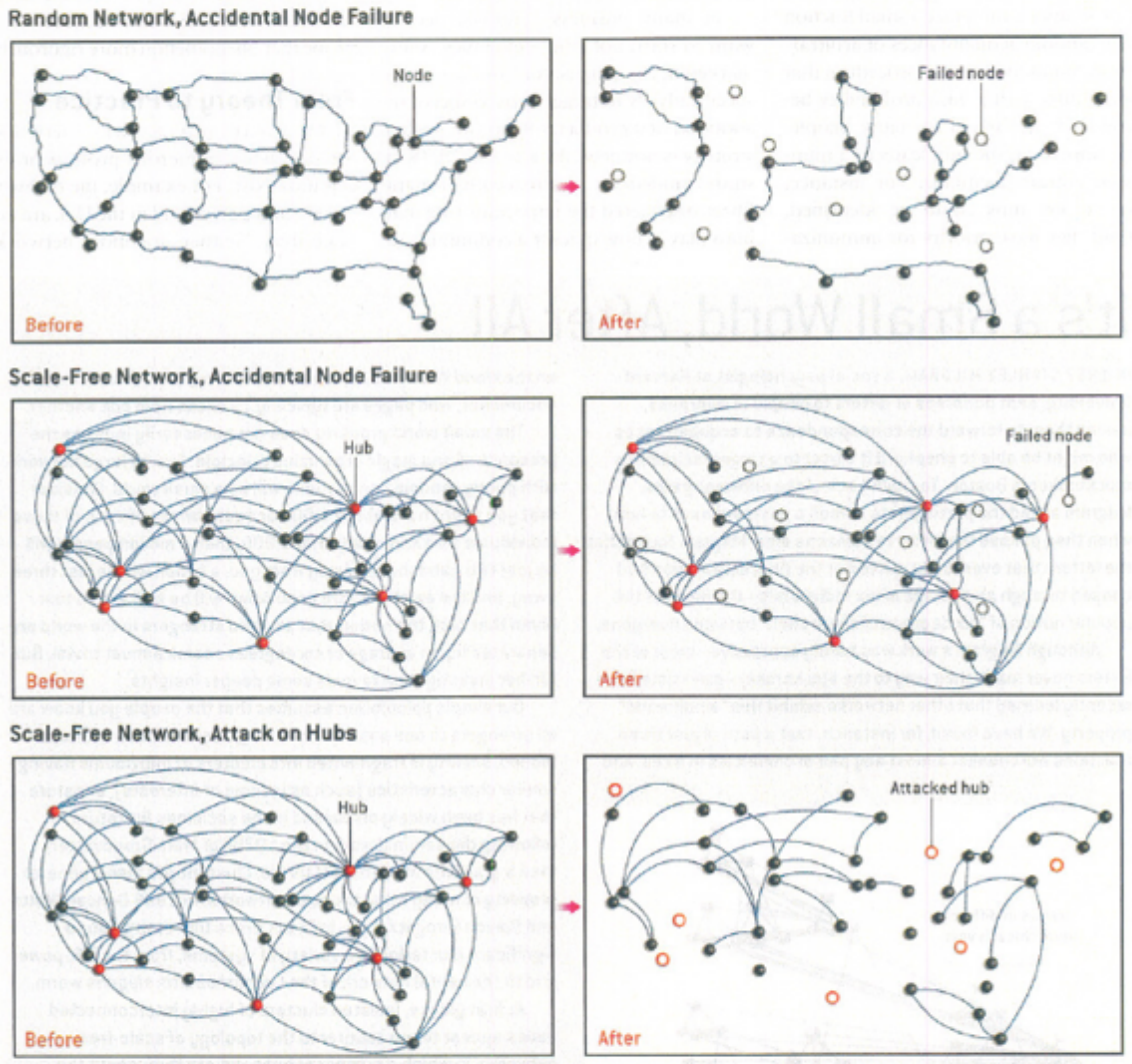
Network / Graph topology: It's a Scale Free World After All



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

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

Wang, X. F., & Chen, G. (2003). Complex Networks: small-world, scale-free and beyond. Circuits and Systems Magazine, IEEE, 3(1), 6–20. IEEE. Retrieved May 18, 2011, from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1228503.



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

(cf. internet on 9/11)

when more hub nodes fail though....

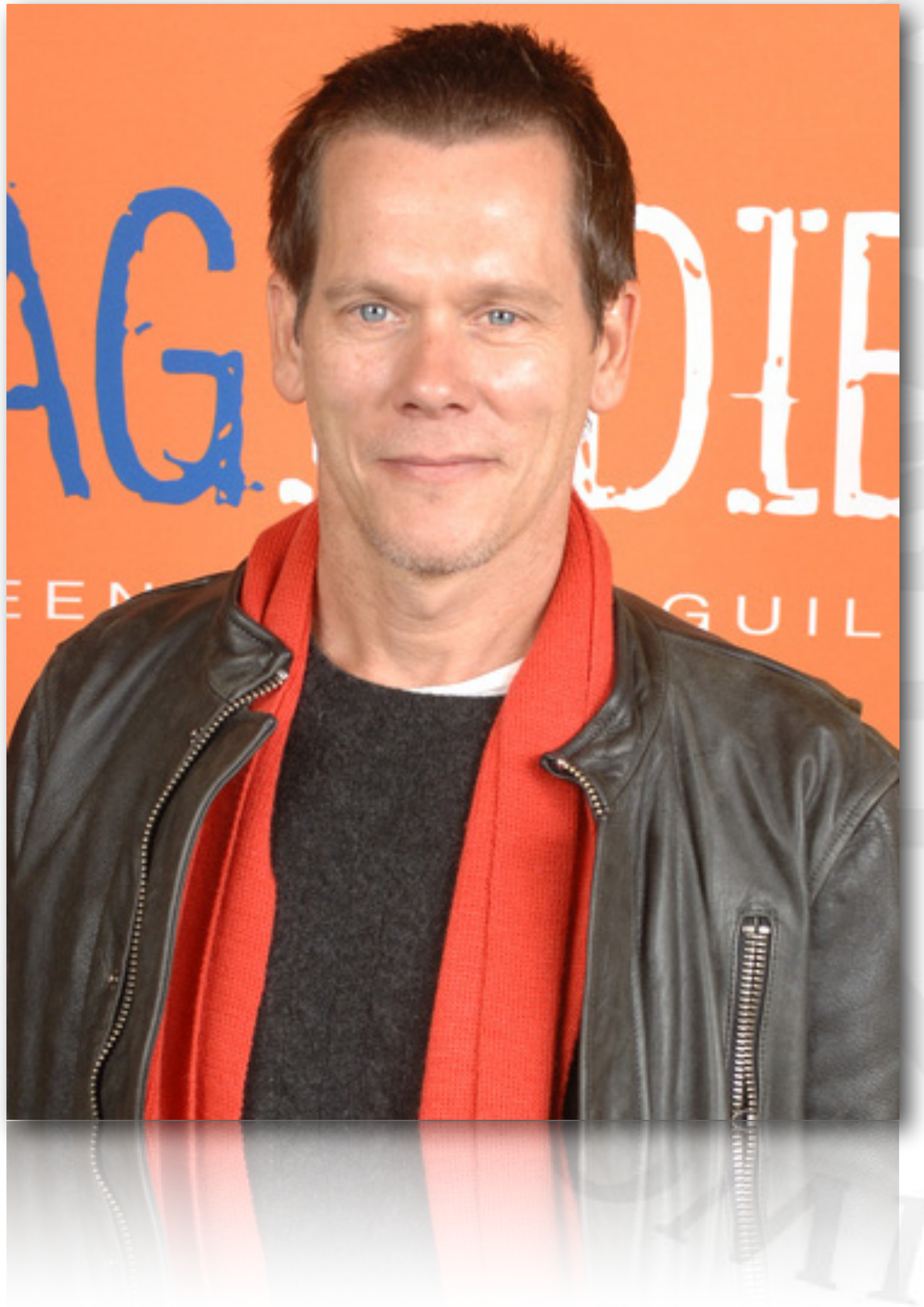
targeted attack!

Bonabeau, E., with Albert-László. (2003). Scale-free networks. *Scientific American, 288(5)*, 50–9.

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

Effectiveness / Connectivity: 6 degrees of separation

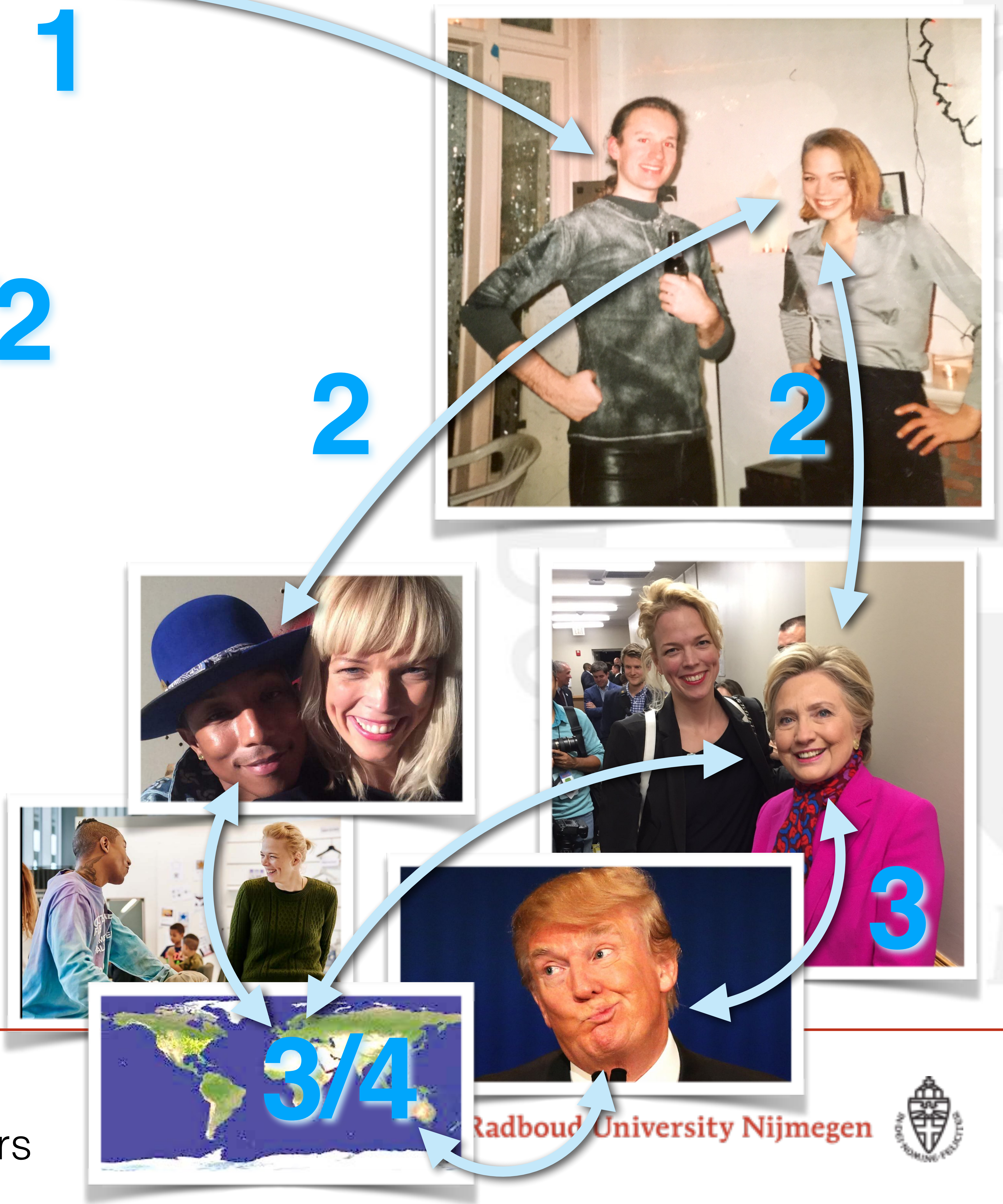
1

Your degree of separation from:

Nobel Laureate 1/2

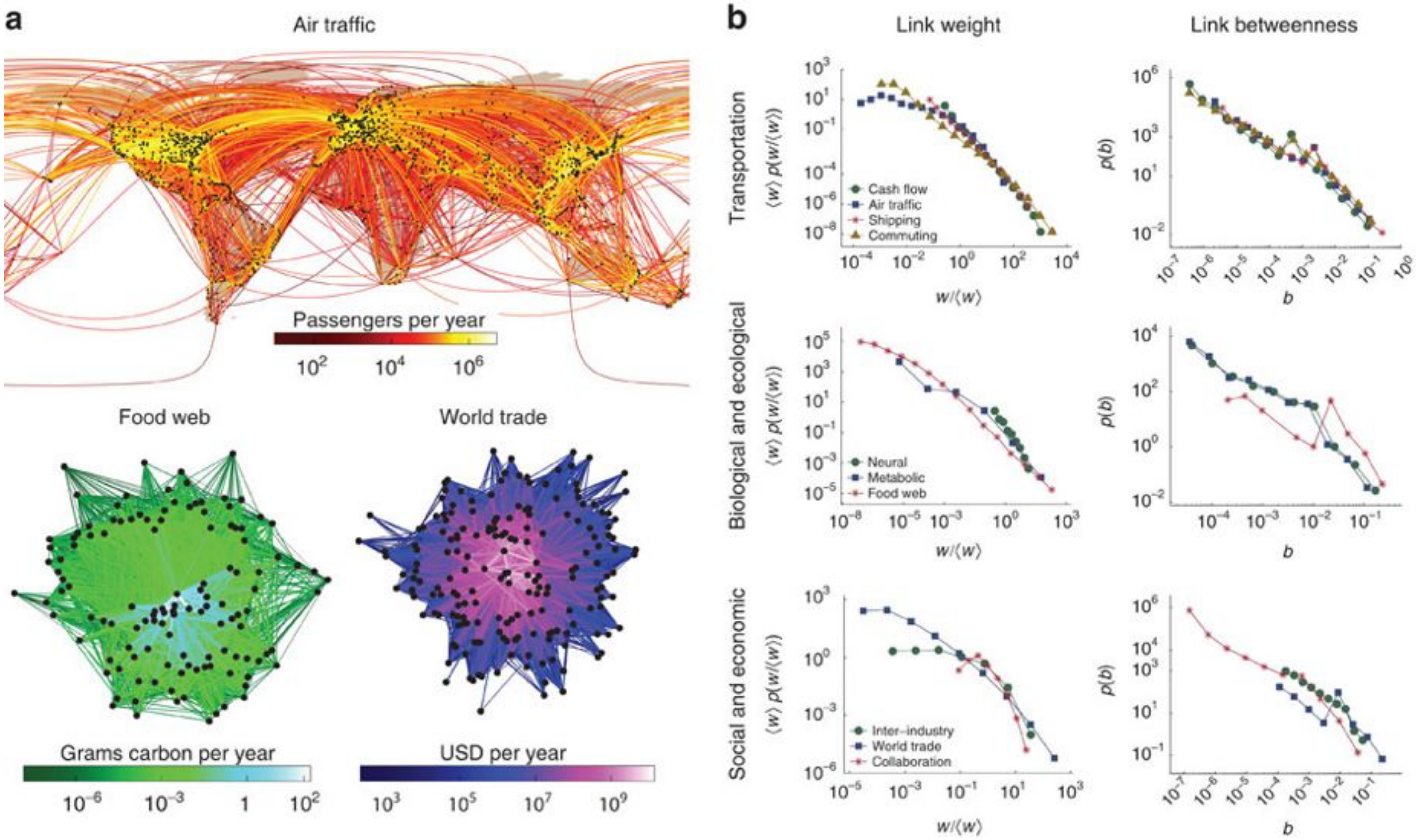
Pharrell Williams

Hillary Clinton
Donald Trump



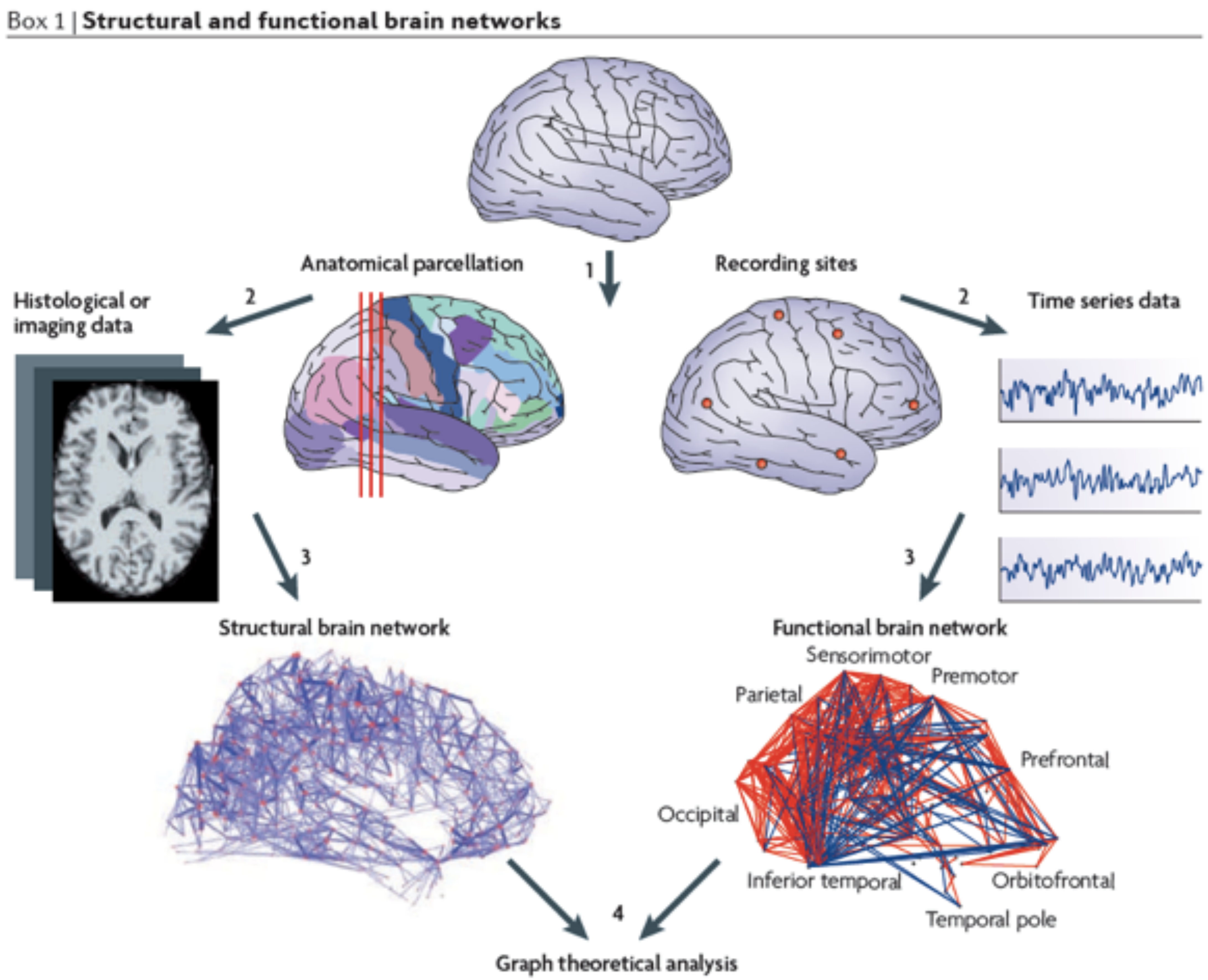
http://en.wikipedia.org/wiki/Bacon_number#Bacon_numbers

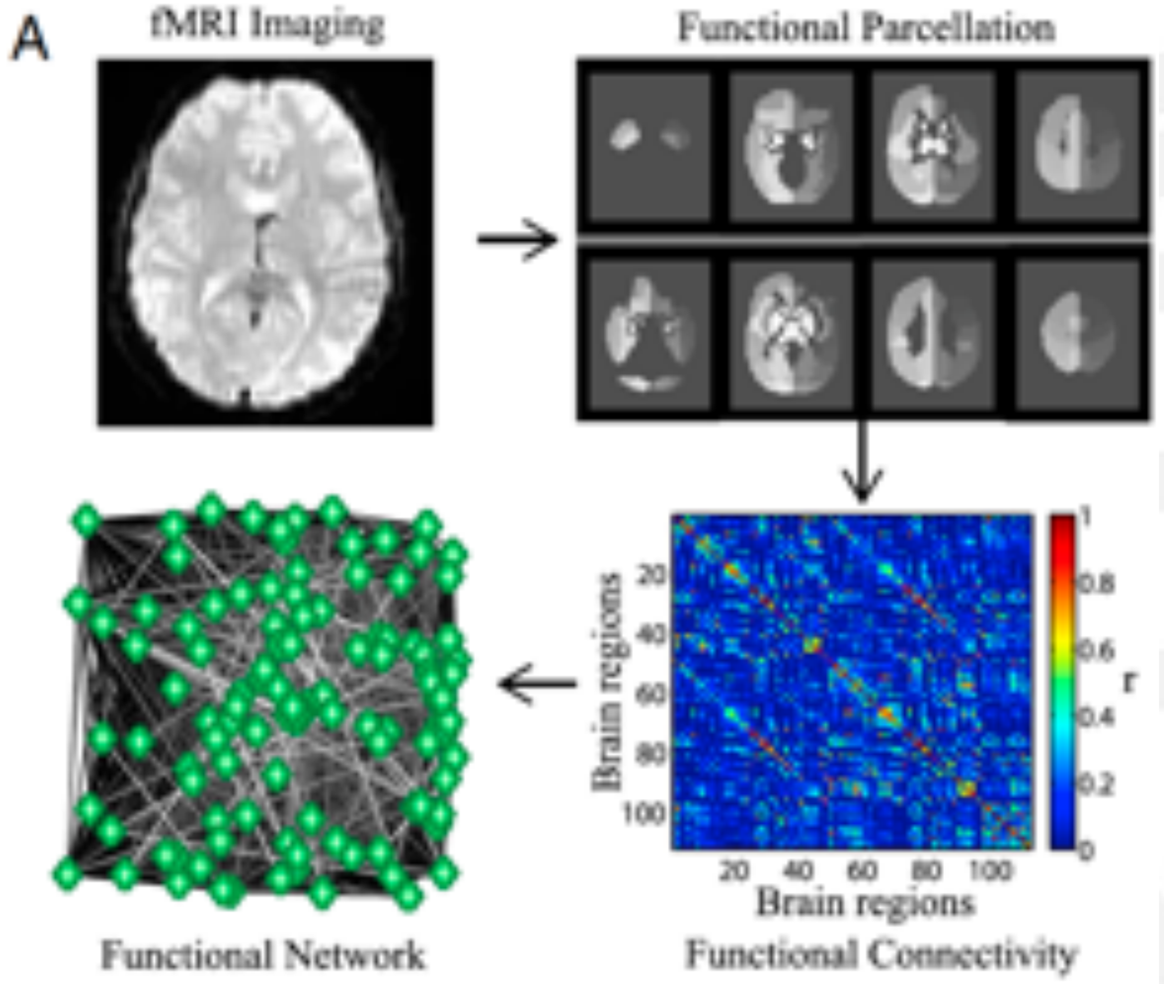
Scale-free structure



Network / Graph topology

Functional vs. Structural 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.

Network / Graph topology

Functional vs. Structural networks

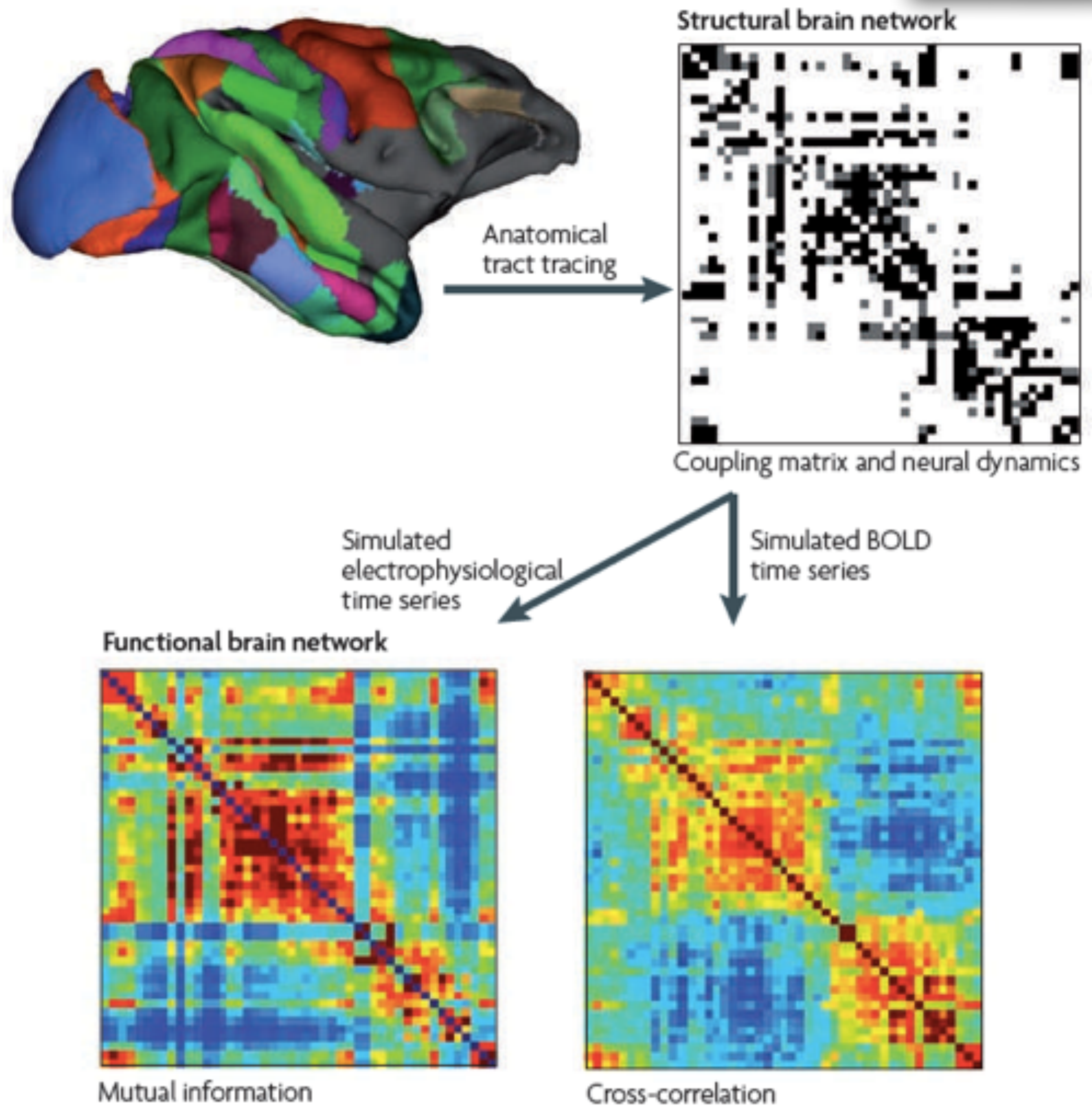


Figure 1 | **Computational modelling of structural and functional brain networks.**

adjacency matrix
similarity matrix
coupling matrix

Compare:
Recurrence matrix

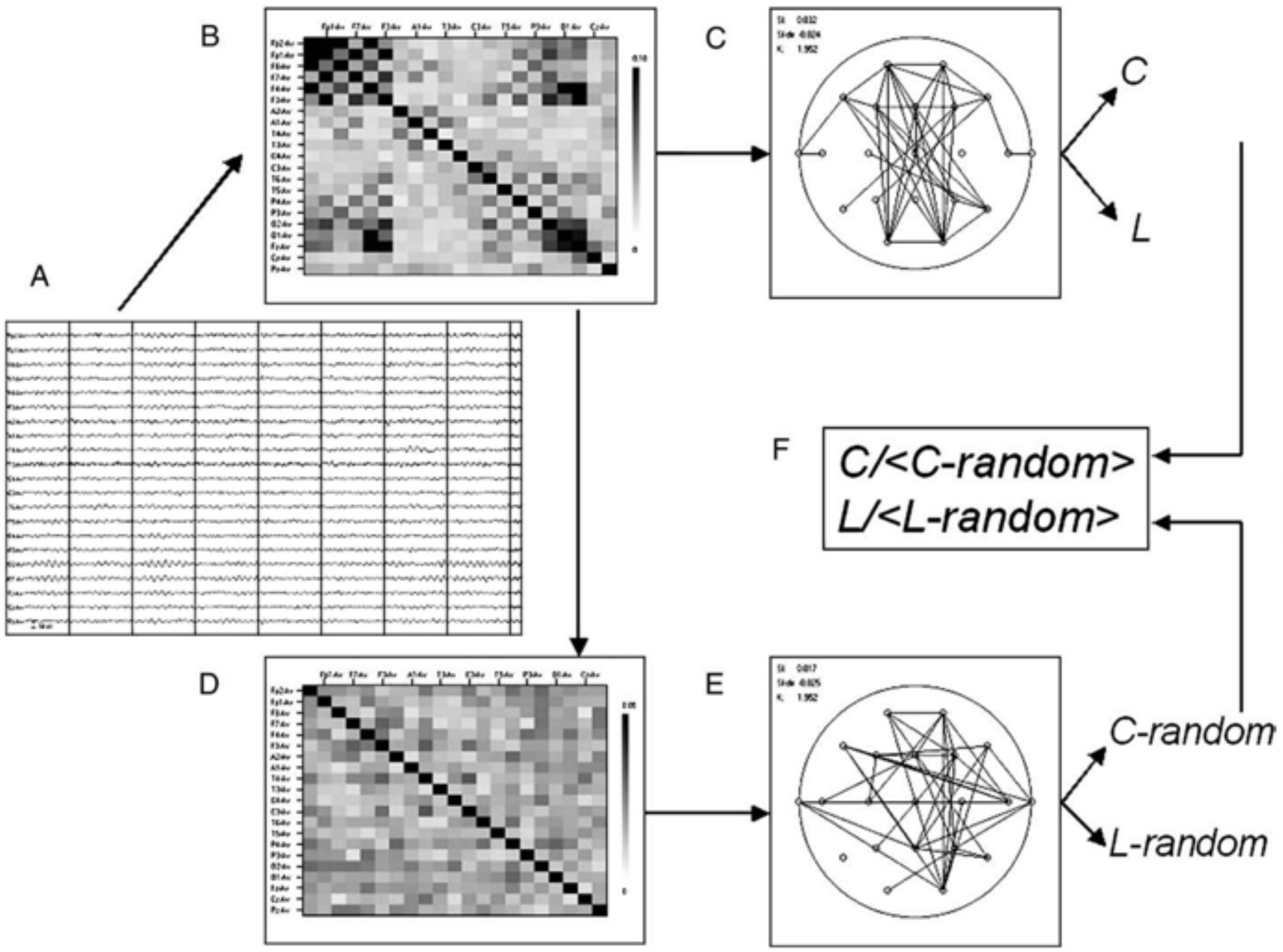
“neural dynamics”

Compare:
Surrogate data generation from recurrence matrix

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.

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

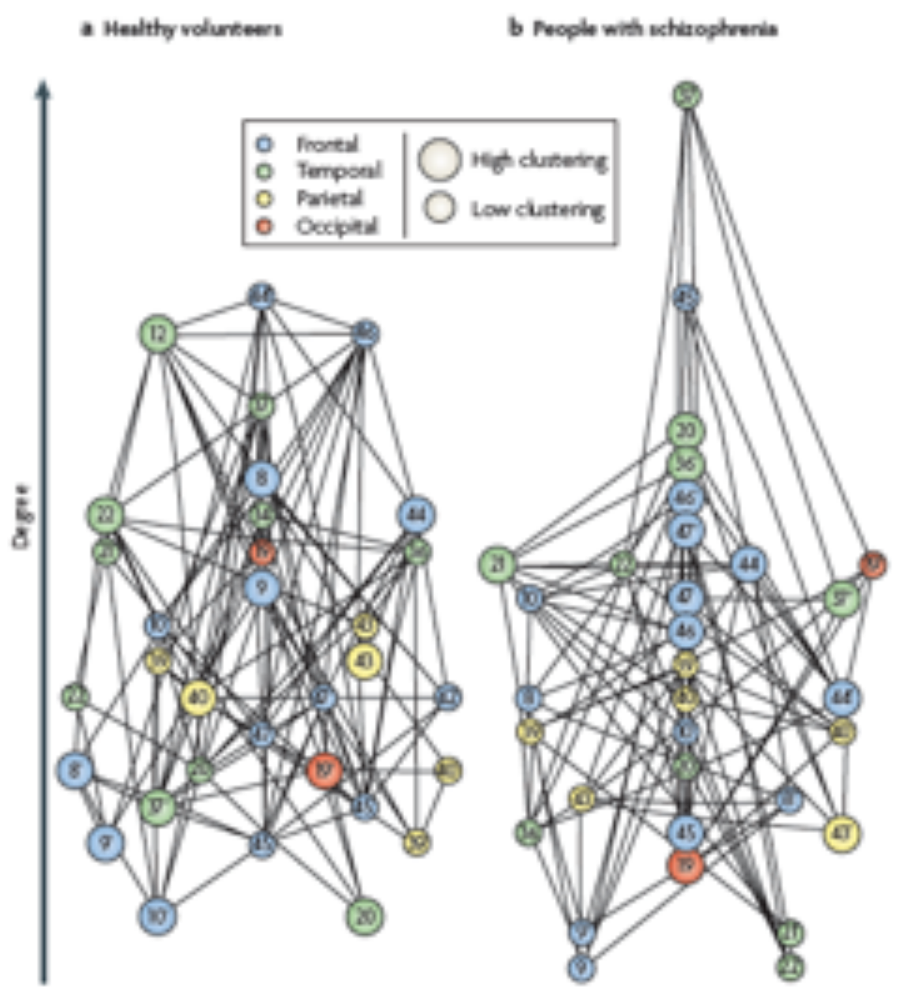
That's about 6-7 seconds!

Stam, C. J. (2010). Characterization of anatomical and functional connectivity in the brain: A complex networks perspective. International journal of psychophysiology : official journal of the International Organization of Psychophysiology, 77(3), 186-194. Elsevier B.V. doi: 10.1016/j.ijpsycho.2010.06.024.

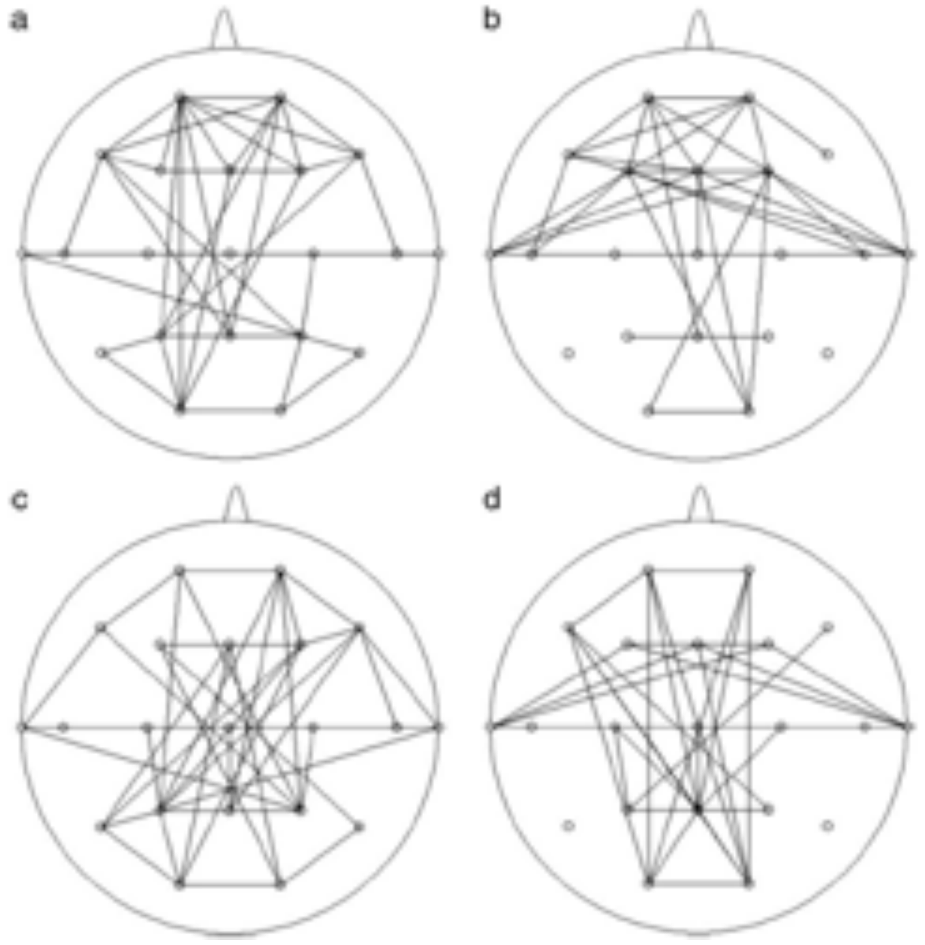
Network / Graph topology

Pathology studies

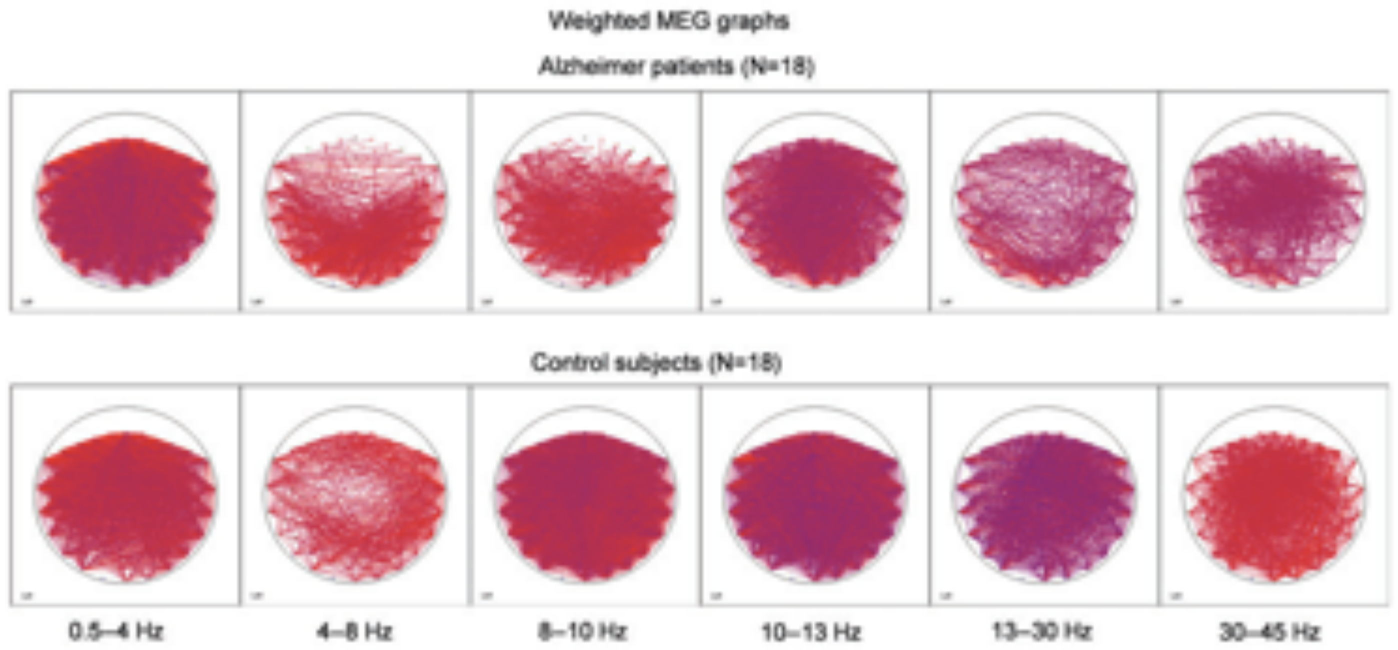
Based on a few samples we can distinguish healthy subjects from patients:



Schizophrenia



Absence seizure

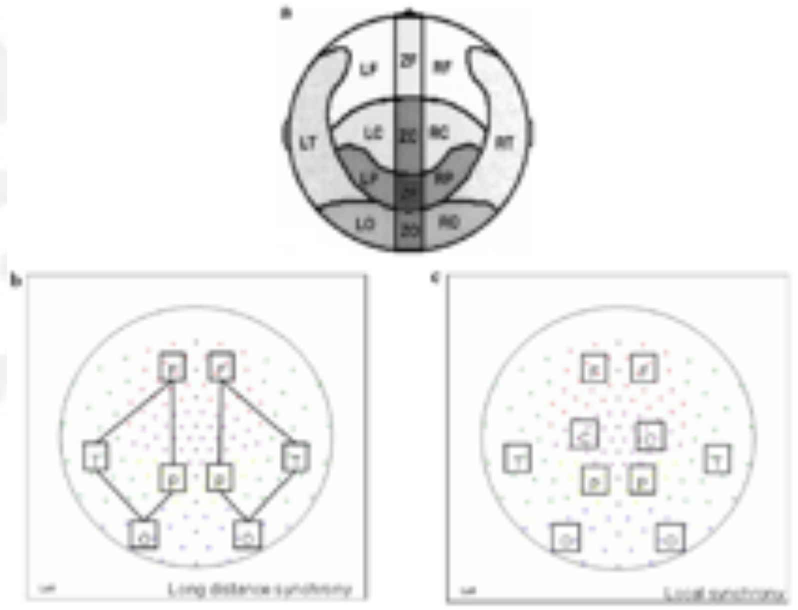


Alzheimer's disease: Targeted attack on hubs!

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.

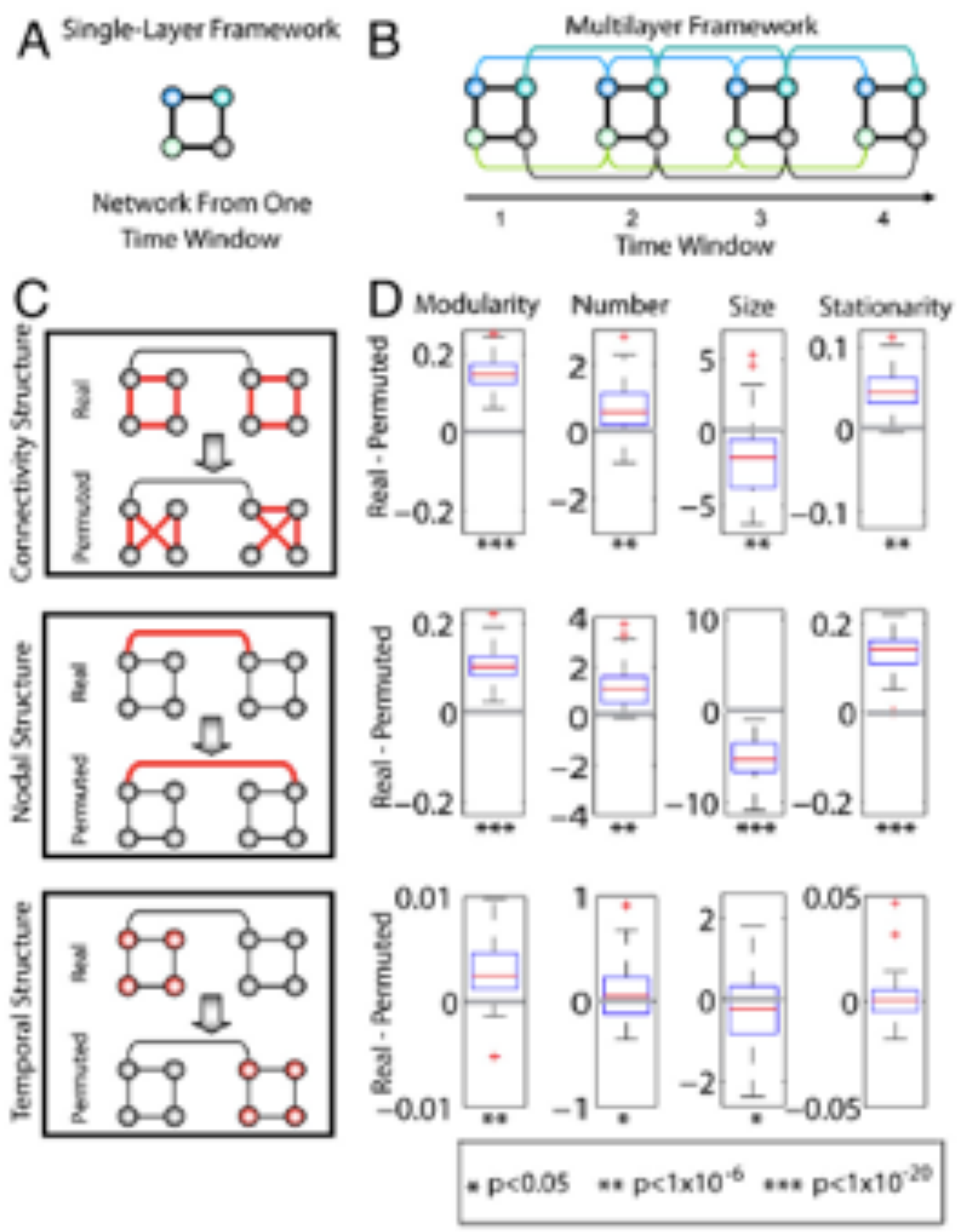
Stam, C. J., Haan, W. de, Daffertshofer, a, Jones, B. F., Manshanden, I., Cappellen van Walsum, a M. van, et al. (2009). Graph theoretical analysis of magnetoencephalographic functional connectivity in Alzheimer's disease. Brain : a journal of neurology, 132(Pt 1), 213-24. doi: 10.1093/brain/awn262.

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



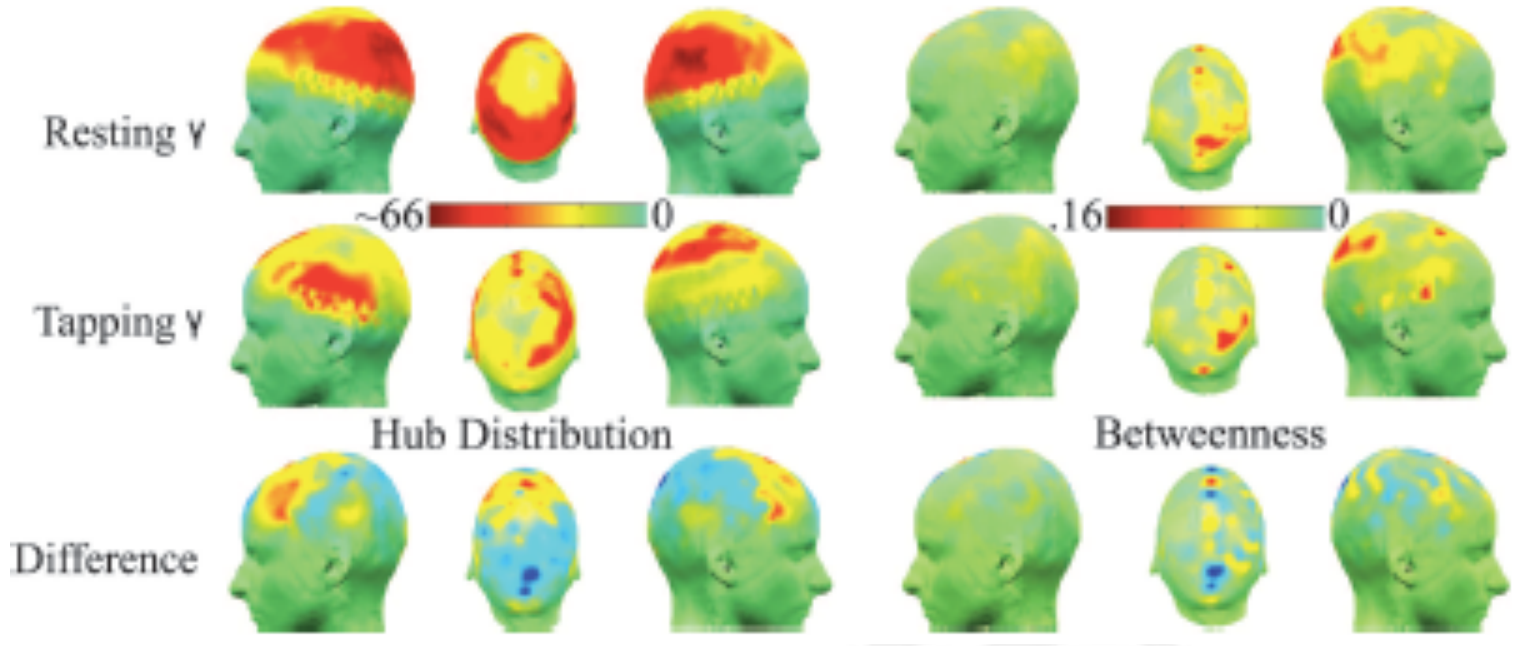
Cognitive abilities

Gender

Age

Learning

Tapping



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.

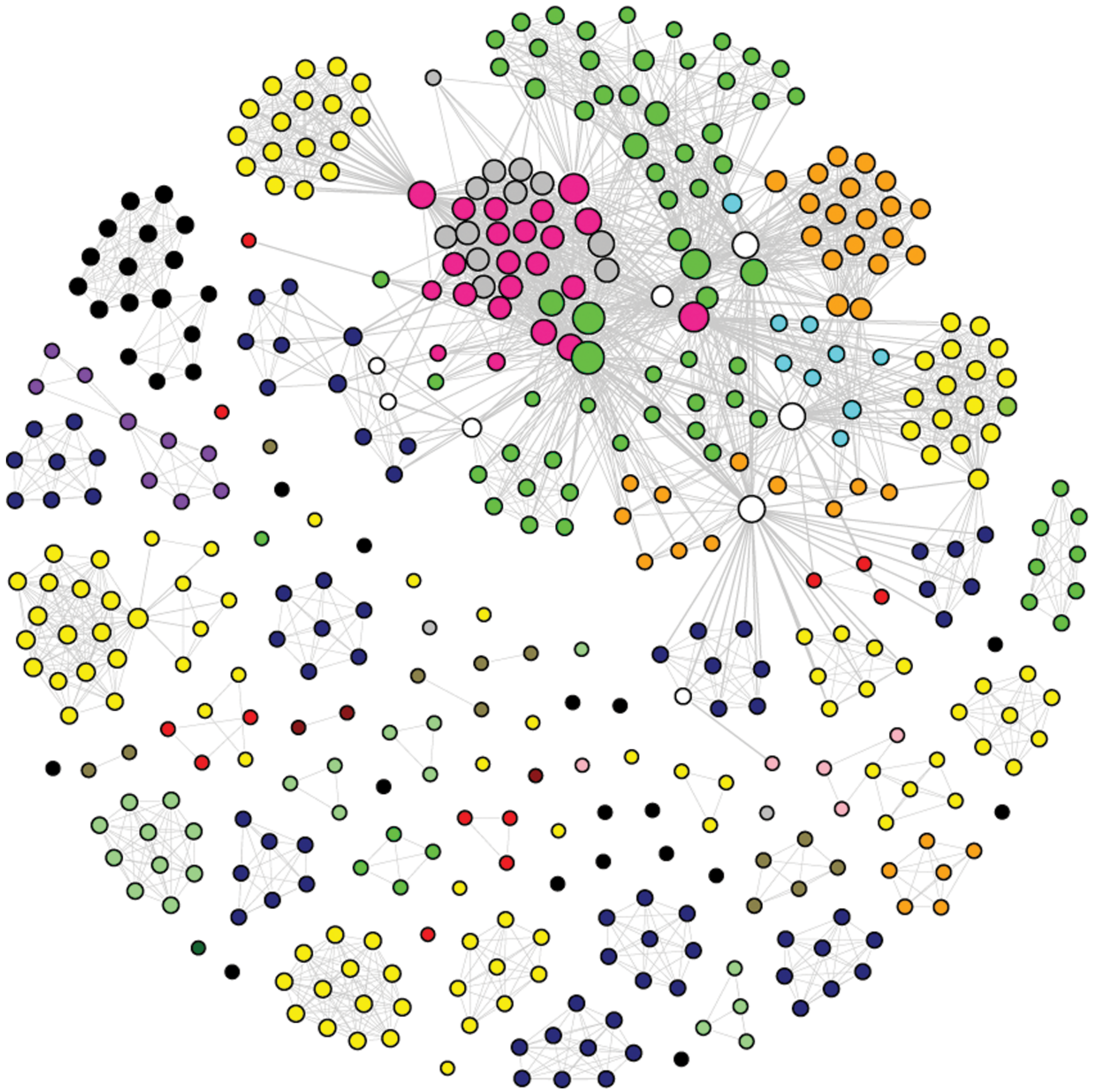
Bassett, D. S., Wymbs, N. F., Porter, M. a, Mucha, P. J., Carlson, J. M., & Grafton, S. T. (2011). Dynamic reconfiguration of human brain networks during learning. Proceedings of the National Academy of Sciences. doi: 10.1073/pnas.1018985108.

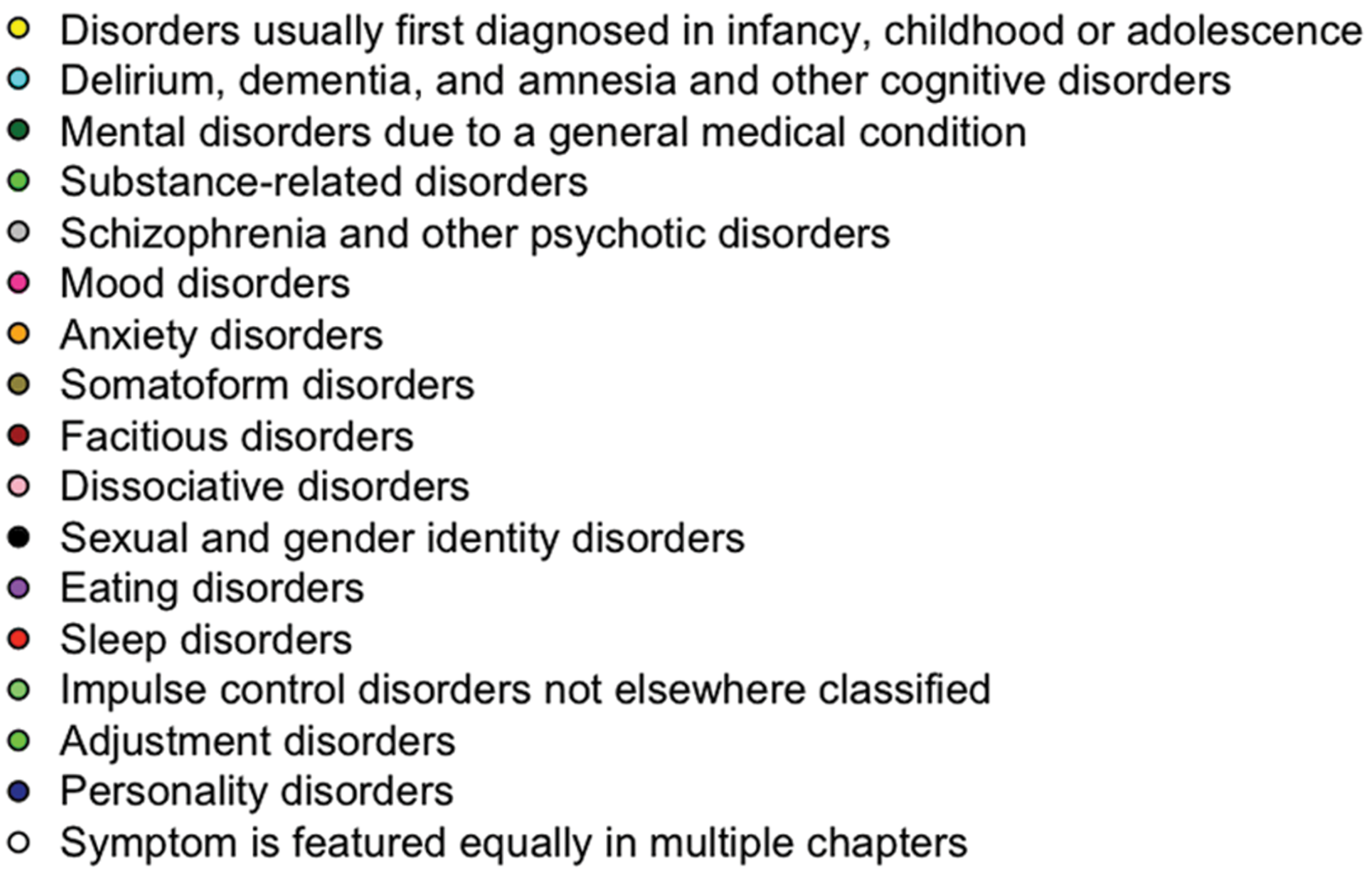
Douw, L., Schoonheim, M. M., Landi, D., Meer, M. L. van der, Geurts, J. J. G., Reijneveld, J. C., et al. (2011). Cognition is related to resting-state small-world network topology: an magnetoencephalographic study. Neuroscience, 175, 169-77. Elsevier Inc. doi: 10.1016/j.neuroscience.2010.11.039.

Symptoom netwerken
Small-world of DSM-IV

Problemen met het medisch model by psychopathologie:

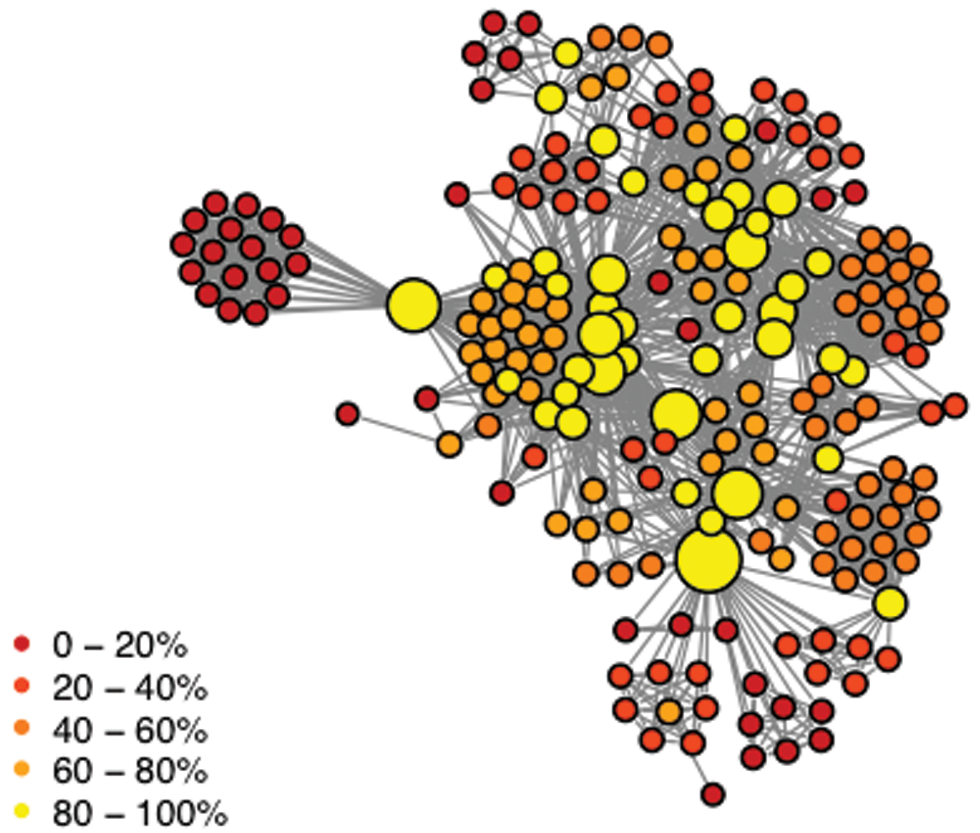
- geen unieke veroorzaker voor symptomen, zoals griepvirus
- symptomen zijn vaak de diagnose en oorzaak tegelijk

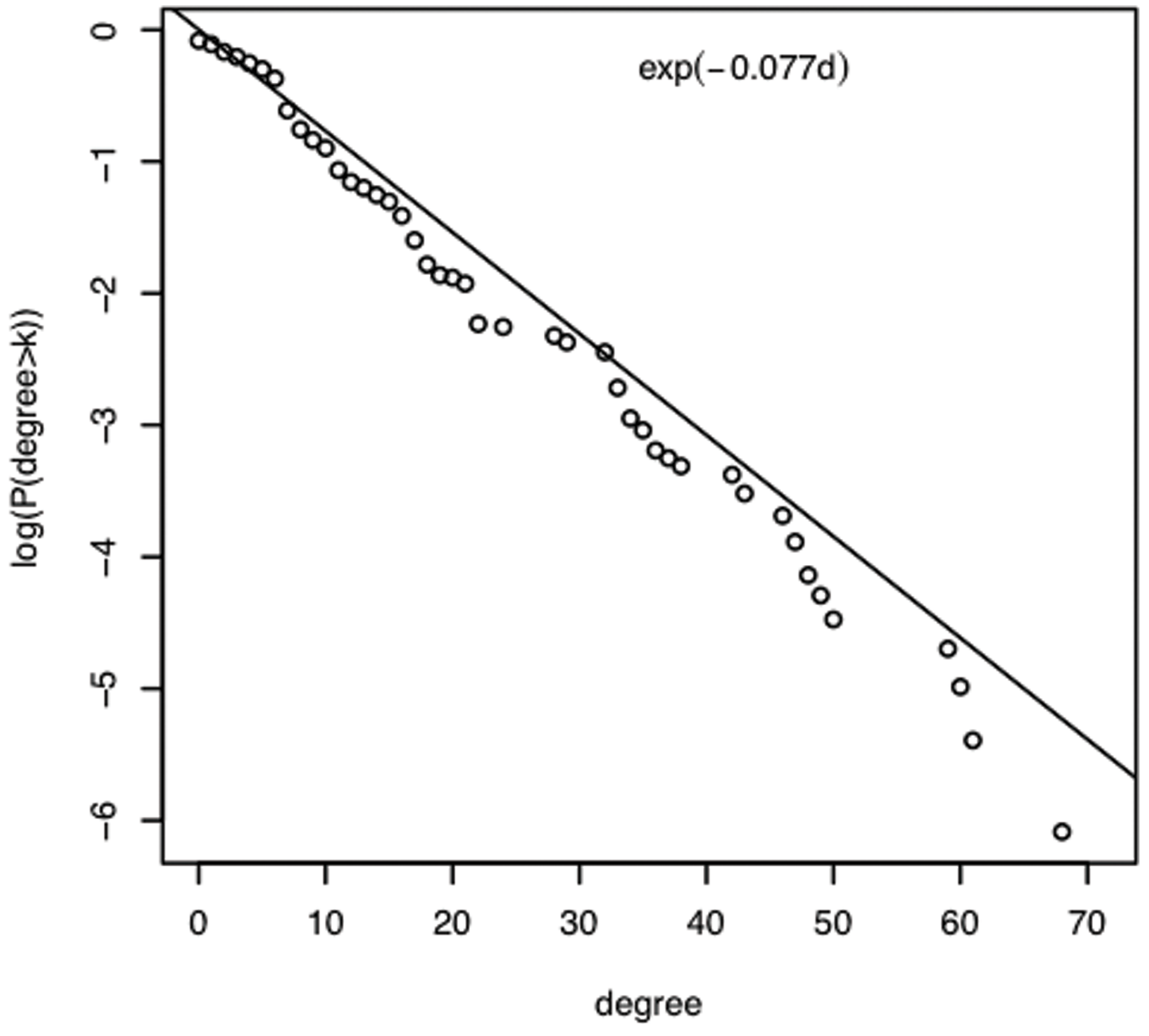




Borsboom D, Cramer AOJ, Schmittmann VD, Epskamp S, Waldorp LJ (2011) The Small World of Psychopathology. PLoS ONE 6(11): e27407. doi:10.1371/journal.pone.0027407

Symptom netwerken





We show that

a) half of the symptoms in the DSM-IV network are connected,

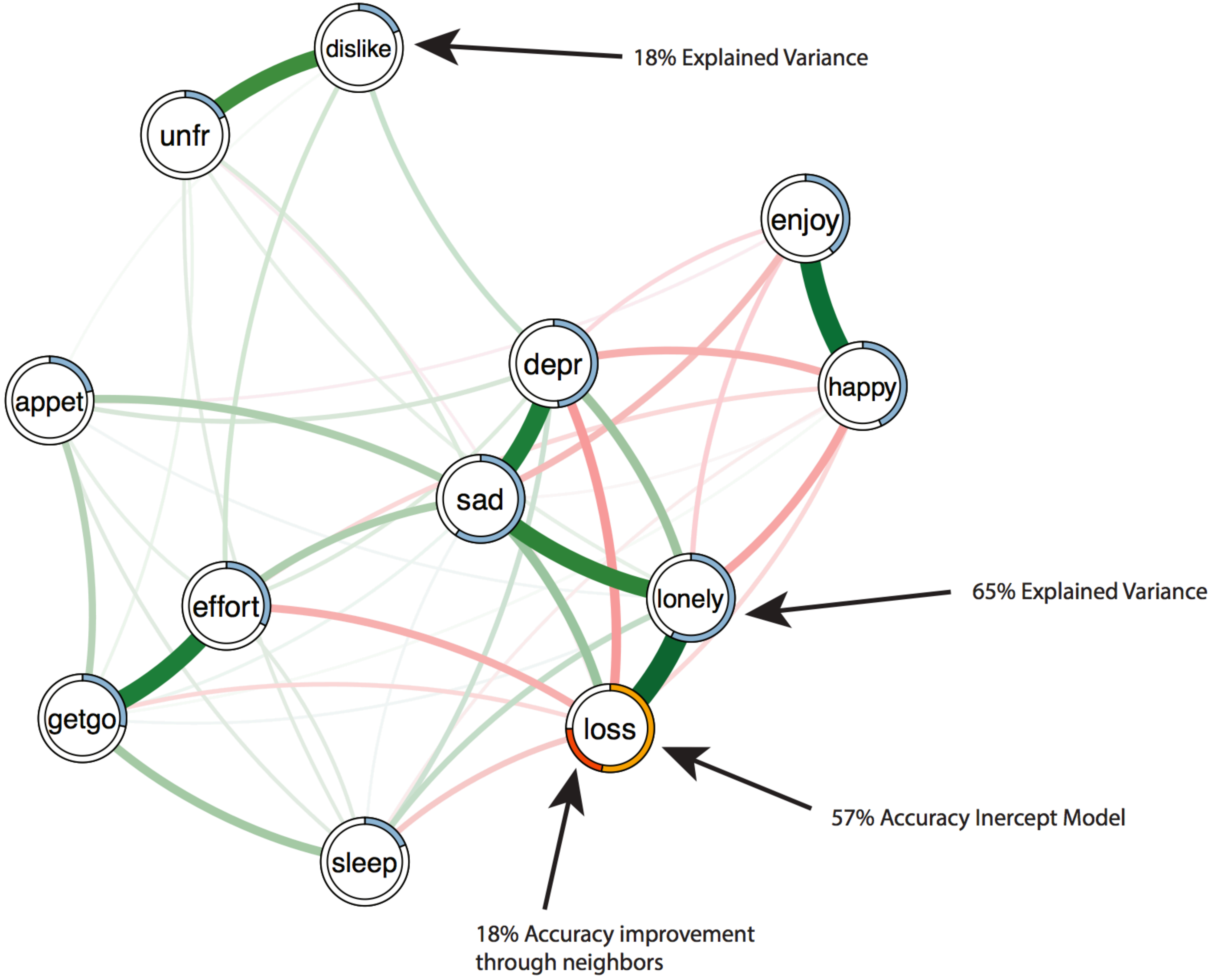
b) the architecture of these connections conforms to **a small world structure**, featuring a **high degree of clustering** but a **short average path length**, and

c) distances between disorders in this **structure predict empirical comorbidity rates**. Network simulations of Major Depressive Episode and Generalized Anxiety Disorder show that the model faithfully reproduces empirical population statistics for these disorders.

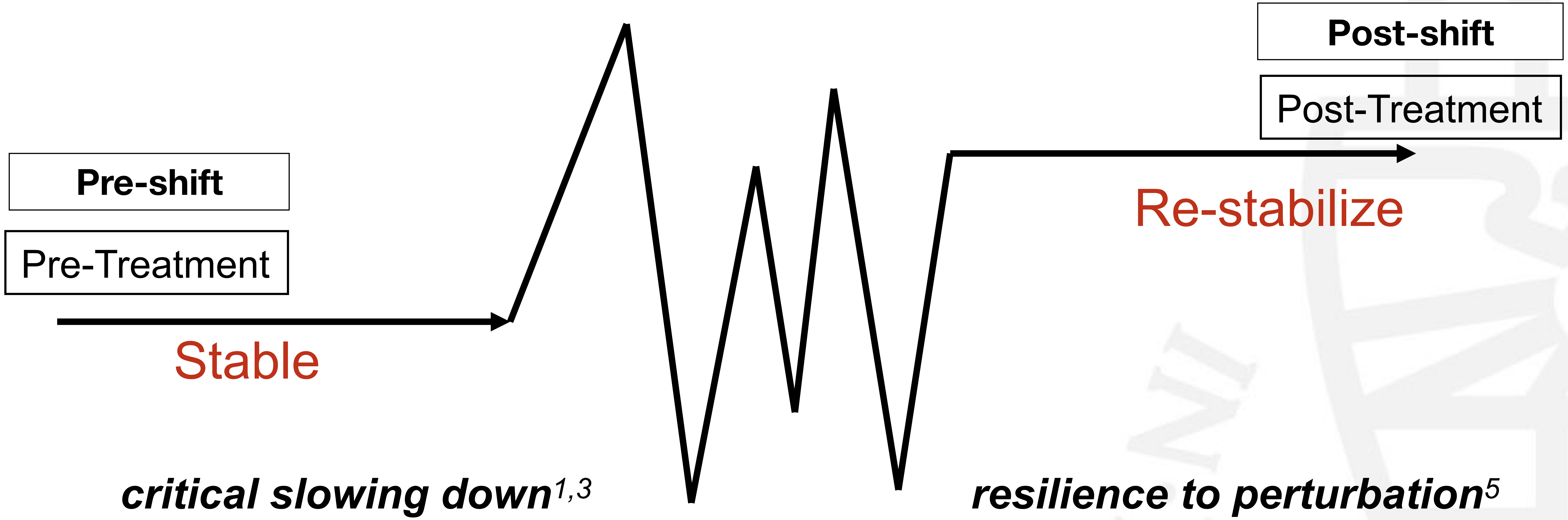
Borsboom D, Cramer AOJ, Schmittmann VD, Epskamp S, Waldorp LJ (2011) The Small World of Psychopathology. PLoS ONE 6(11): e27407. doi:10.1371/journal.pone.0027407

Symptom netwerken

psychosystems.org



Period of Destabilization



critical slowing down[1,3]

critical fluctuations[3,4]

resilience to perturbation[5]

- increase in recovery and switching time after perturbation
- increase in variance, autocorrelation, long-range dependence
- increase in occurrence and diversity of unstable states
- increase in the entropy of the distribution of state occurrences

[1]Scholz JP, Kelso JAS, Schöner G. (1987). Nonequilibrium phase transitions in coordinated biological motion: critical slowing down and switching time. *Physics Letters A 123,* 390–394.

[2]Scheffer M, Bascompte J, Brock W A, Brovkin V, Carpenter SR, Dakos V, Held H, van Nes EH, Rietkerk M, Sugihara G. (2009). Early-warning signals for critical transitions. *Nature 461,* 53–9.

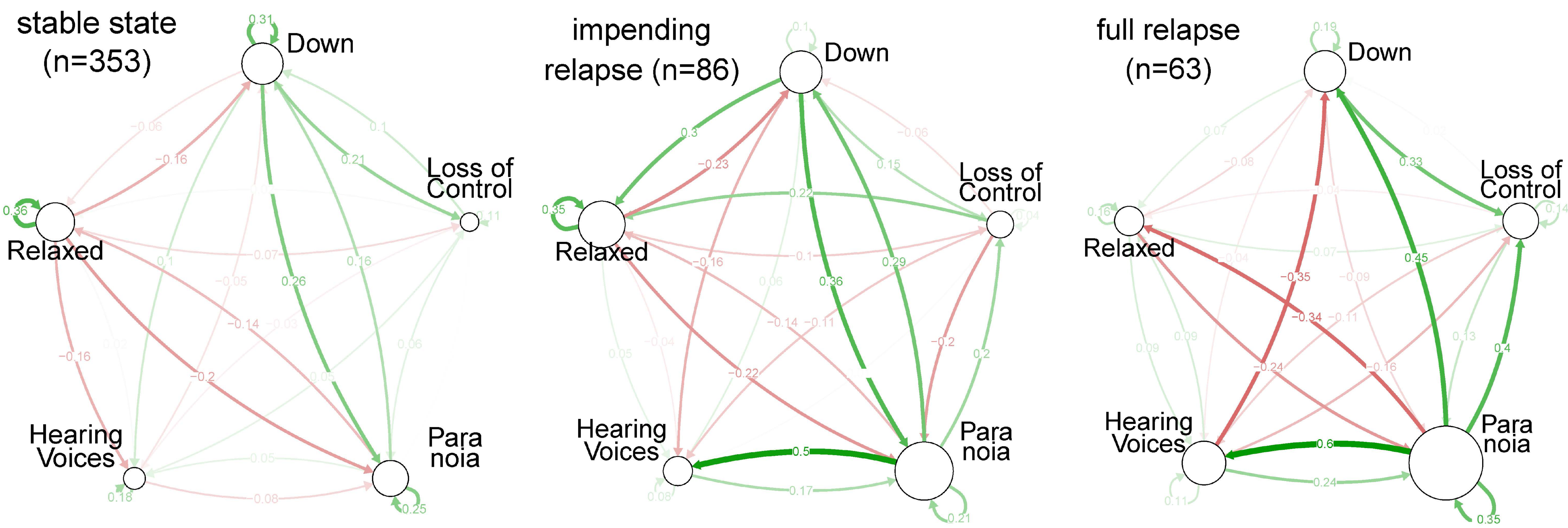
[3]Stephen DG, Dixon JA, Isenhower RW. (2009). Dynamics of representational change: Entropy, Action and Cognition. *JEP: Human Perception and Performance 35,* 1811–1832.

[4]Schiepek G, Strunk G. (2010). The identification of critical fluctuations and phase transitions in short term and coarse-grained time series … *Biological cybernetics 102,*197–207.

An n=1 Clinical Network Analysis of Symptoms and Treatment in Psychosis

variation in 'hearing voices', 'down', 'paranoia', 'loss of control' and 'relaxed' (range 1-7) during a year

An n=1 Clinical Network Analysis of Symptoms and Treatment in Psychosis



An n=1 Clinical Network Analysis of Symptoms and Treatment in Psychosis

	Betweenness	Closeness	Inward degree	Outward degree	Node strength
Stable state					
'Down'	5	0.032	0.78	0.92	1.70
'Loss of control'	0	0.015	0.45	0.31	0.76
'Paranoia'	4	0.026	0.87	0.62	1.48
'Hearing Voices'	0	0.015	0.51	0.39	0.90
'Relaxed'	1	0.036	0.61	0.98	1.59
Impending relapse					
'Down'	2	0.056	0.74	1.07	1.81
'Loss of control'	0	0.040	0.51	0.64	1.15
'Paranoia'	7	0.058	1.16	1.34	2.49
'Hearing Voices'	0	0.026	0.90	0.35	1.25
'Relaxed'	0	0.039	1.05	0.95	2.00
Full Relapse state					
'Down'	1	0.025	1.08	0.72	1.80
'Loss of control'	3	0.027	1.12	0.44	1.56
'Paranoia'	7	0.109	1.04	2.18	3.22
'Hearing Voices'	0	0.050	0.95	0.95	1.90
'Relaxed'	0	0.041	0.69	0.59	1.28

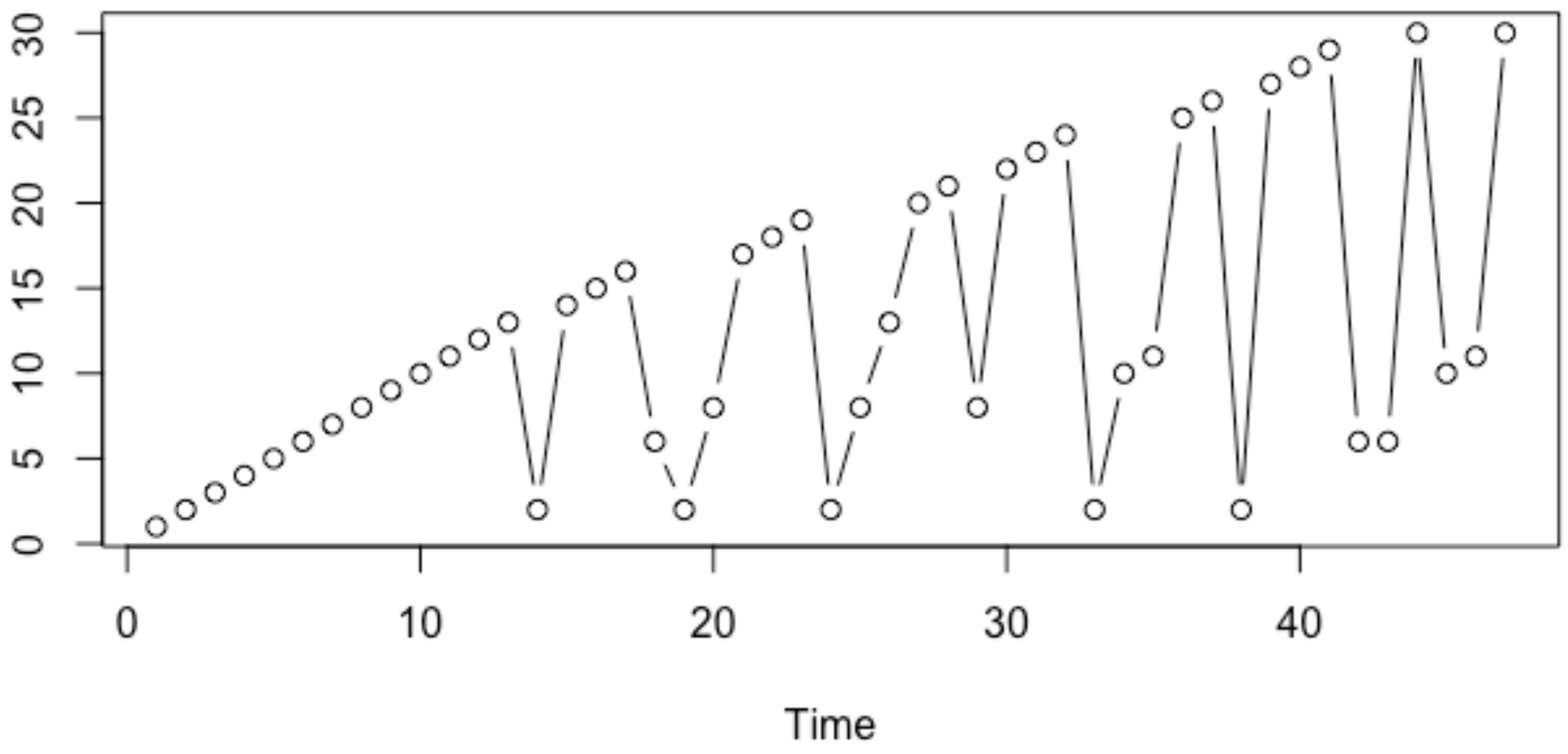
The Spearman correlations as suggested by reviewer #1

doi:10.1371/journal.pone.0162811.t002

Recurrence Quantification Analysis: Nominale Tijdseries

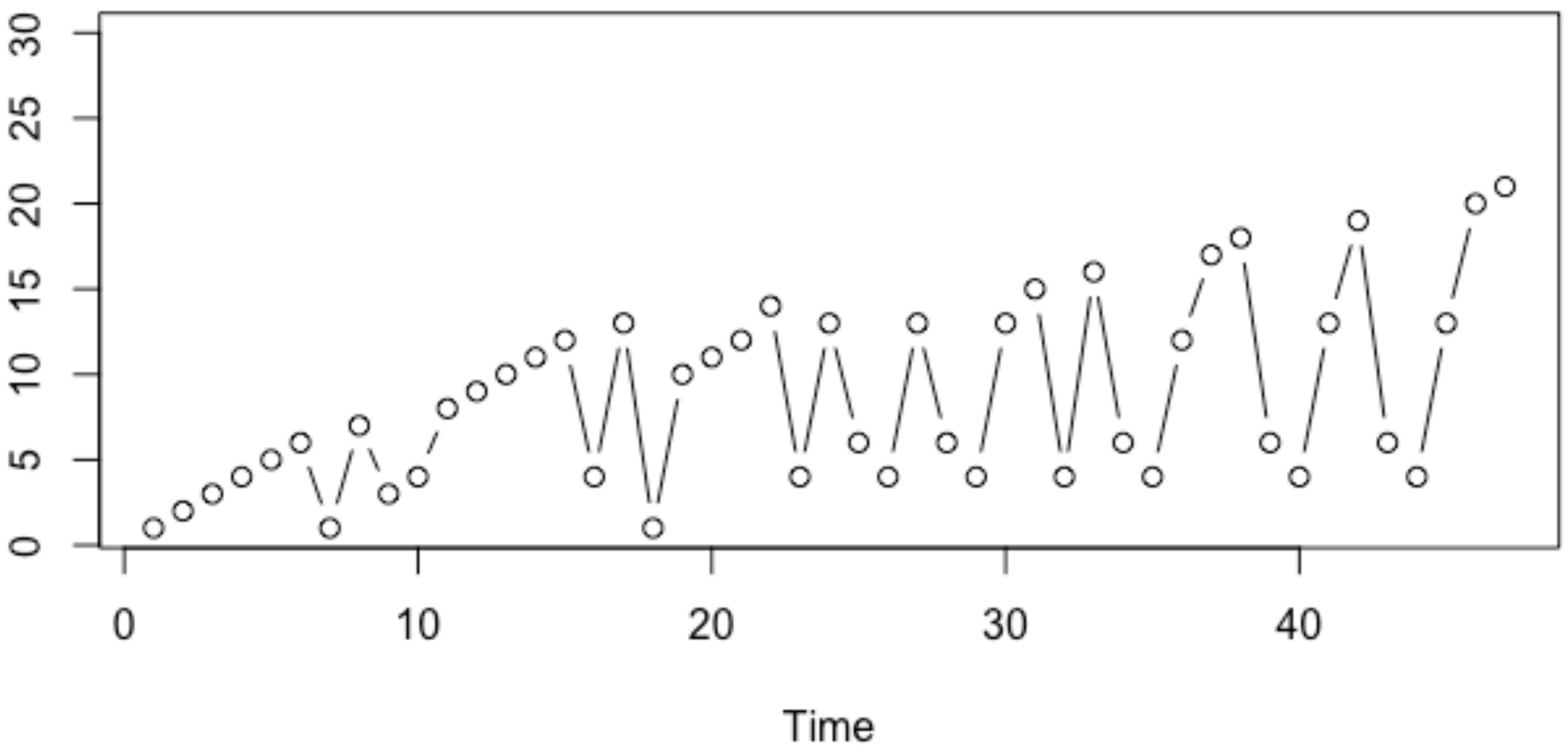
VERHAAL 1

“1 2 3 4 5 6 7 8 9 10 11 12 13 2 14 15 16 6 2 8 17 18 19 2 8 13 20 21 8 22 23 24 2 10 11 25 26 2 27 28 29 6 6 30 10 11 30”



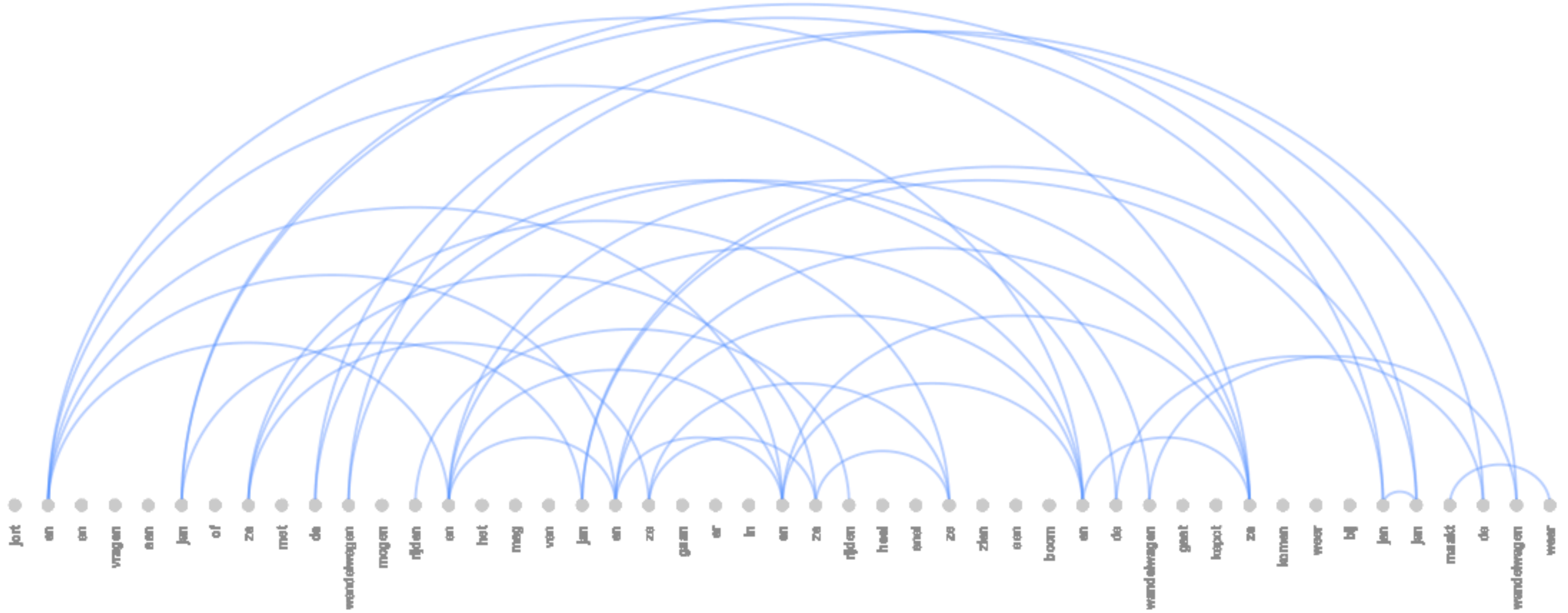
VERHAAL 2

“1 2 3 4 5 6 1 7 3 4 8 9 10 11 12 4 13 1 10 11 12 14 4 13 6 4 13 6 4 13 15 4 16 6 4 12 17 18 6 4 13 19 6 4 13 20 21”

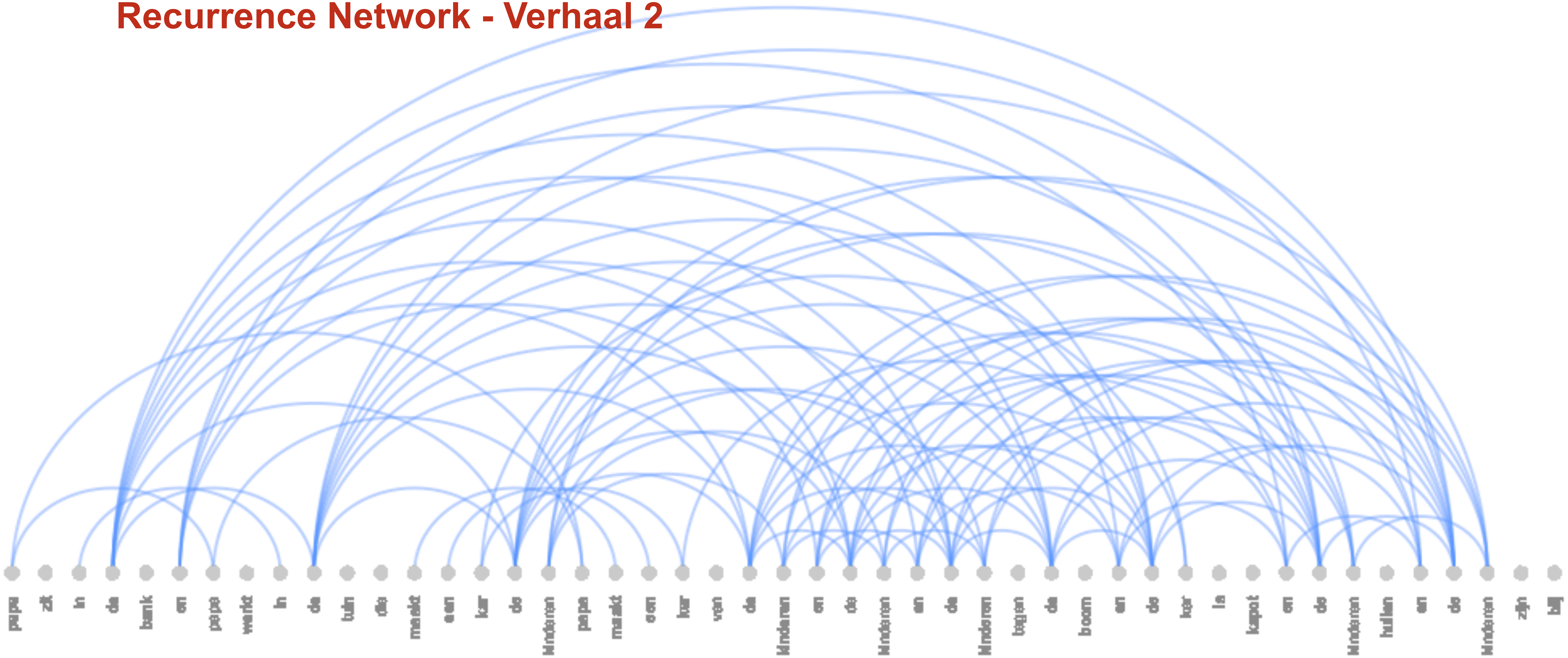


Data from: Huijgevoort, M. A. E. V. (2008). *Improving beginning literacy skills by means of an interactive computer environment* (Doctoral dissertation). http://repository.ubn.ru.nl/bitstream/handle/2066/45170/45170_imprbelis.pdf

Recurrence Network - Verhaal 1

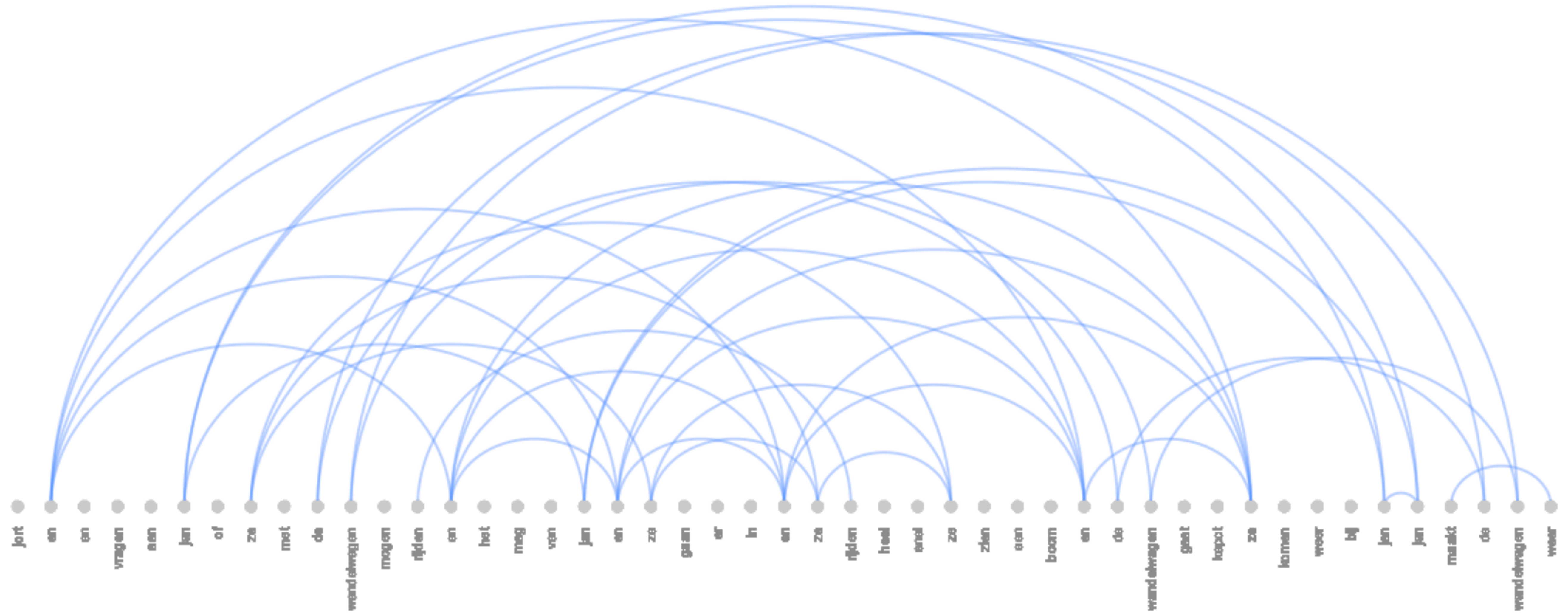


Recurrence Network - Verhaal 2

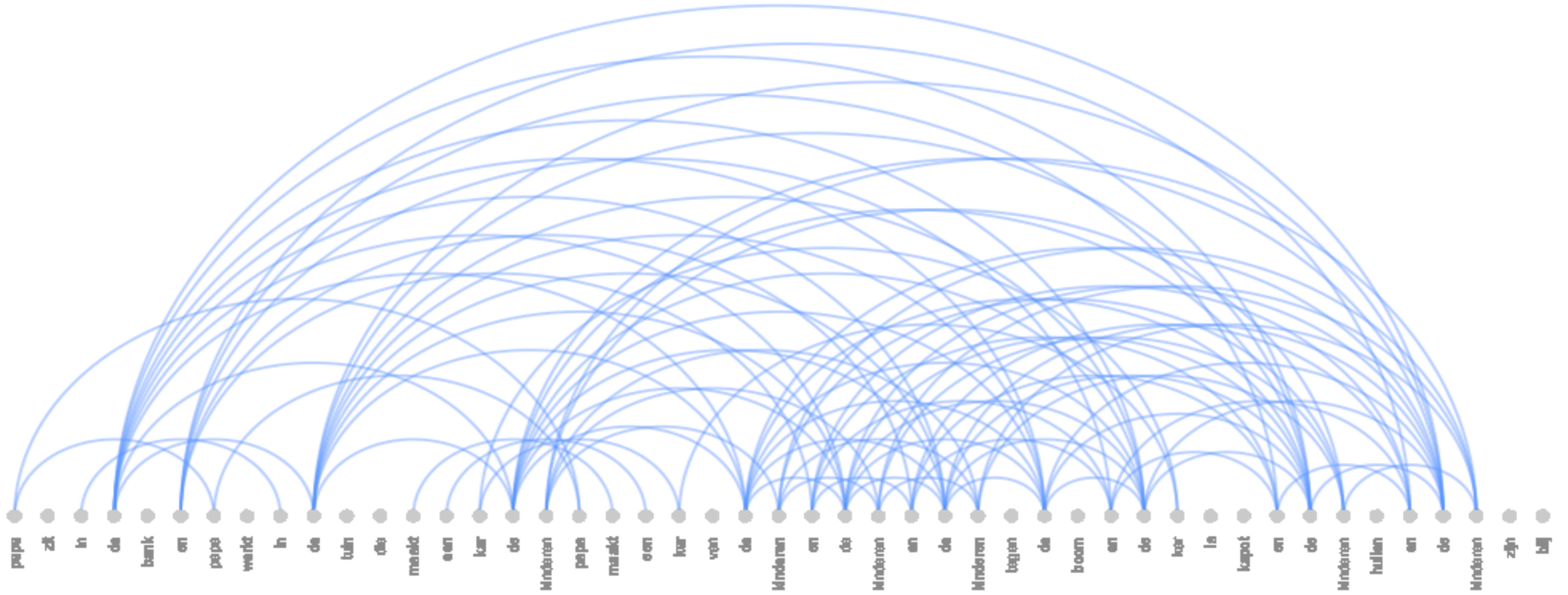


Recurrence Network

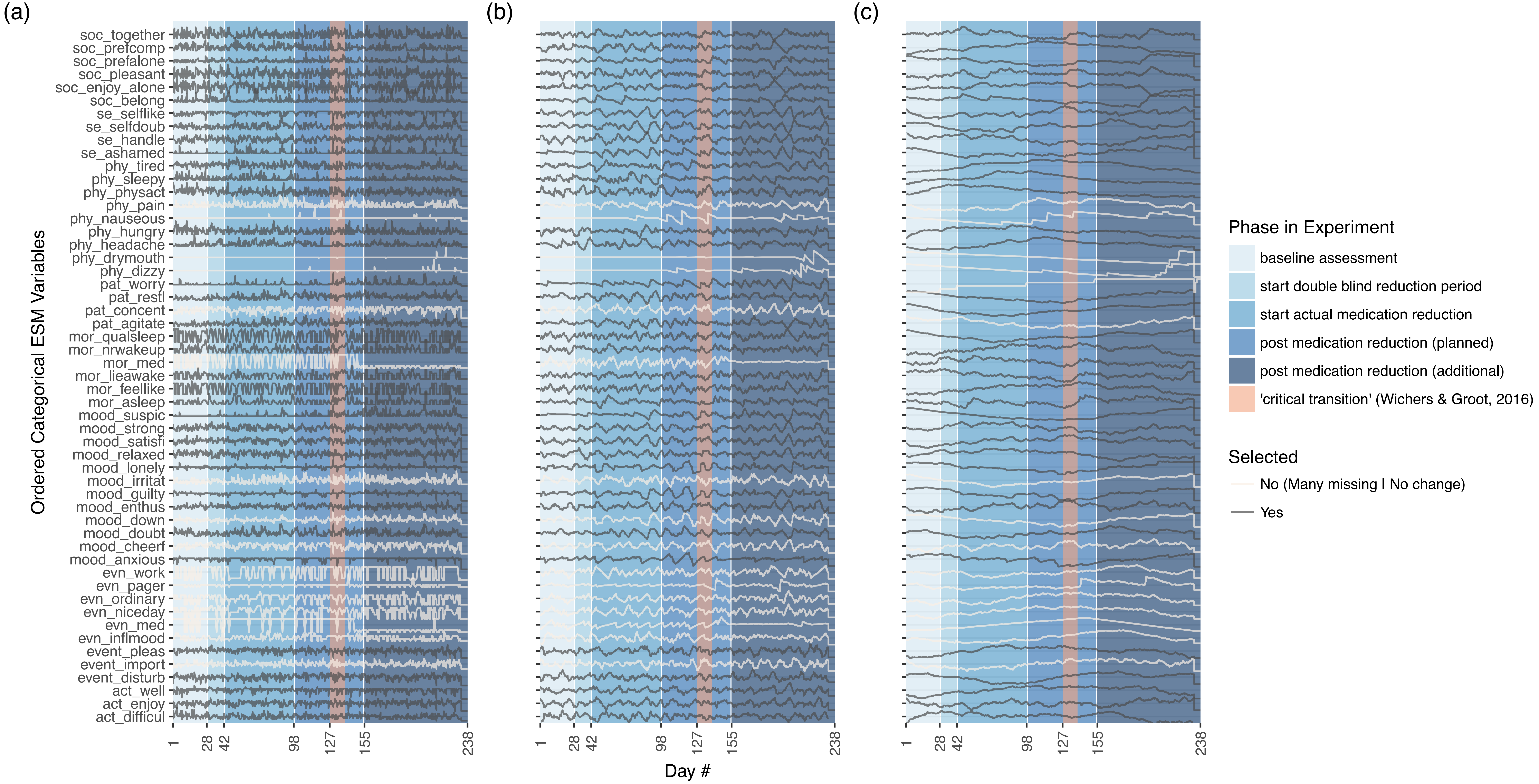
Total Degree = 70 *verhaal 1*



Total Degree = 168 *verhaal 2*



Critical Slowing Down as a Personalized Early Warning Signal for Depression

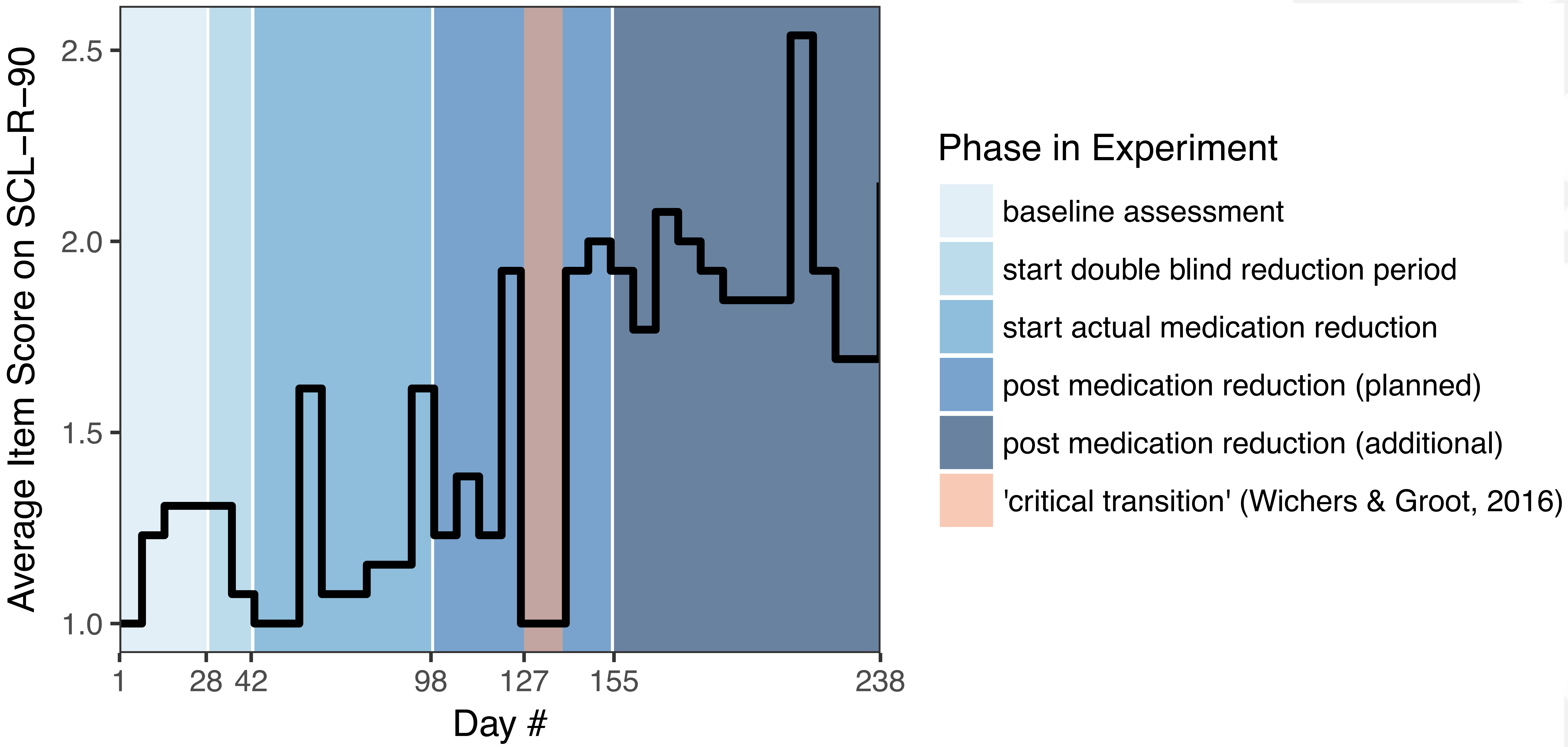


Wichers, M., Groot, P. C., Psychosystems, ESM Grp, & EWS Grp (2016). Critical Slowing Down as a Personalized Early Warning Signal for Depression. Psychotherapy and psychosomatics, 85(2), 114-116. DOI: 10.1159/000441458

Kossakowski, J., Groot, P., Haslbeck, J., Borsboom, D., and Wichers, M. (2017). Data from 'critical slowing down as a personalized early warning signal for depression'. Journal of Open Psychology Data, 5(1).

Critical Slowing Down as a Personalized Early Warning Signal for Depression

Wichers, Maria; Groot, Peter C.; Psychosystems; ESM Grp; EWS Grp



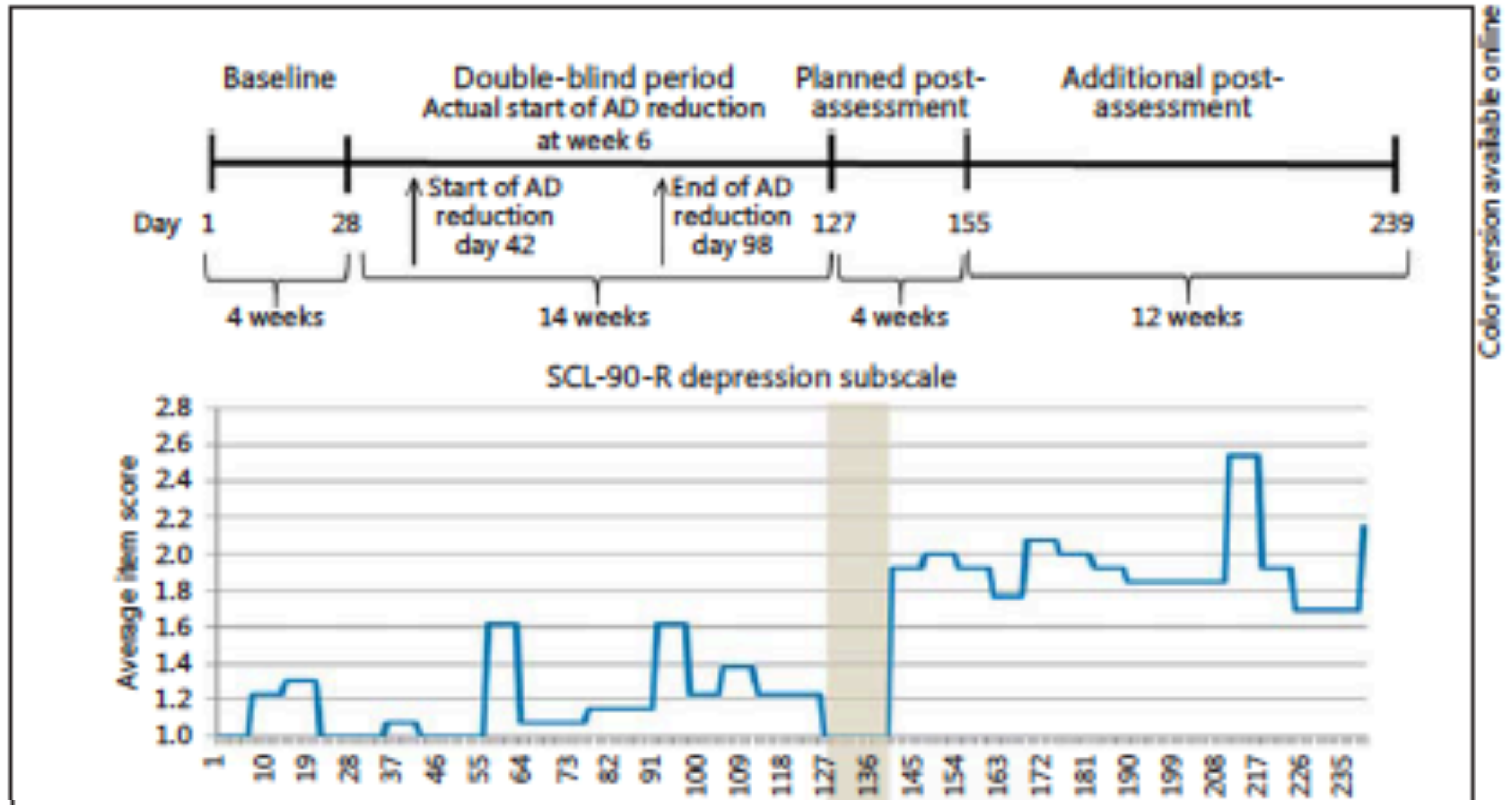
Wichers, M., Groot, P. C., Psychosystems, ESM Grp, & EWS Grp (2016). Critical Slowing Down as a Personalized Early Warning Signal for Depression. Psychotherapy and psychosomatics, 85(2), 114-116. DOI: 10.1159/000441458

Kossakowski, J., Groot, P., Haslbeck, J., Borsboom, D., and Wichers, M. (2017). Data from 'critical slowing down as a personalized early warning signal for depression'. Journal of Open Psychology Data, 5(1).

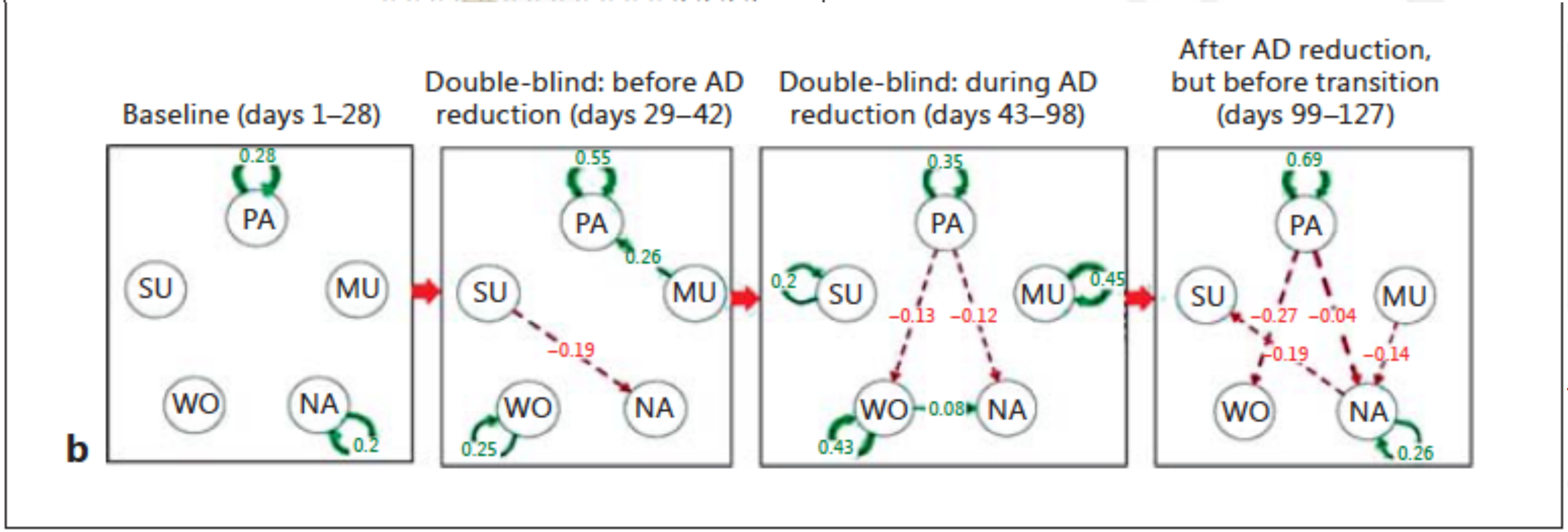
Wichers, M., Groot, P. C., Psychosystems, ESM Grp, & EWS Grp (2016). Critical Slowing Down as a Personalized Early Warning Signal for Depression. Psychotherapy and psychosomatics, 85(2), 114-116. DOI: 10.1159/000441458

Critical Slowing Down as a Personalized Early Warning Signal for Depression

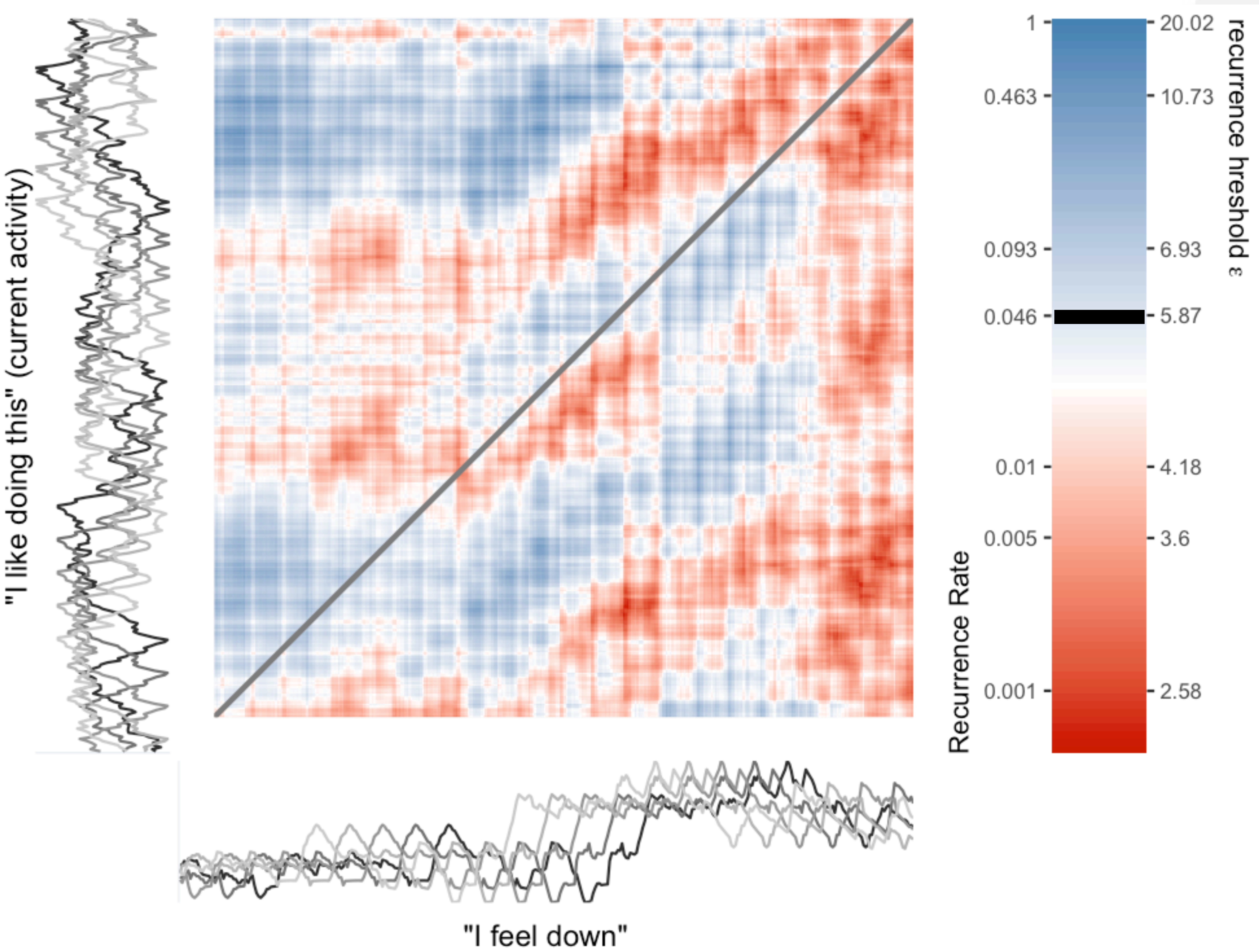
Wichers, Maria; Groot, Peter C.; Psychosystems, ESM Grp; EWS Grp



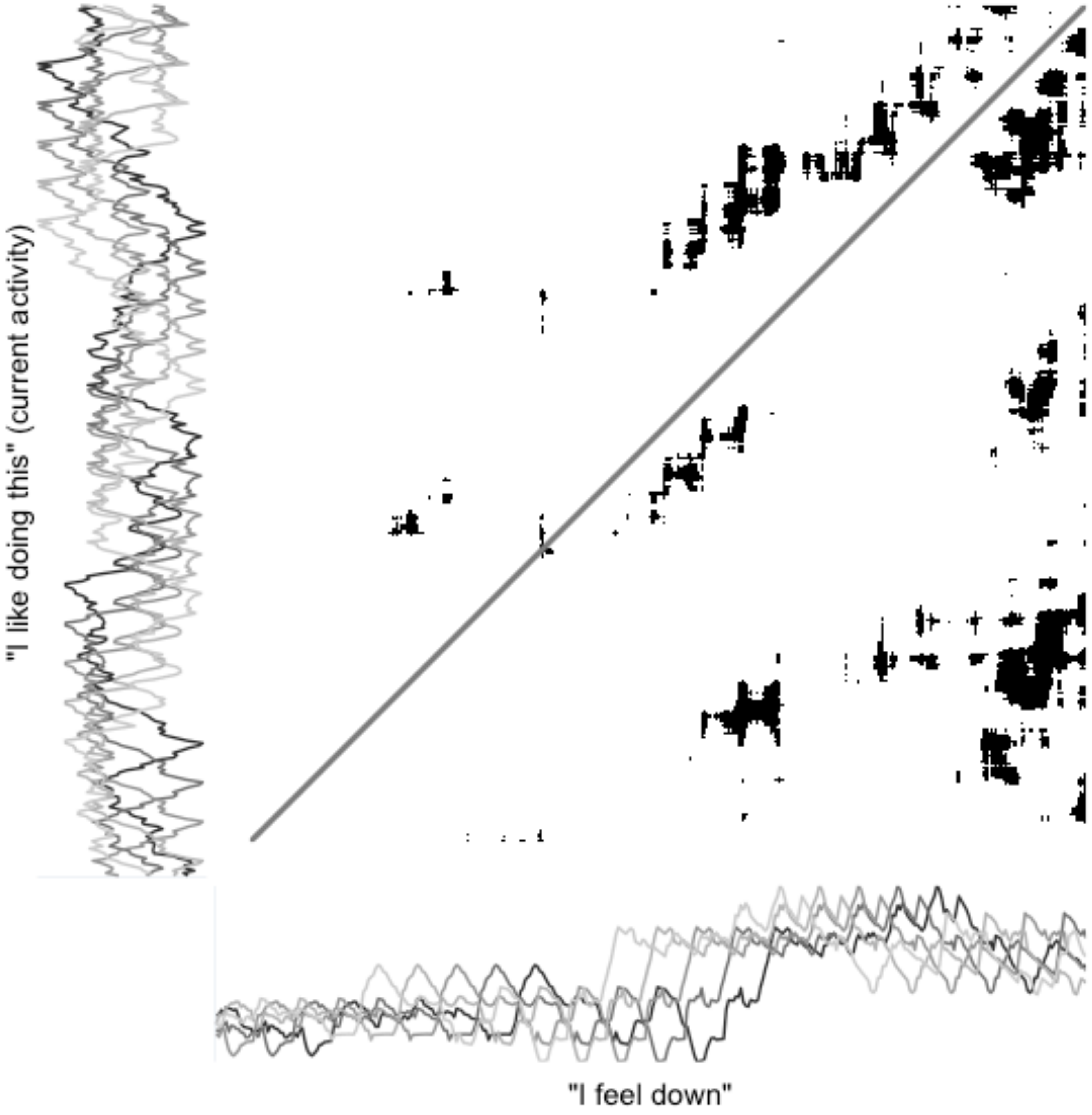
- Autocorrelation increase (30 day window)
- Variance increase (30 day window)



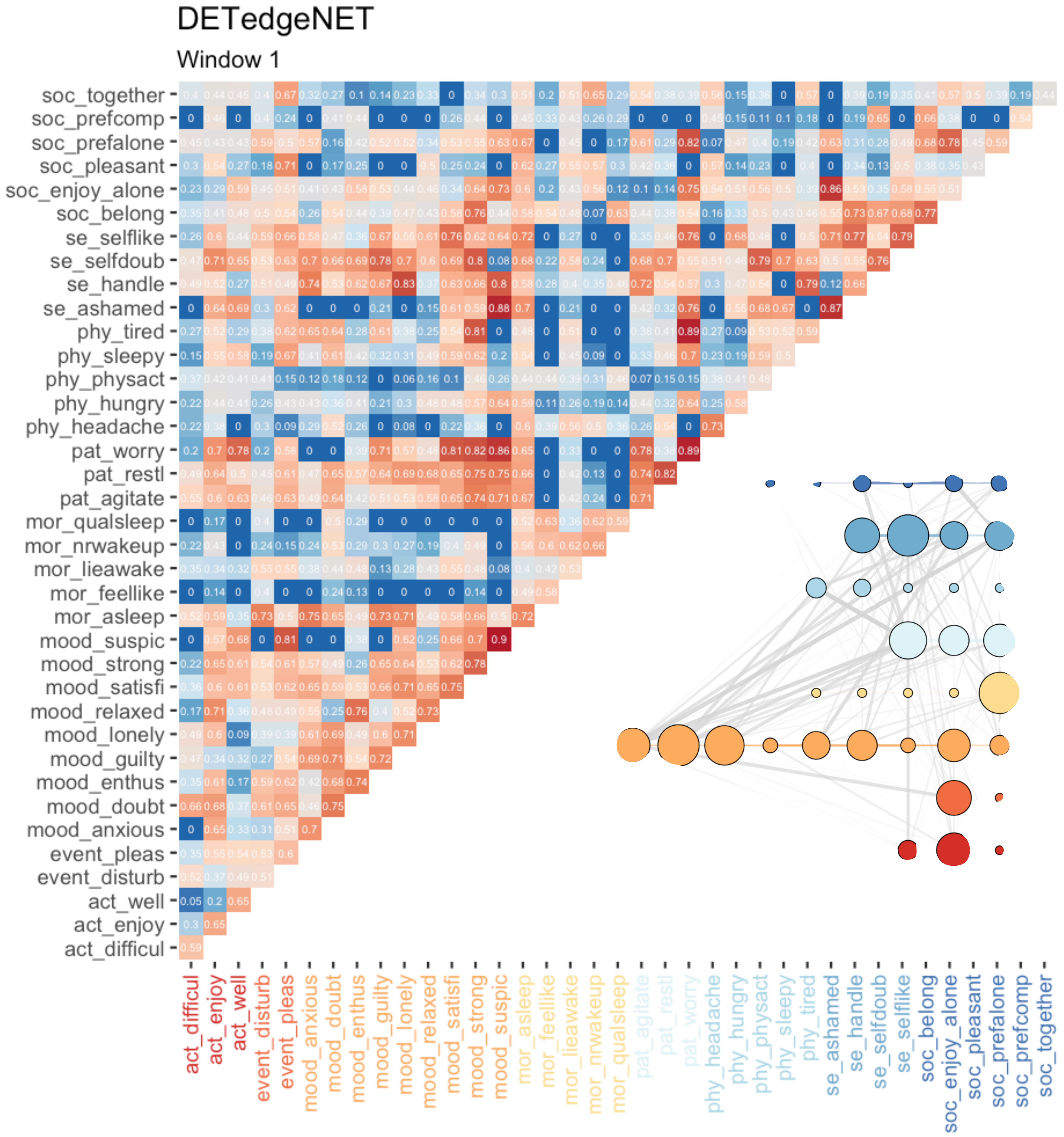
Cross Recurrence Plot (unthresholded)

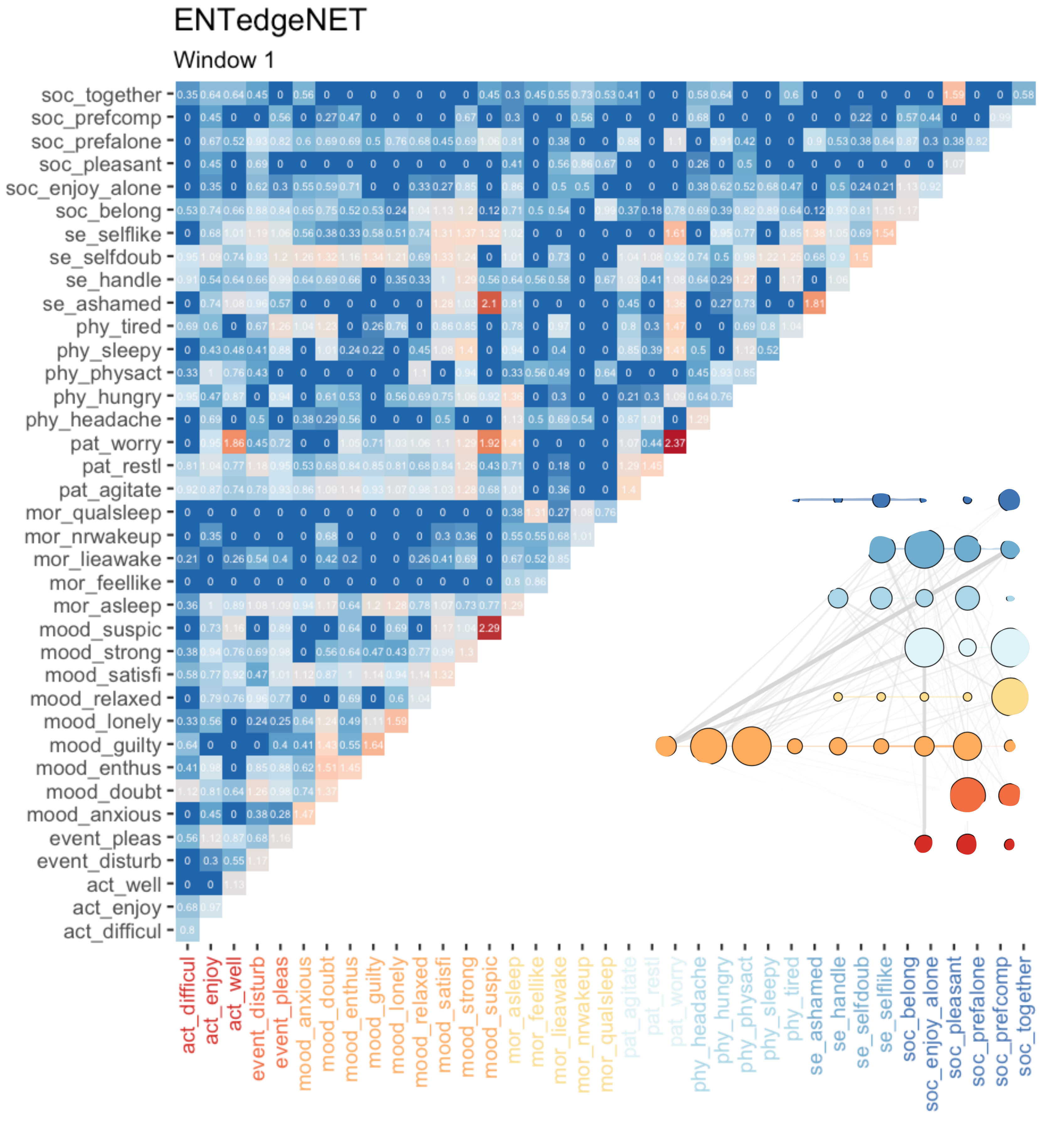


Cross Recurrence Plot (thresholded)



Multiplex Cross-Recurrence Network

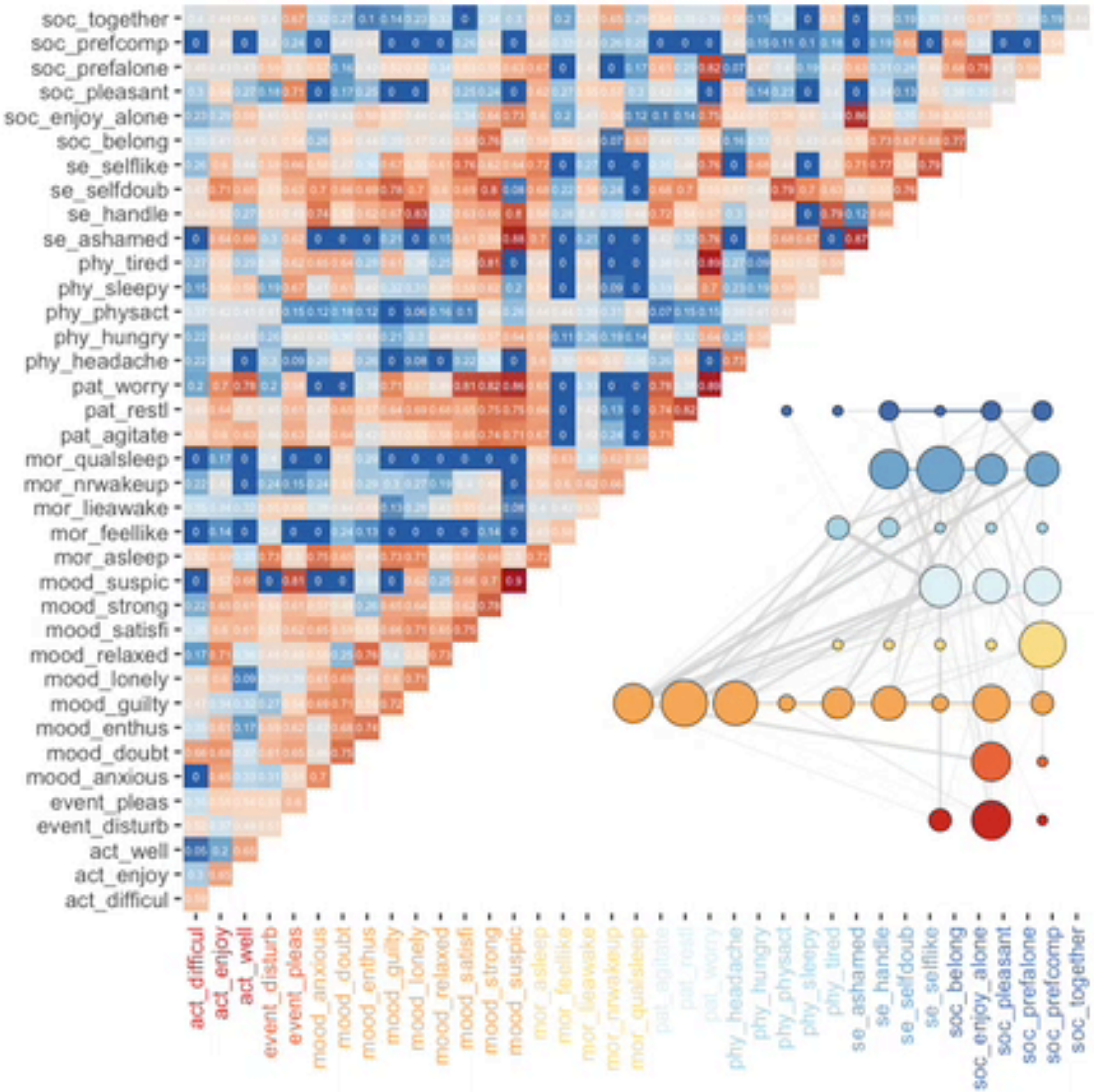




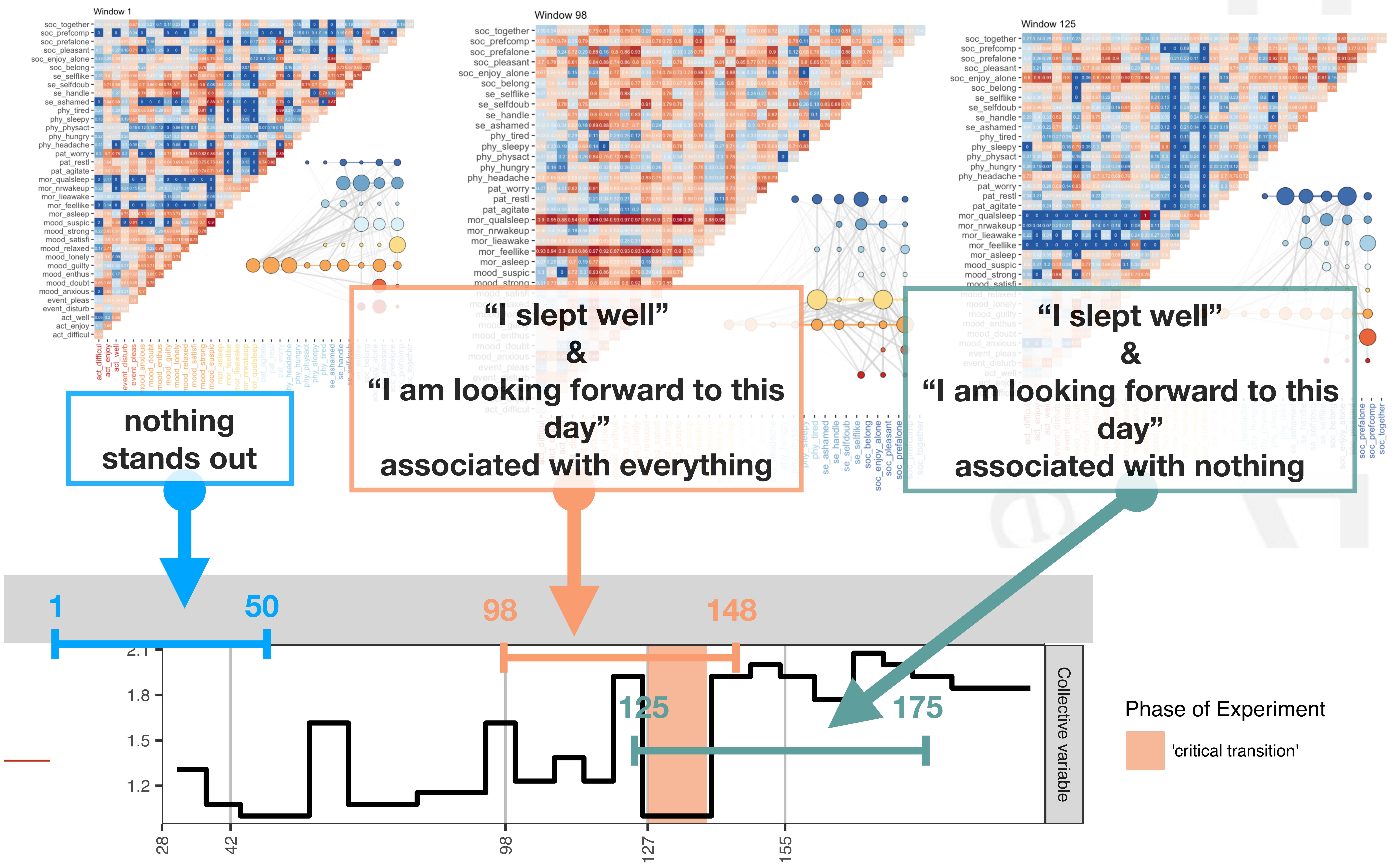
Hasselman, F., Cox., R.F.A., & Bringmann, L.F (submitted). Detecting Order Transitions in Multivariate Time Series of Intra-individual Psychological Dynamics Using Multiplex Cross Recurrence Networks

DETedgeNET

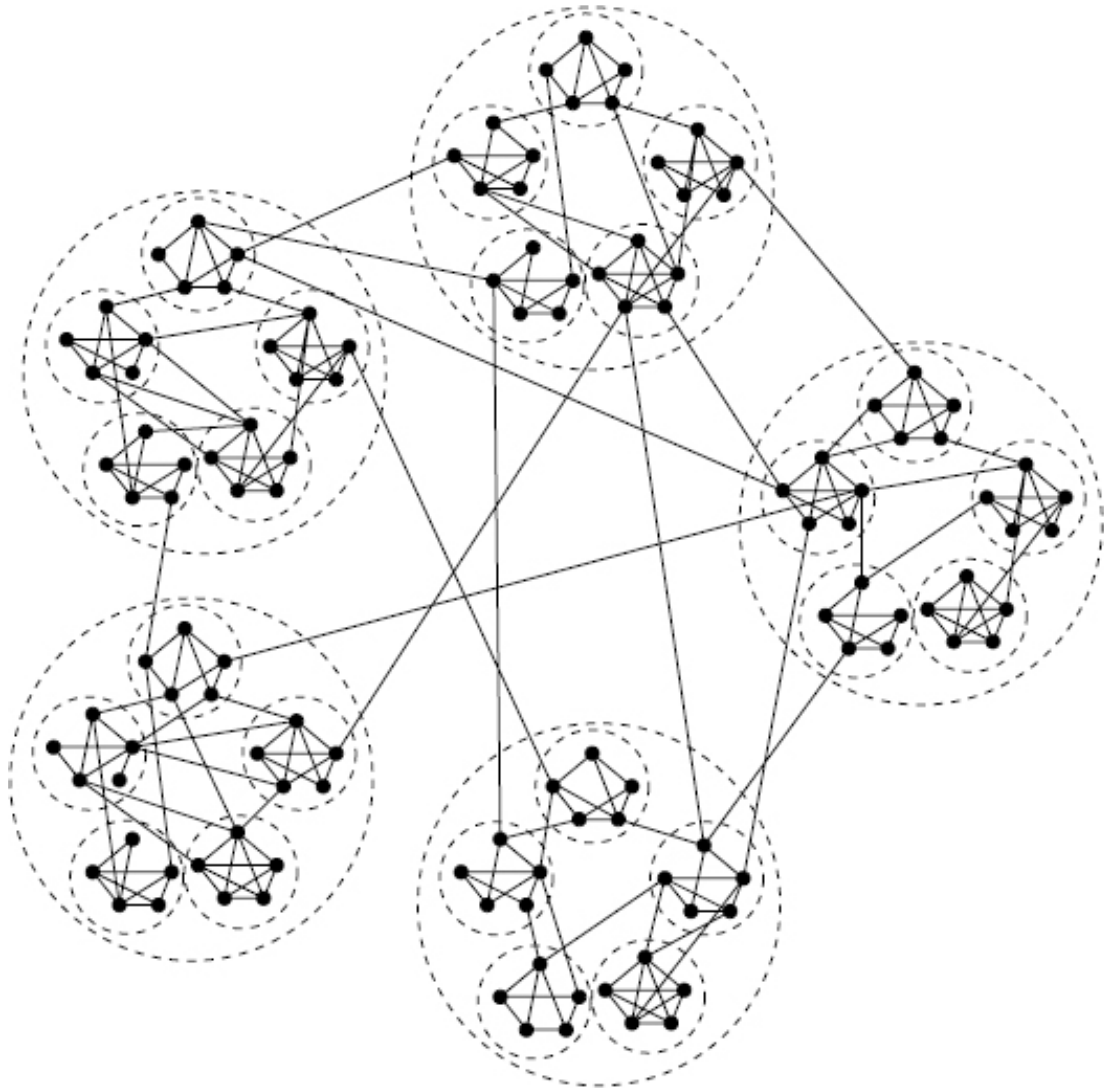
Window 1

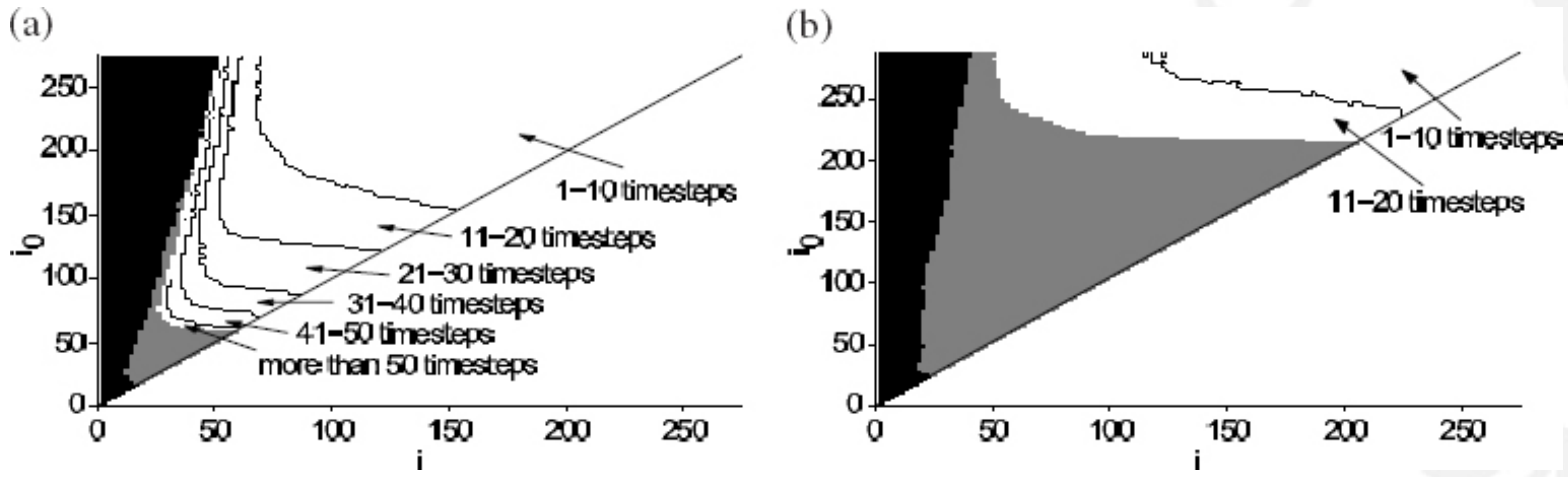


Digging deeper … into the 'raw' data: DETerminism-edge Network

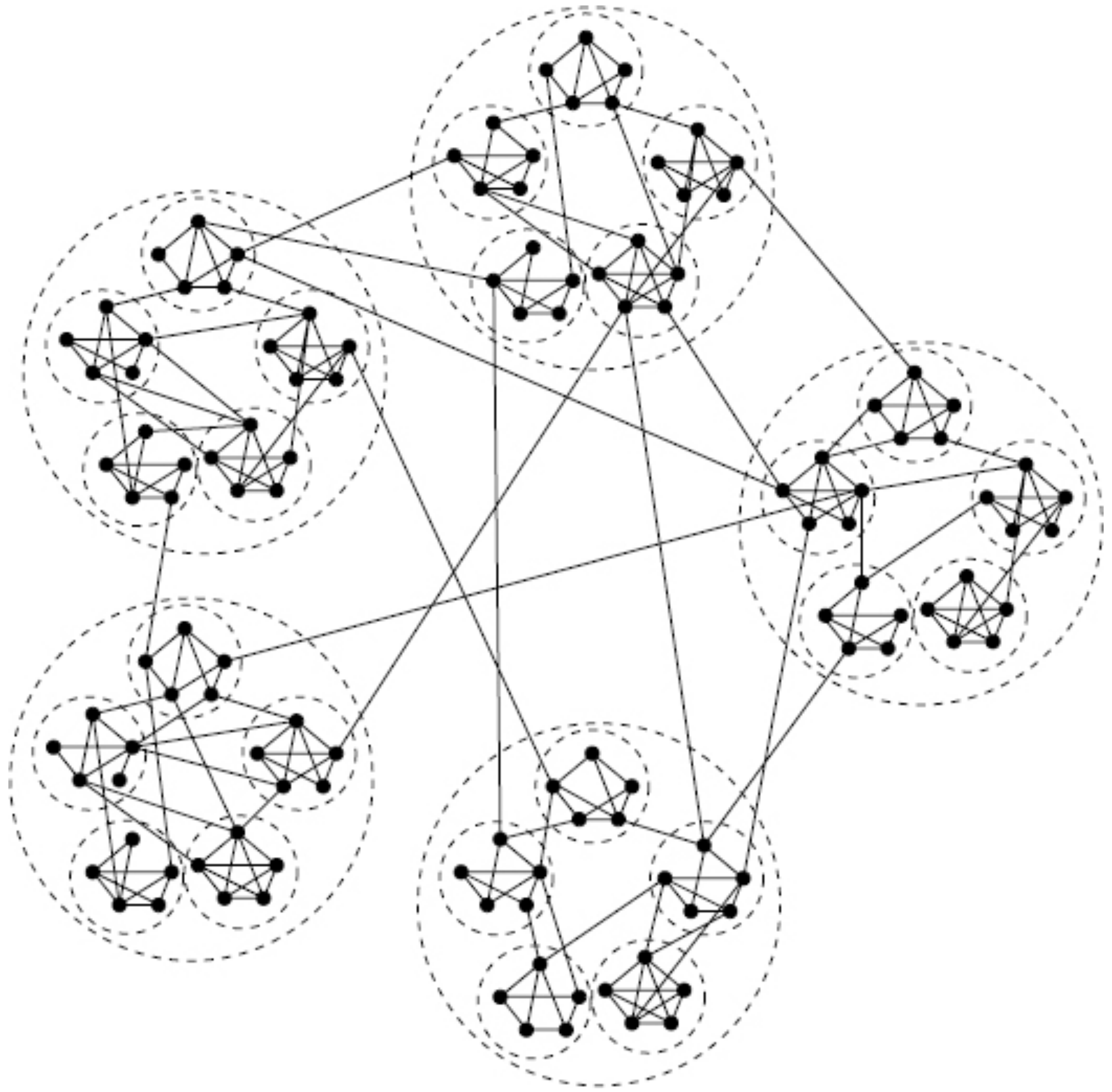


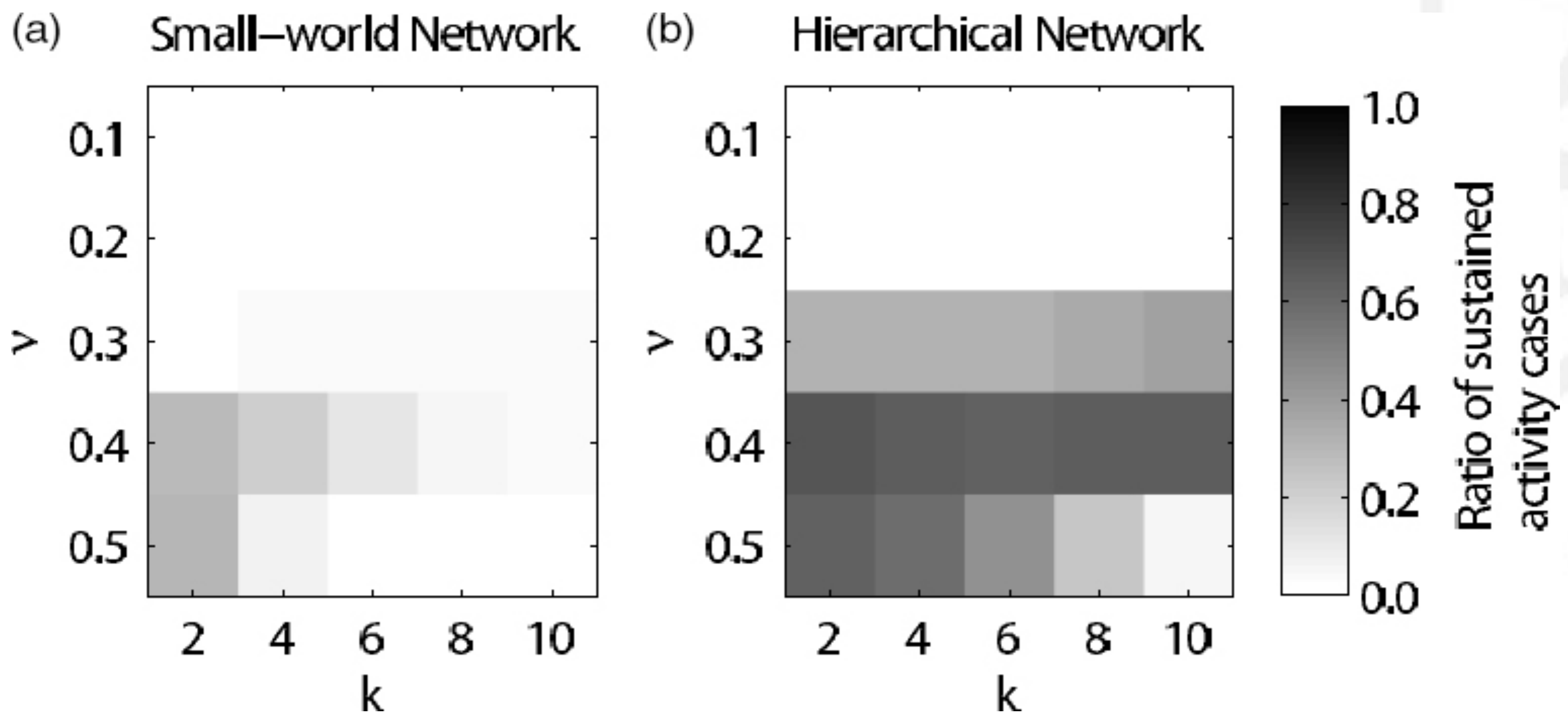
Extended (stretched) criticality = Hierarchical topology



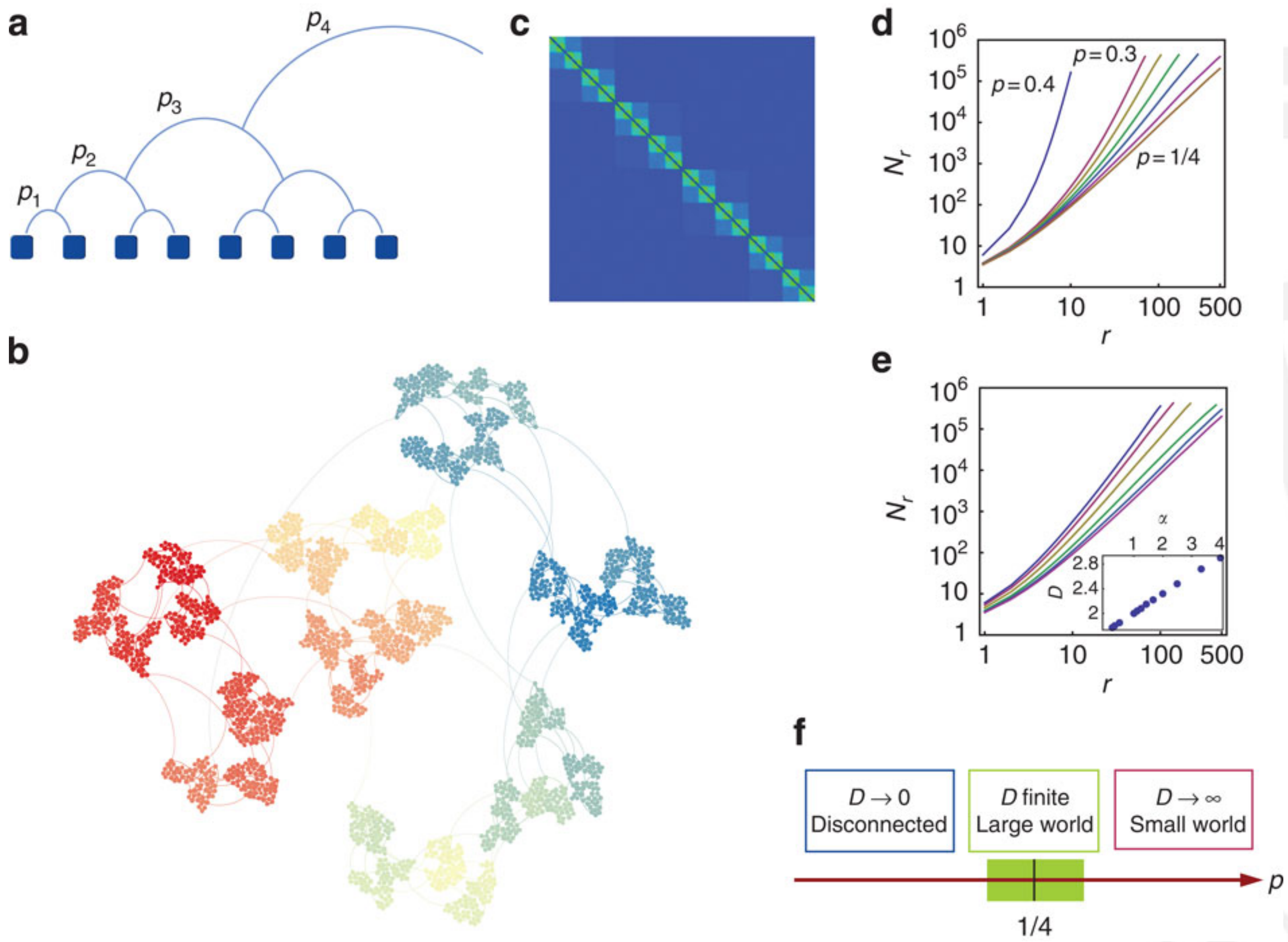


Extended (stretched) criticality = Hierarchical topology



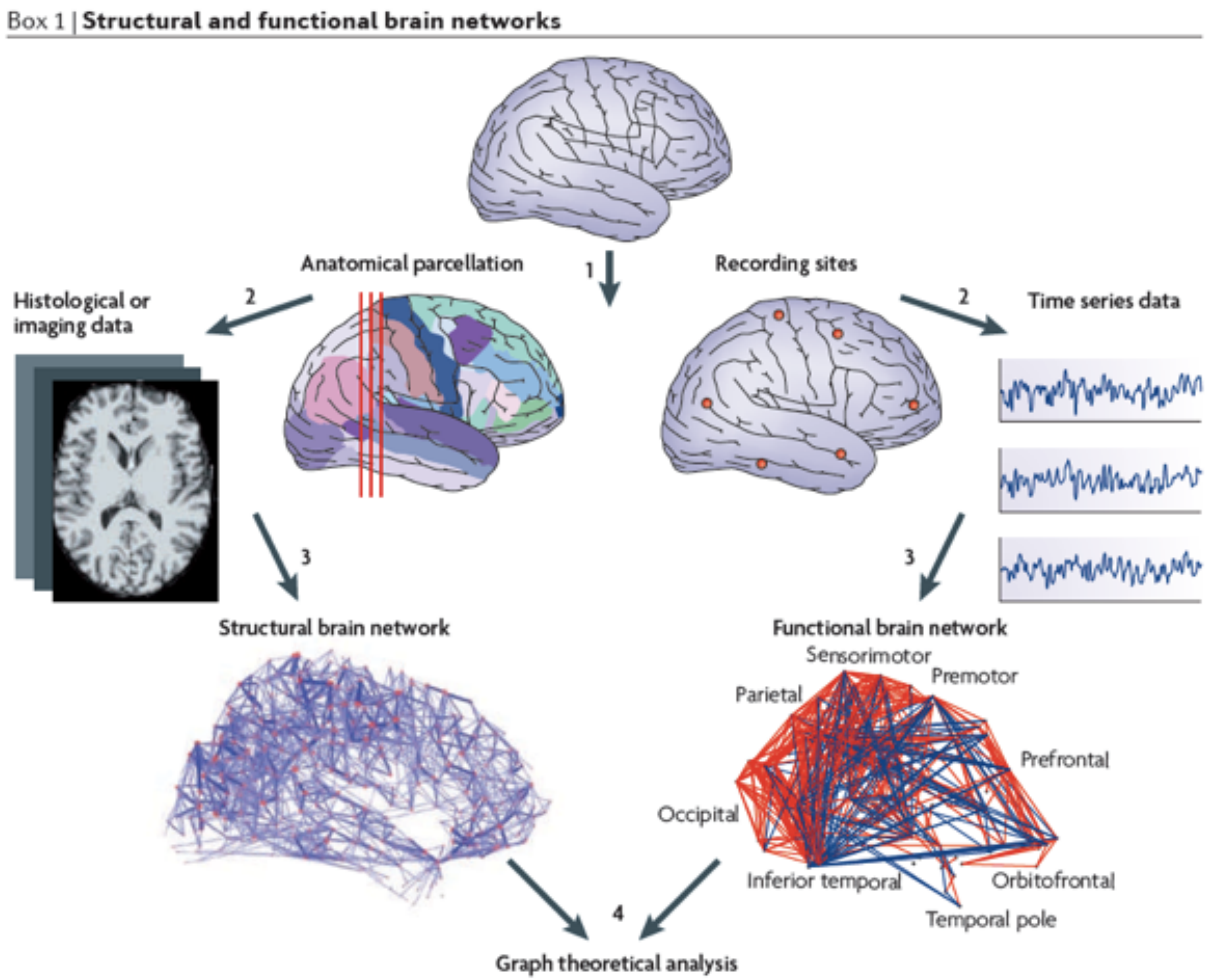


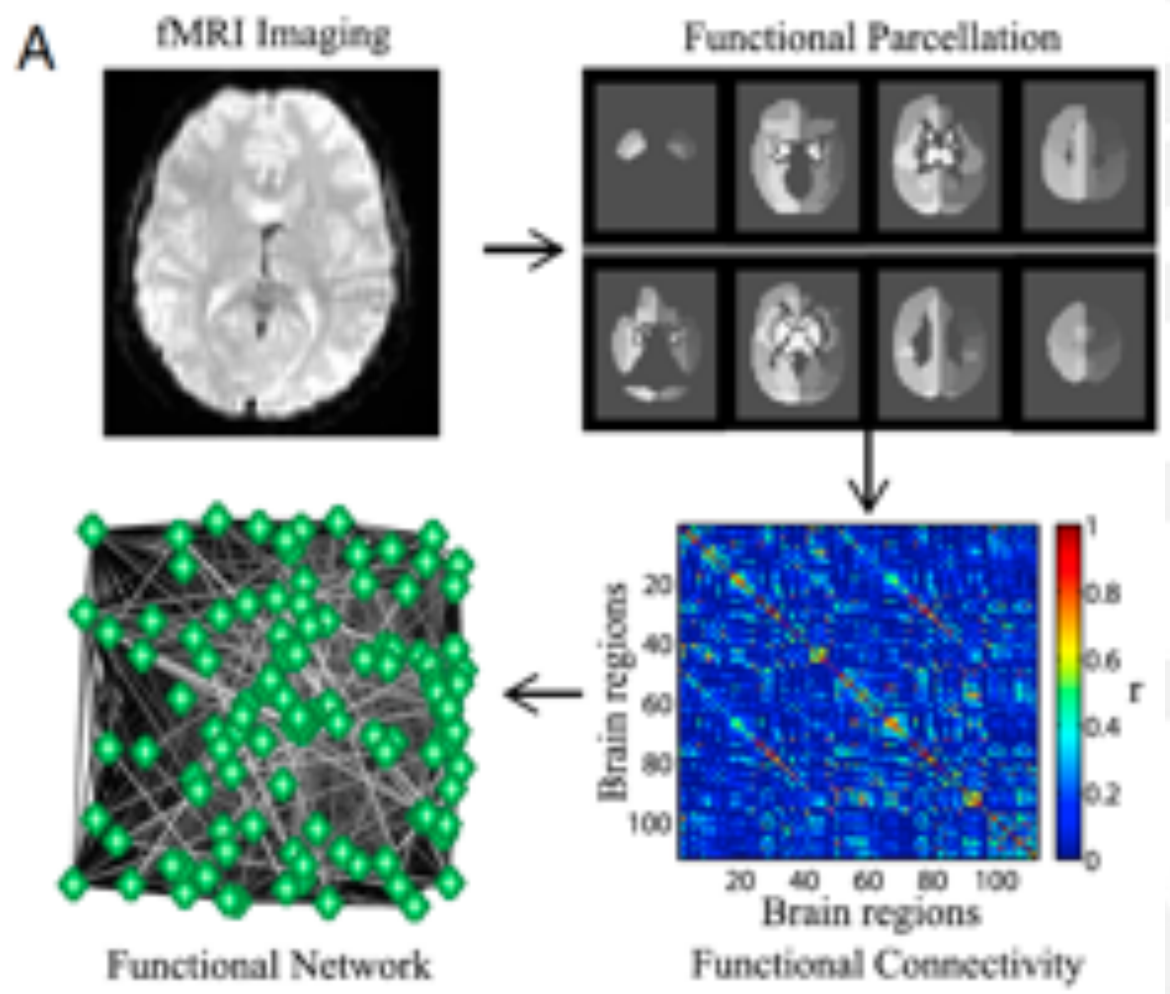
Extended (stretched) criticality = Hierarchical topology



Network / Graph topology

Functional vs. Structural 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.

Network / Graph topology

Functional vs. Structural networks

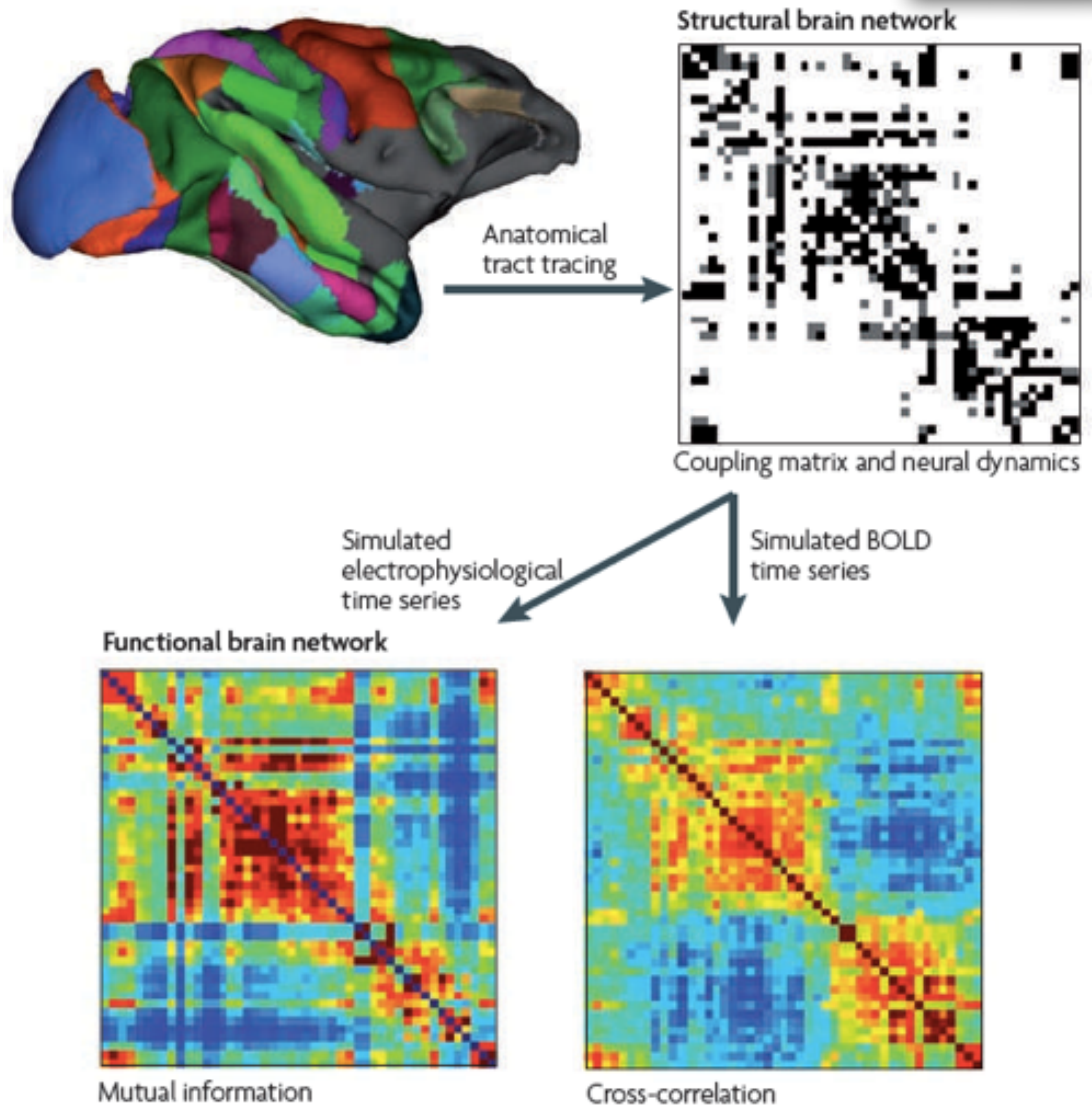


Figure 1 | **Computational modelling of structural and functional brain networks.**

adjacency matrix
similarity matrix
coupling matrix

Compare:
Recurrence matrix

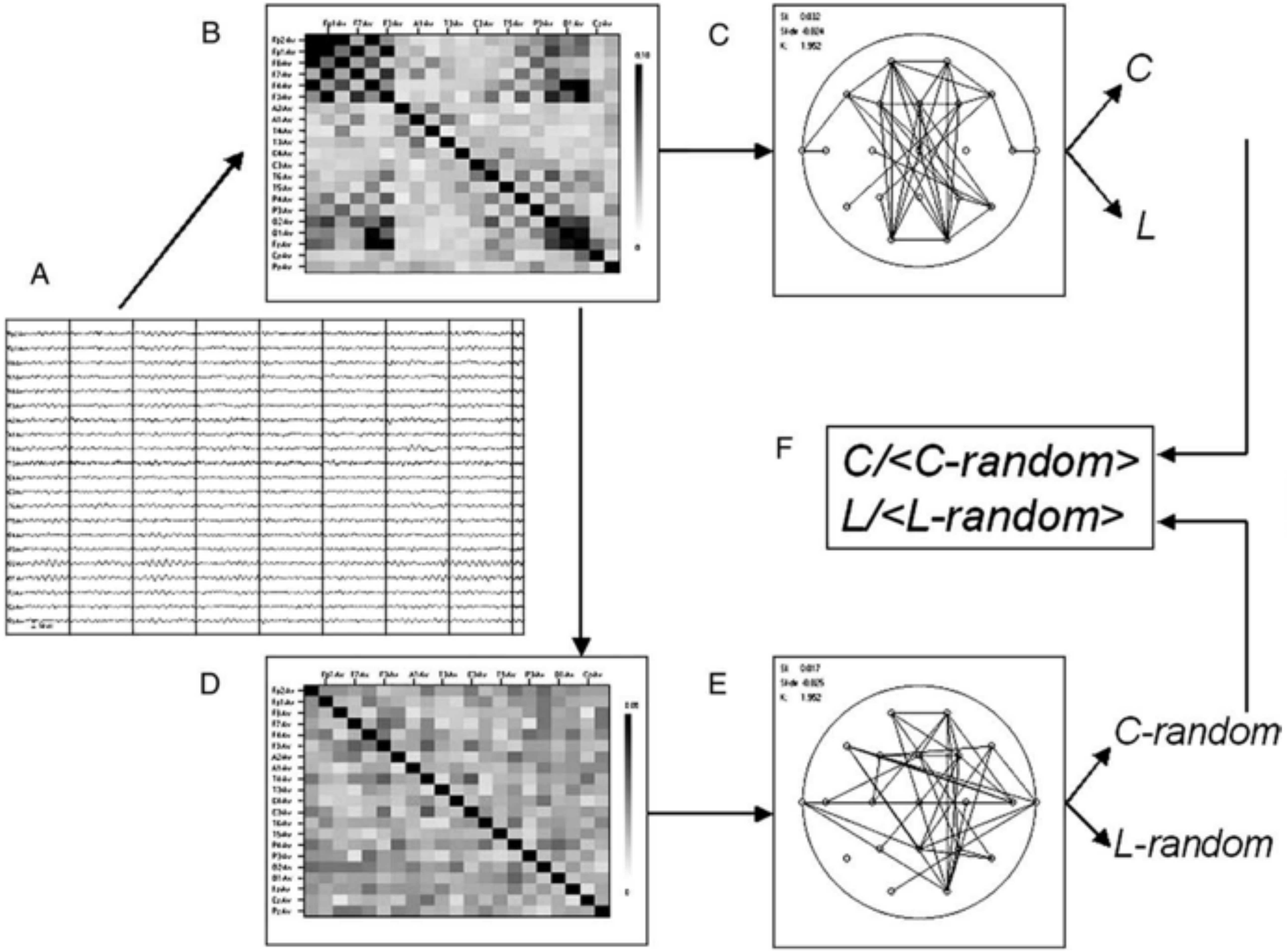
“neural dynamics”

Compare:
Surrogate data generation from recurrence matrix

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.

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

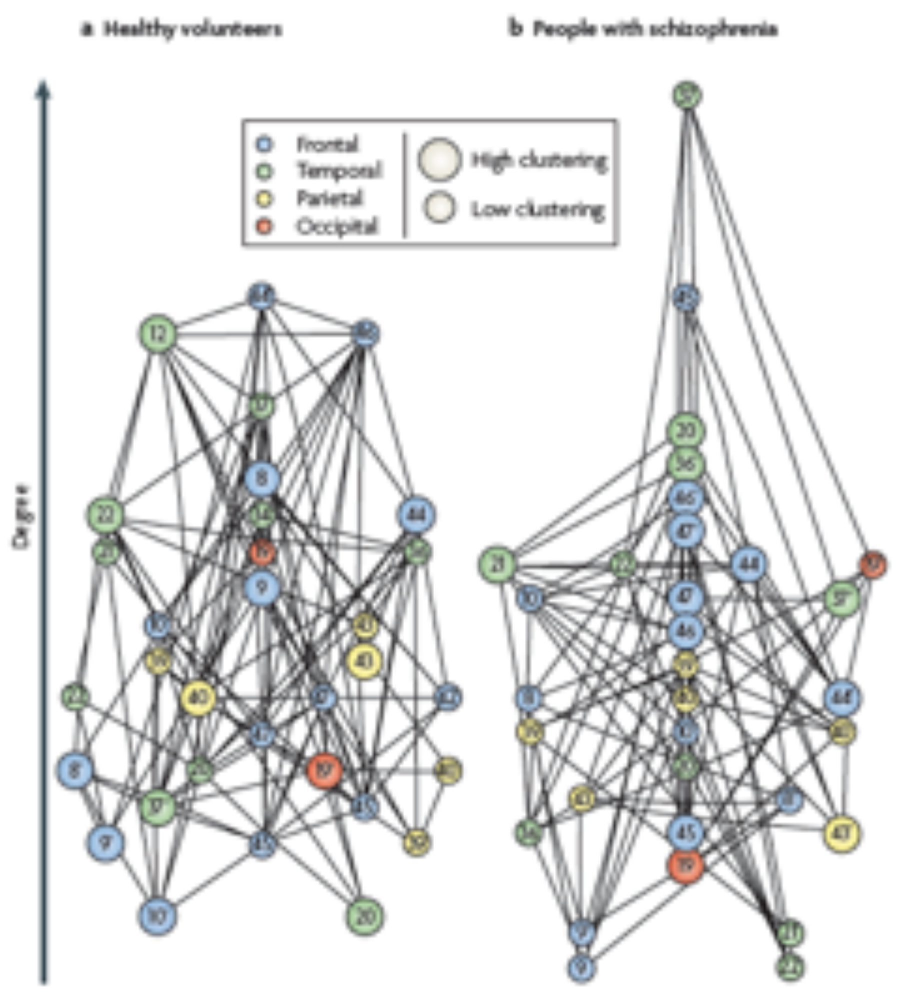
That's about 6-7 seconds!

Stam, C. J. (2010). Characterization of anatomical and functional connectivity in the brain: A complex networks perspective. International journal of psychophysiology : official journal of the International Organization of Psychophysiology, 77(3), 186-194. Elsevier B.V. doi: 10.1016/j.ijpsycho.2010.06.024.

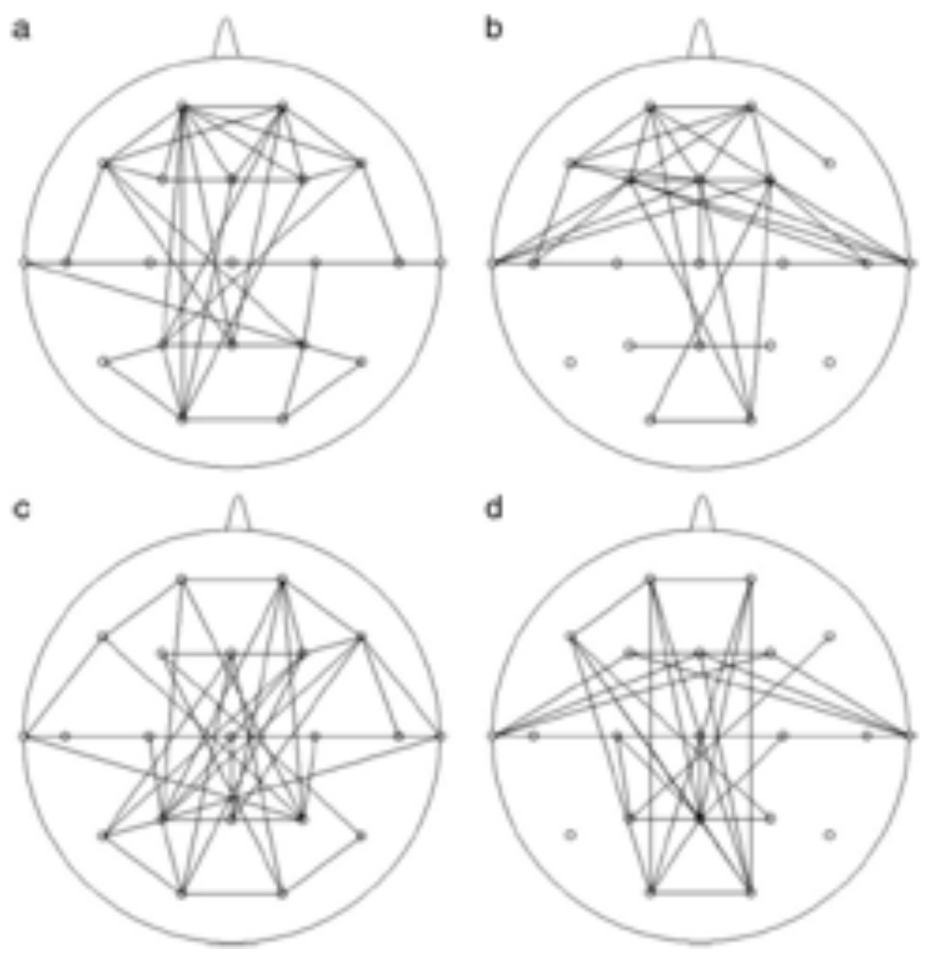
Network / Graph topology

Pathology studies

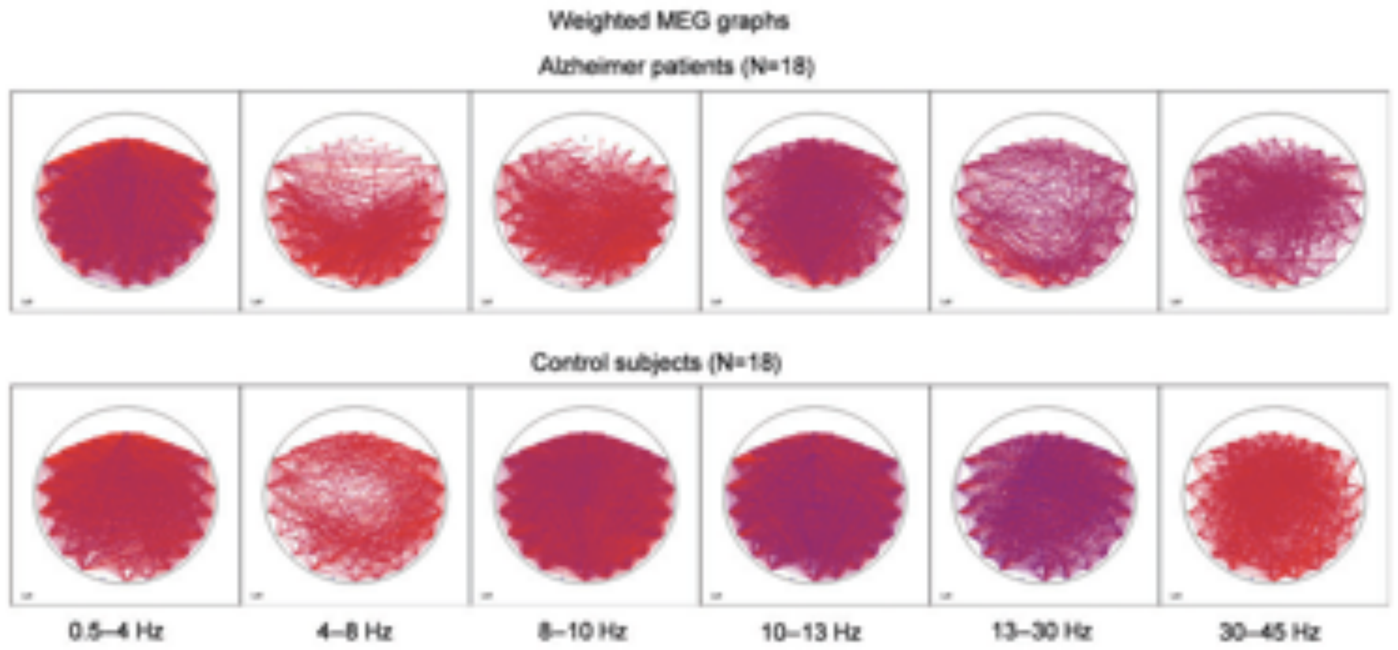
Based on a few samples we can distinguish healthy subjects from patients:



Schizophrenia



Absence seizure

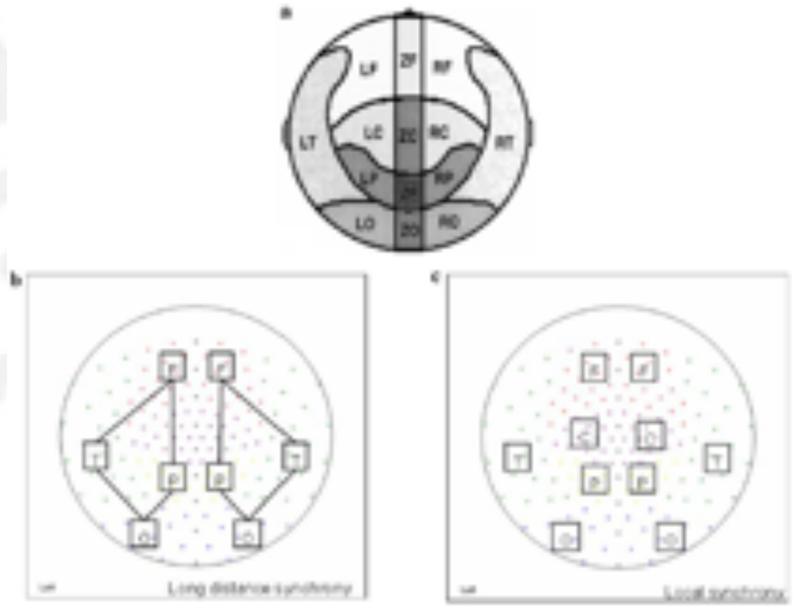


Alzheimer's disease: Targeted attack on hubs!

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.

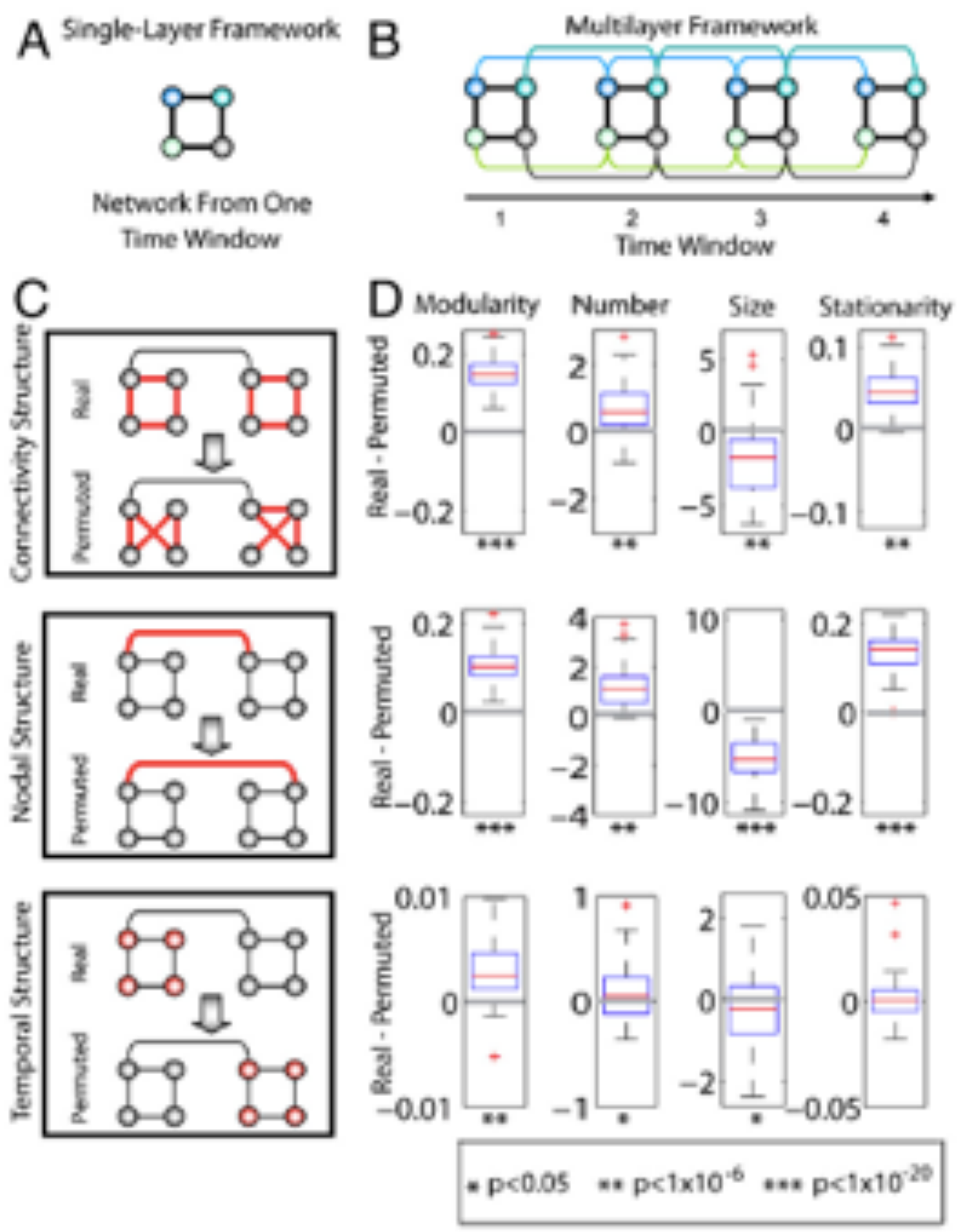
Stam, C. J., Haan, W. de, Daffertshofer, a, Jones, B. F., Manshanden, I., Cappellen van Walsum, a M. van, et al. (2009). Graph theoretical analysis of magnetoencephalographic functional connectivity in Alzheimer's disease. Brain : a journal of neurology, 132(Pt 1), 213-24. doi: 10.1093/brain/awn262.

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



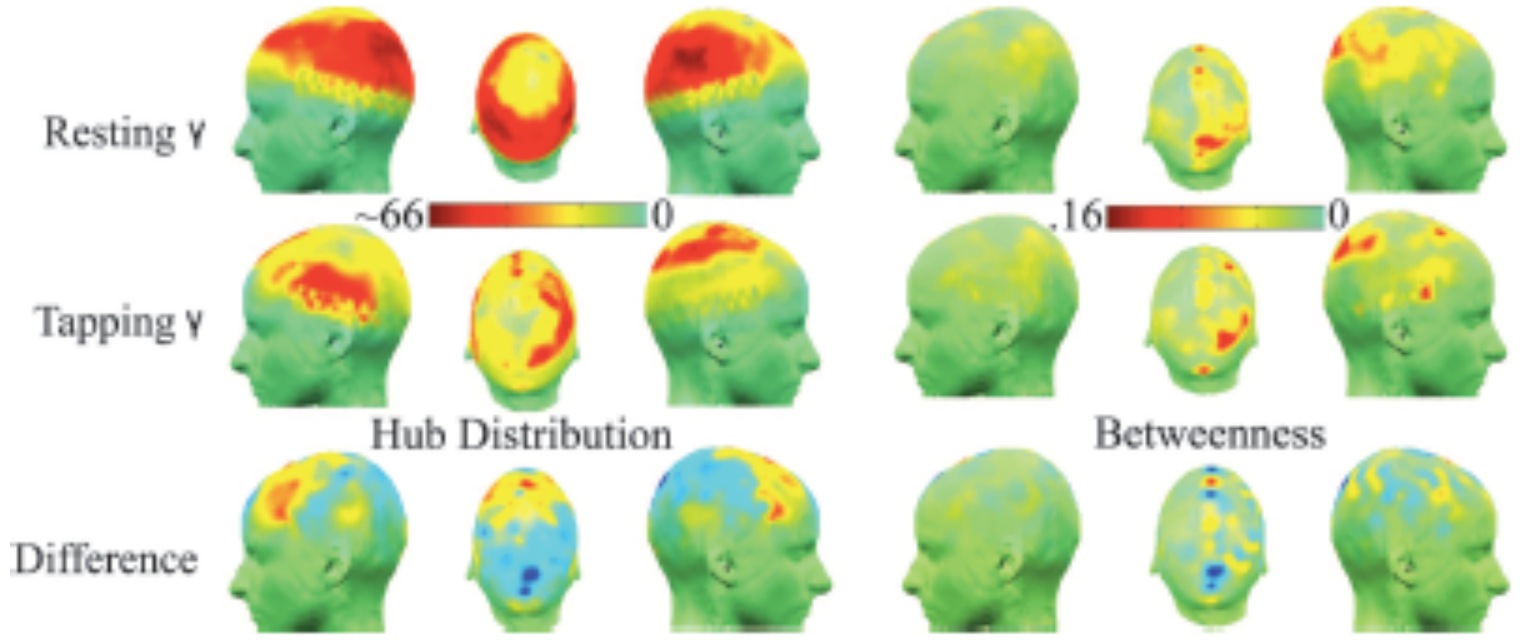
Cognitive abilities

Gender

Age

Learning

Tapping



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	■				+				−	−		+								+	−			
M	2	−	■							+						+				+			−	−	
F	3			■			+	−			−		+				+					−			
F	4				■						−		+	+			+			−	−				
F	5	+				■					−			+	+					−	−				
F	6	−		+			■						+			−	+						−		
M	7		+					■			−	+								−		−		+	
F	8				+		−		■					+				−		+					−
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											+						+			−	−	+	−	■
	+	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.

http://www.distributed-systems.net/gtcn/

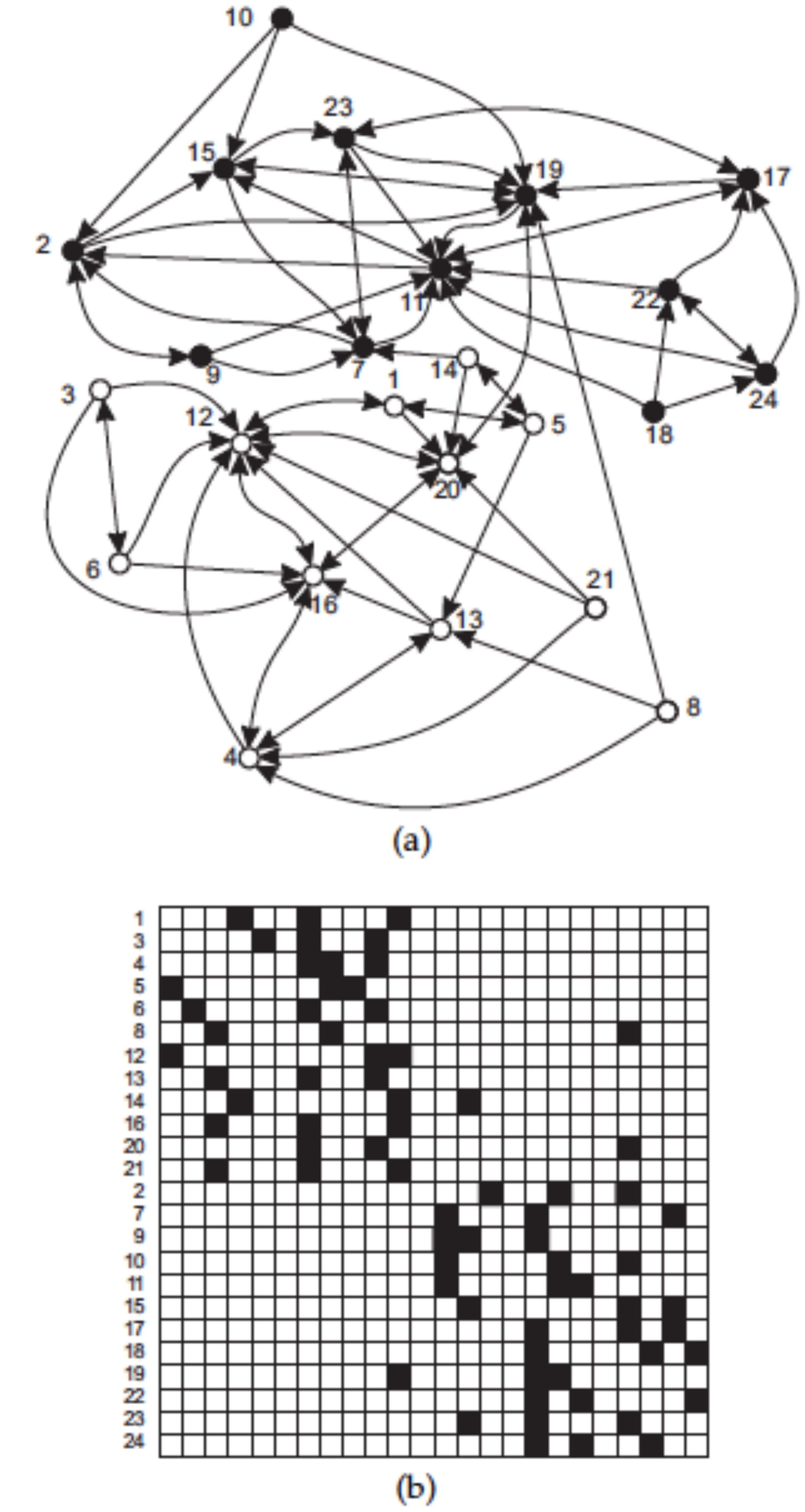


Figure 9.7: (a) The sociogram for positive nominations represented as a directed graph. Boys are represented by black-colored vertices; girls by white-colored ver-

Network / Graph topology - Social networks

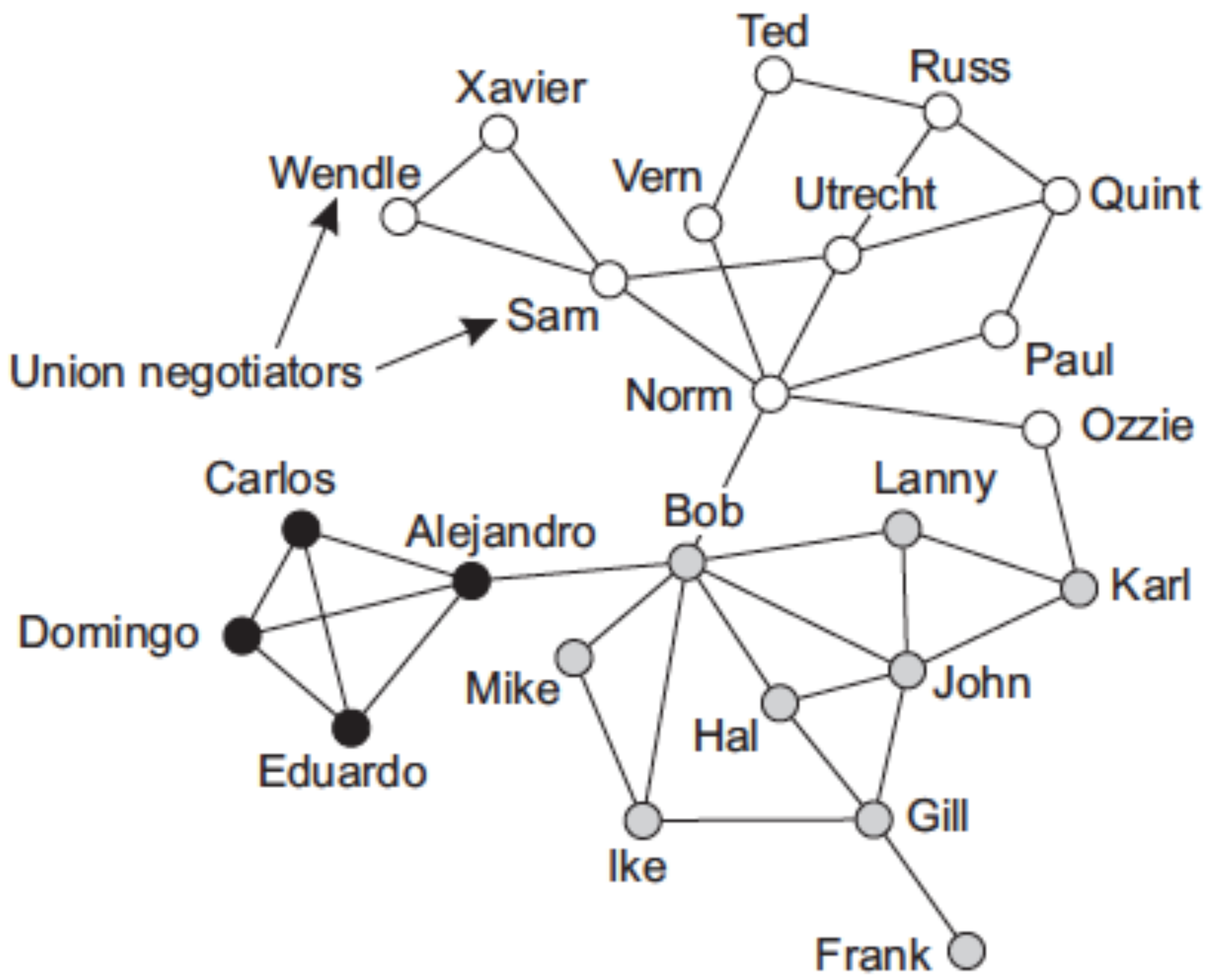


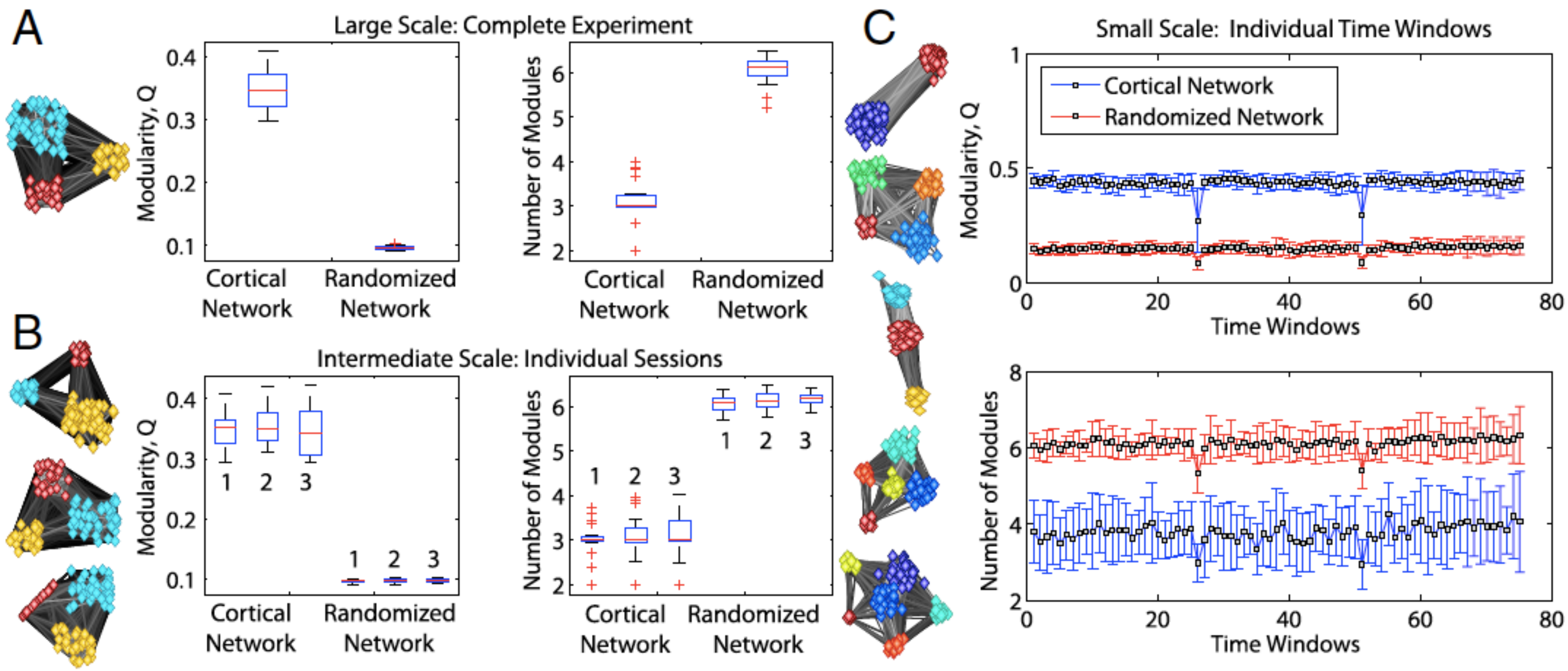
Figure 9.1: The relationship between workers on strike in a wood-processing firm.

http://www.distributed-systems.net/gtcn/

Can complex networks provide a suitable structure?

Multi-scale analysis

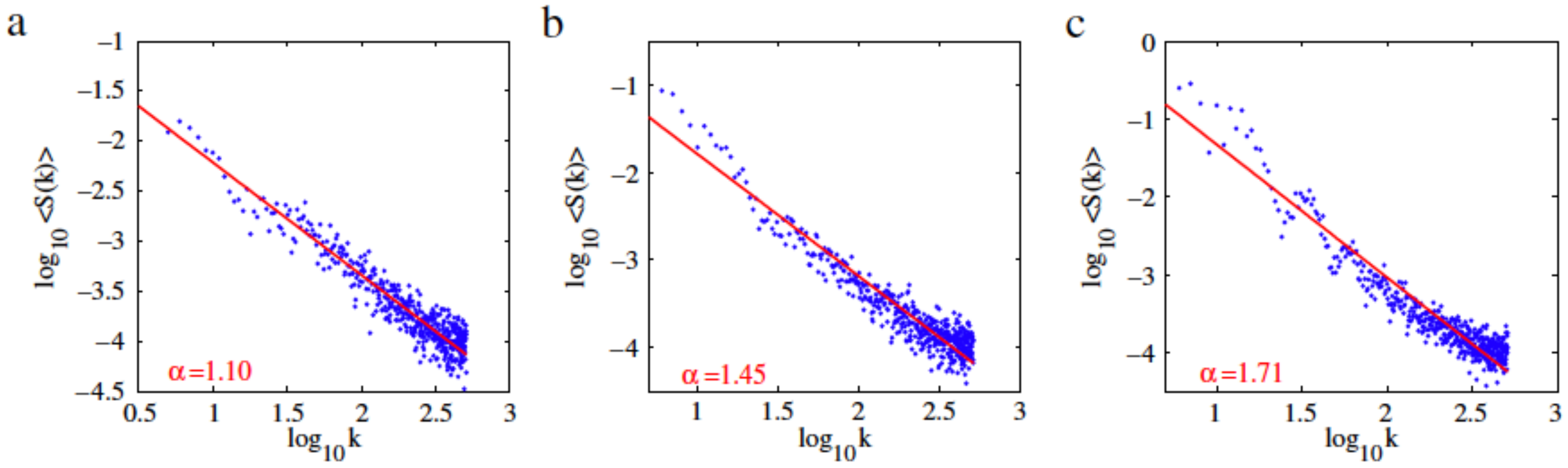
see also: Wijnants, M. L., Cox, R. F. A., Hasselman, F., Bosman, A. M. T., & Van Orden, G. (2012). A Trade-Off Study Revealing Nested Timescales of Constraint. *Frontiers in Fractal Physiology*, *3*(May), 1-15. doi:10.3389/fphys.2012.00116



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*, 1-36. doi:10.1073/pnas.1018985108

1/fα Noise in Spectral Fluctuations of Complex Networks

Random | Small-world | Scale-free

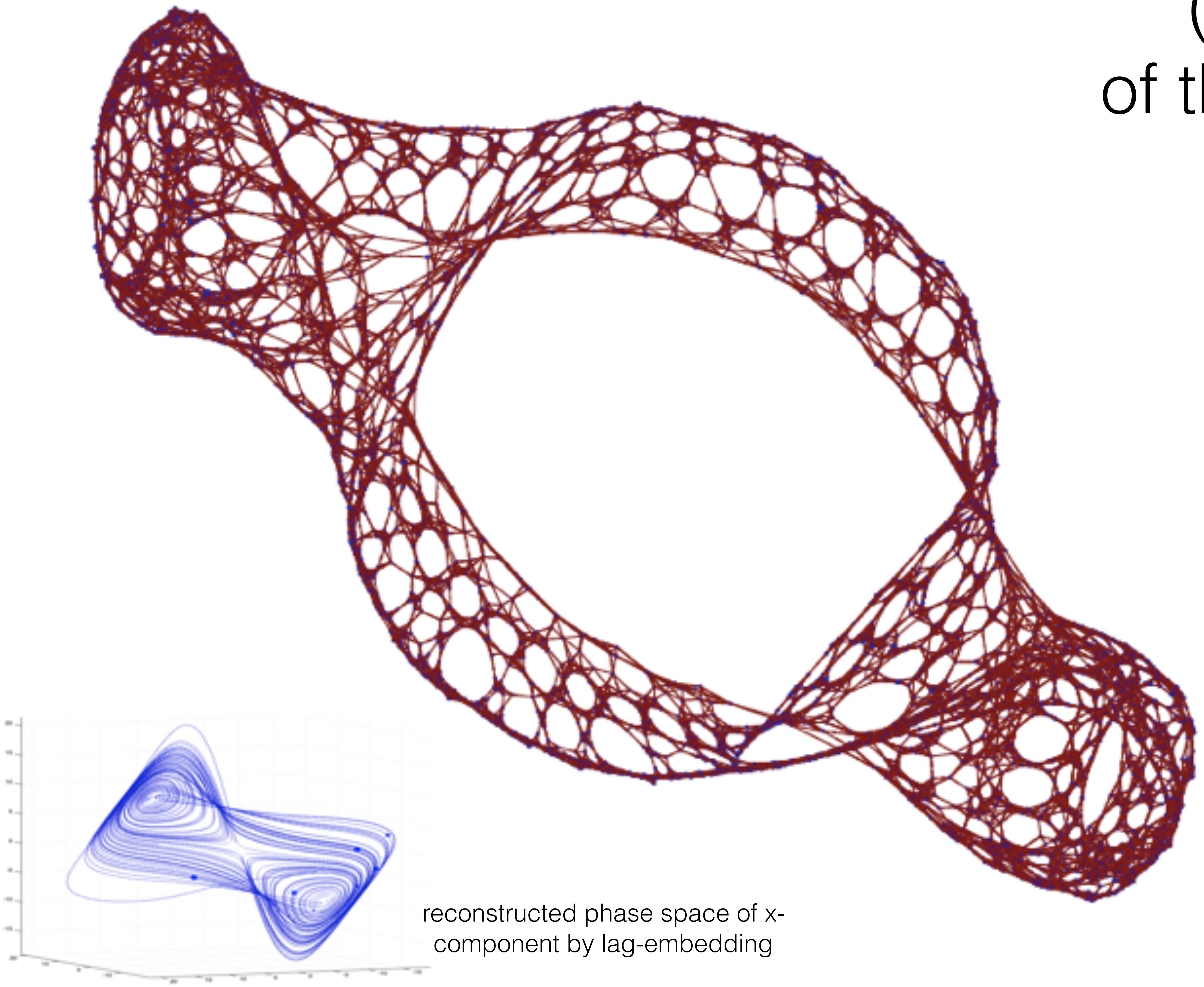


Spectrum of nearest-neighbour spacing
in the adjacency matrix

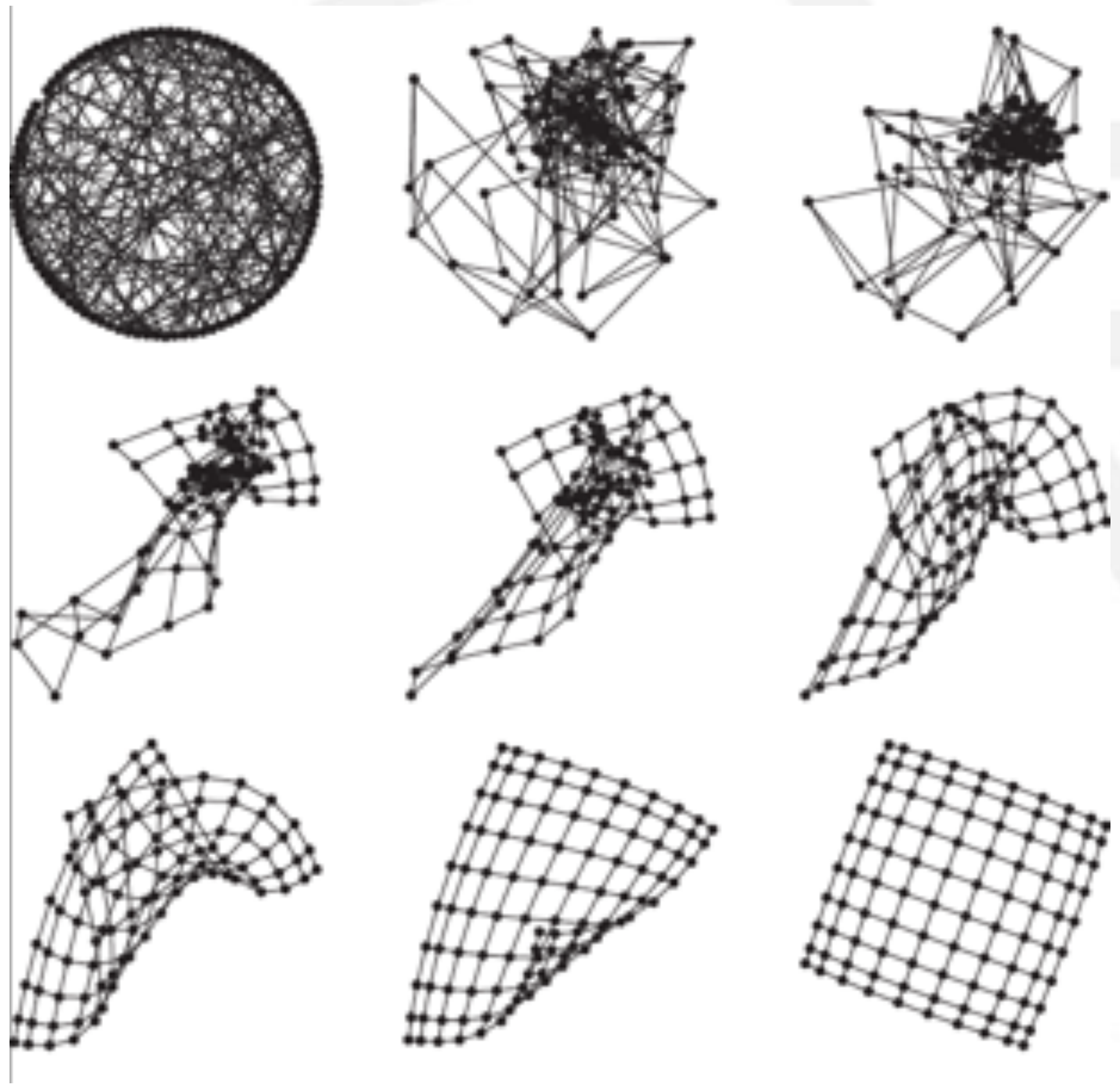
Ye, B., Li, H.-jun, & Ma, X.-ping. (2010). 1/Fα Noise in Spectral Fluctuations of Complex Networks. Physica A: Statistical Mechanics and its Applications, 389(22), 5328-5331. Elsevier B.V. doi: 10.1016/j.physa.2010.07.023.

Network / Graph topology

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



reconstructed phase space of x-component by lag-embedding

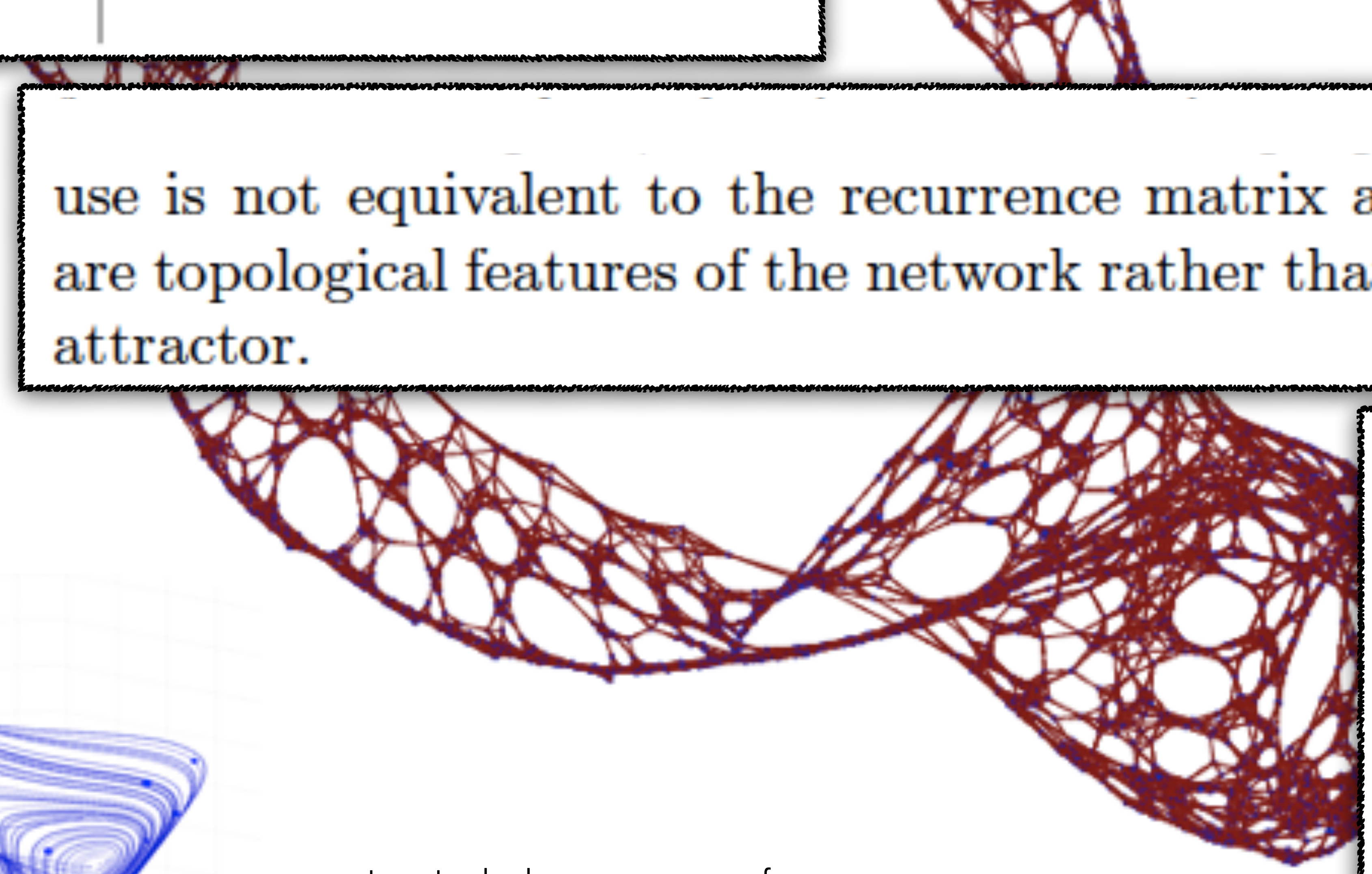


Small, M., Zhang, J., & Xu, X. (2009). Transforming time series into complex networks. Complex Sciences, 2078–2089.

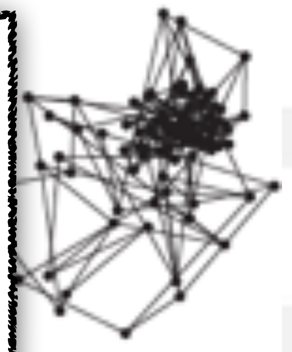
Network / Graph topology

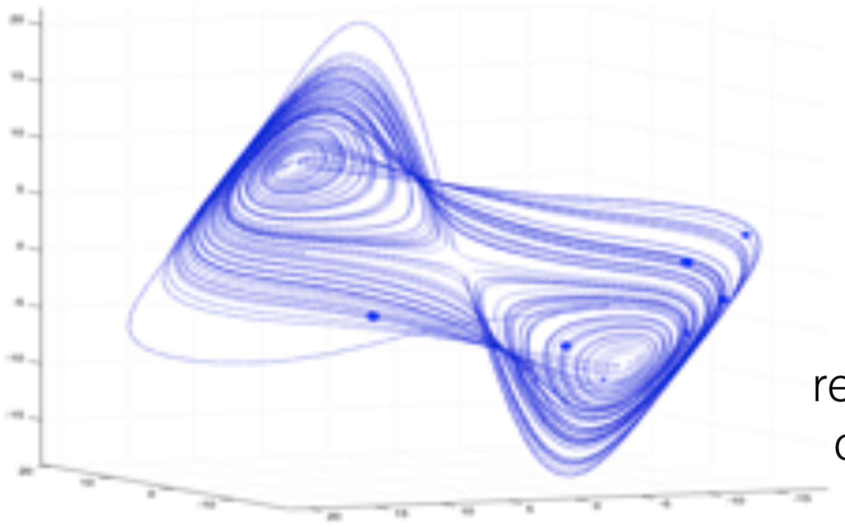
Network representation
(spring embedding)
of the x-component of the
Lorenz-system

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.





reconstructed phase space of x-component by lag-embedding

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	

Small, M., Zhang, J., & Xu, X. (2009). Transforming time series into complex networks. Complex Sciences, 2078–2089.

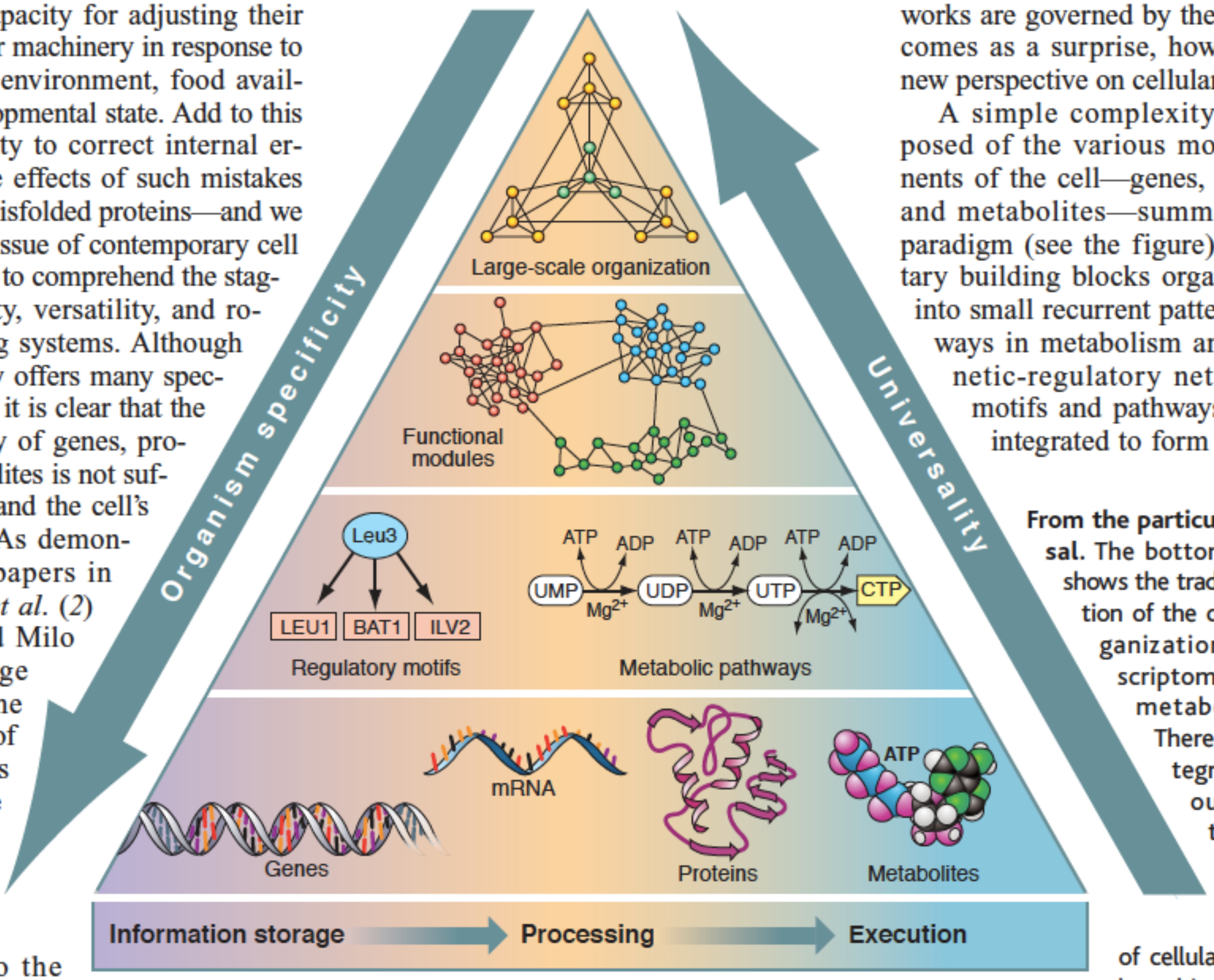
Network / Graph topology: Theory

Life's Complexity Pyramid

Zoltán N. Oltvai and Albert-László Barabási

Cells and microorganisms have an impressive capacity for adjusting their intracellular machinery in response to changes in their environment, food availability, and developmental state. Add to this an amazing ability to correct internal errors—battling the effects of such mistakes as mutations or misfolded proteins—and we arrive at a major issue of contemporary cell biology: our need to comprehend the staggering complexity, versatility, and robustness of living systems. Although molecular biology offers many spectacular successes, it is clear that the detailed inventory of genes, proteins, and metabolites is not sufficient to understand the cell's complexity (*1*). As demonstrated by two papers in this issue—Lee *et al.* (*2*) on page 799 and Milo *et al.* (*3*) on page 824—viewing the cell as a network of genes and proteins offers a viable strategy for addressing the complexity of living systems.

According to the basic dogma of molec-



within large networks (*6*, *7*). There is clear evidence for the existence of such cellular networks: For example, the proteome organizes itself into a protein interaction network and metabolites are interconverted through an intricate metabolic web (*7*). The finding that the structures of these networks are governed by the same principles comes as a surprise, however, offering a new perspective on cellular organization.

A simple complexity pyramid composed of the various molecular components of the cell—genes, RNAs, proteins, and metabolites—summarizes this new paradigm (see the figure). These elementary building blocks organize themselves into small recurrent patterns, called pathways in metabolism and motifs in genetic-regulatory networks. In turn, motifs and pathways are seamlessly integrated to form functional mod-

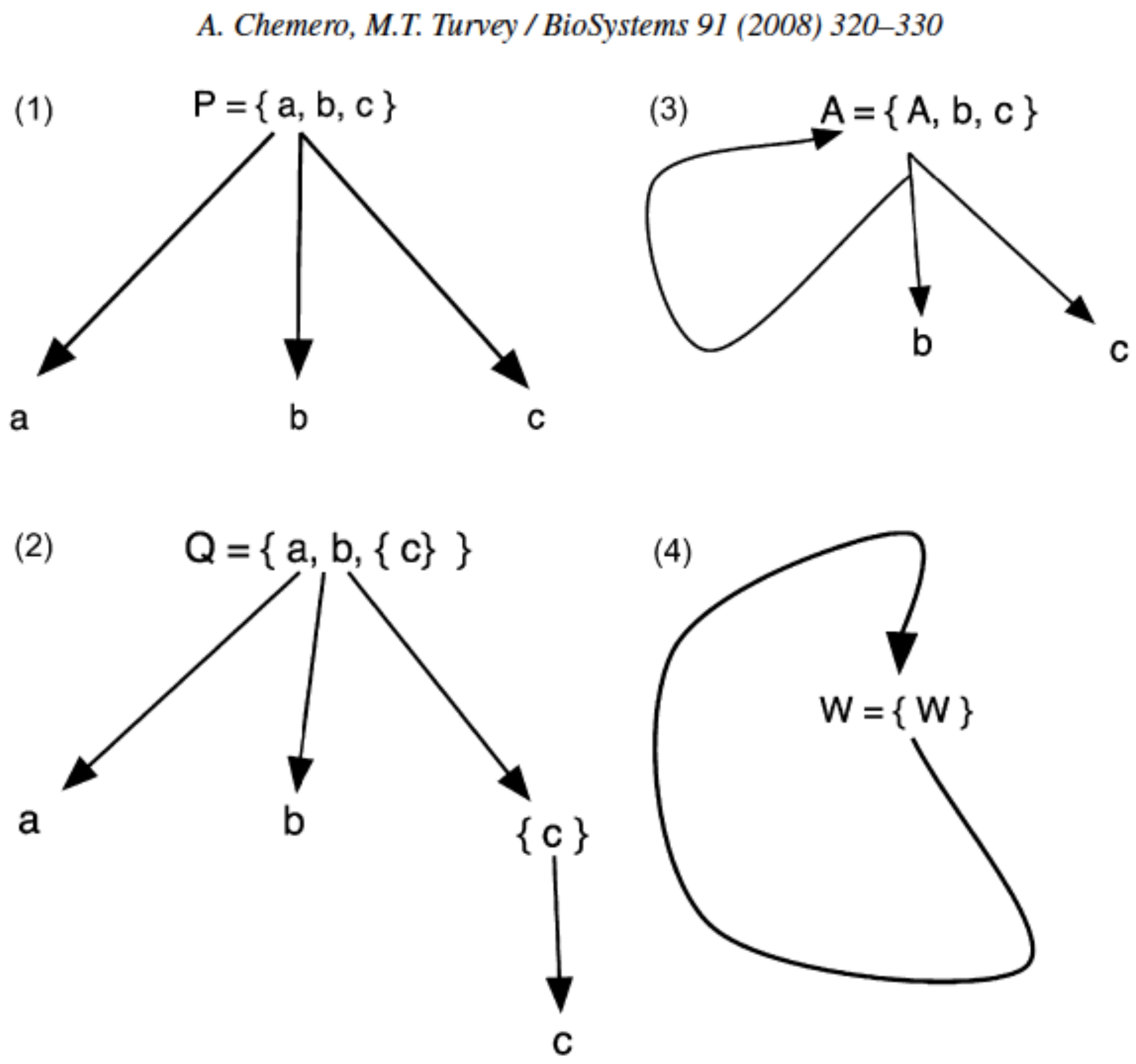
From the particular to the universal. The bottom of the pyramid shows the traditional representation of the cell's functional organization: genome, transcriptome, proteome, and metabolome (level 1). There is remarkable integration of the various layers both at the regulatory and the structural level. Insights into the logic of cellular organization can be achieved when we view

Oltvai, Z. N., & Barabási, A.-L. (2002). Systems biology. Life's complexity pyramid. *Science (New York, N.Y.)*, *298*(5594), 763-4. doi:10.1126/science.1078563

Complex structure:
Hyperset theory + Graph theory = Hyperset Graphs

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



Aczel, P. (1988). *Non-well-founded sets. Foreword by Jon Barwise*. CSLI Lecture Notes, 14.

Complex structure:
Hyperset theory + Graph theory = Hyperset Graphs

Impredicative loop

Hyperset loop

Rosen's definition of a living system

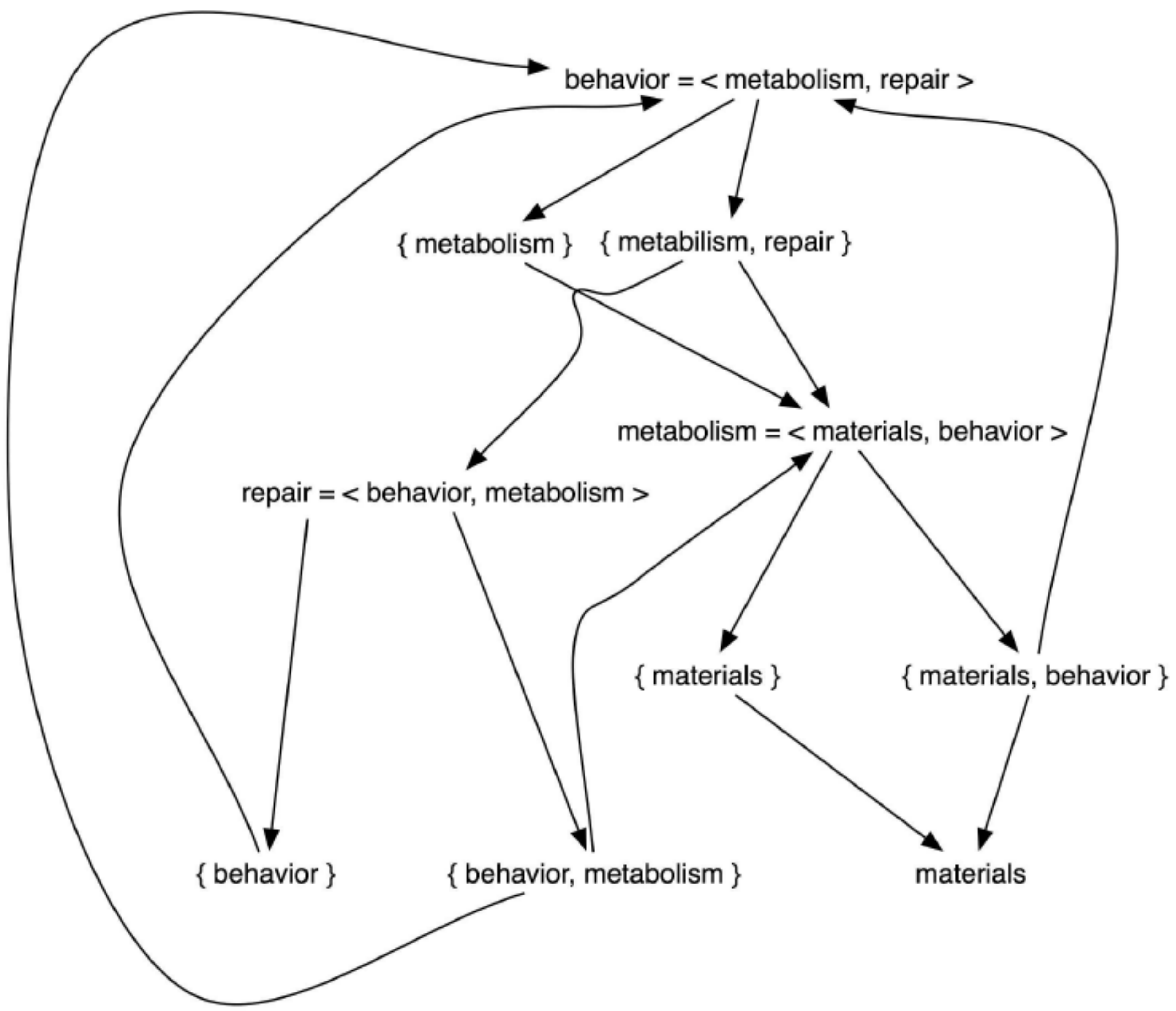


Fig. 6. Hyperset diagram of Rosen's metabolism-repair system. Functions are represented as ordered pairs containing their domain and range. So f (a) = b is represented as f = < a, b >.

Chemero, A., & Turvey, M. T. (2010). Is Life Computable? *Advances in modeling adaptive and cognitive systems*, 29-37.

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 sub-system state spaces,* ***such as classical physics and Bohmian mechanics, <u>are not holistic</u>*** *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*

Seevinck, M. P. (2004). Holism, physical theories and quantum mechanics. [doi: DOI: 10.1016/j.shpsb.2004.08.001]. *Studies In History and Philosophy of Science Part B: Studies In History and Philosophy of Modern Physics, 35*(4), 693-712.

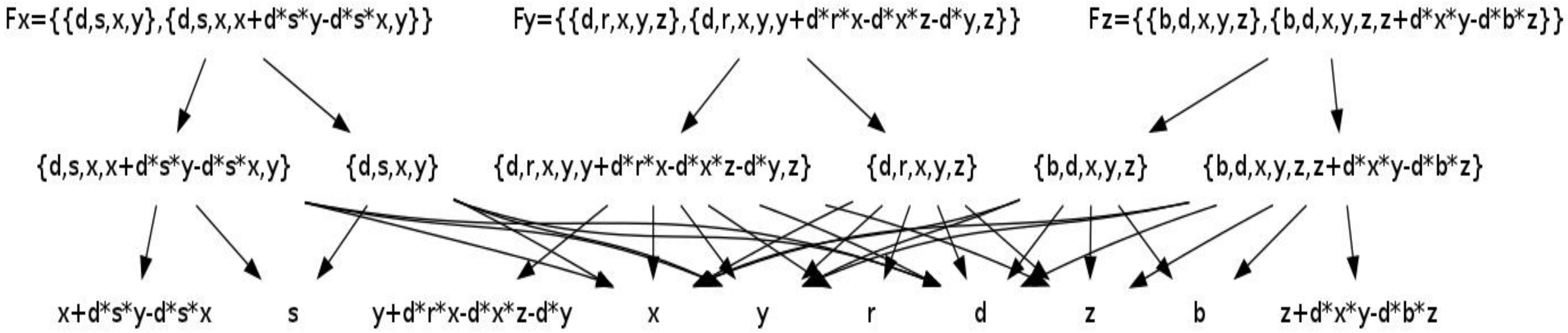
Some additional evidence?
No impredicative loops for the Lorenz system!

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

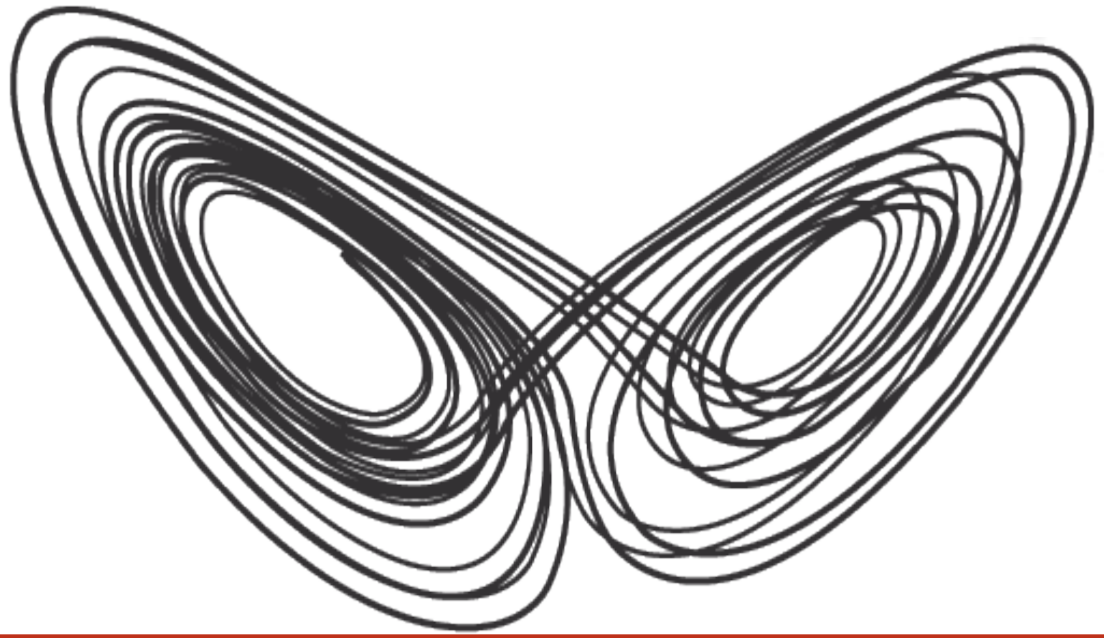
(Hyper)set graphs of some physical systems and their numerical implementations

Dobromir G. Dotov, Nigel Stepp

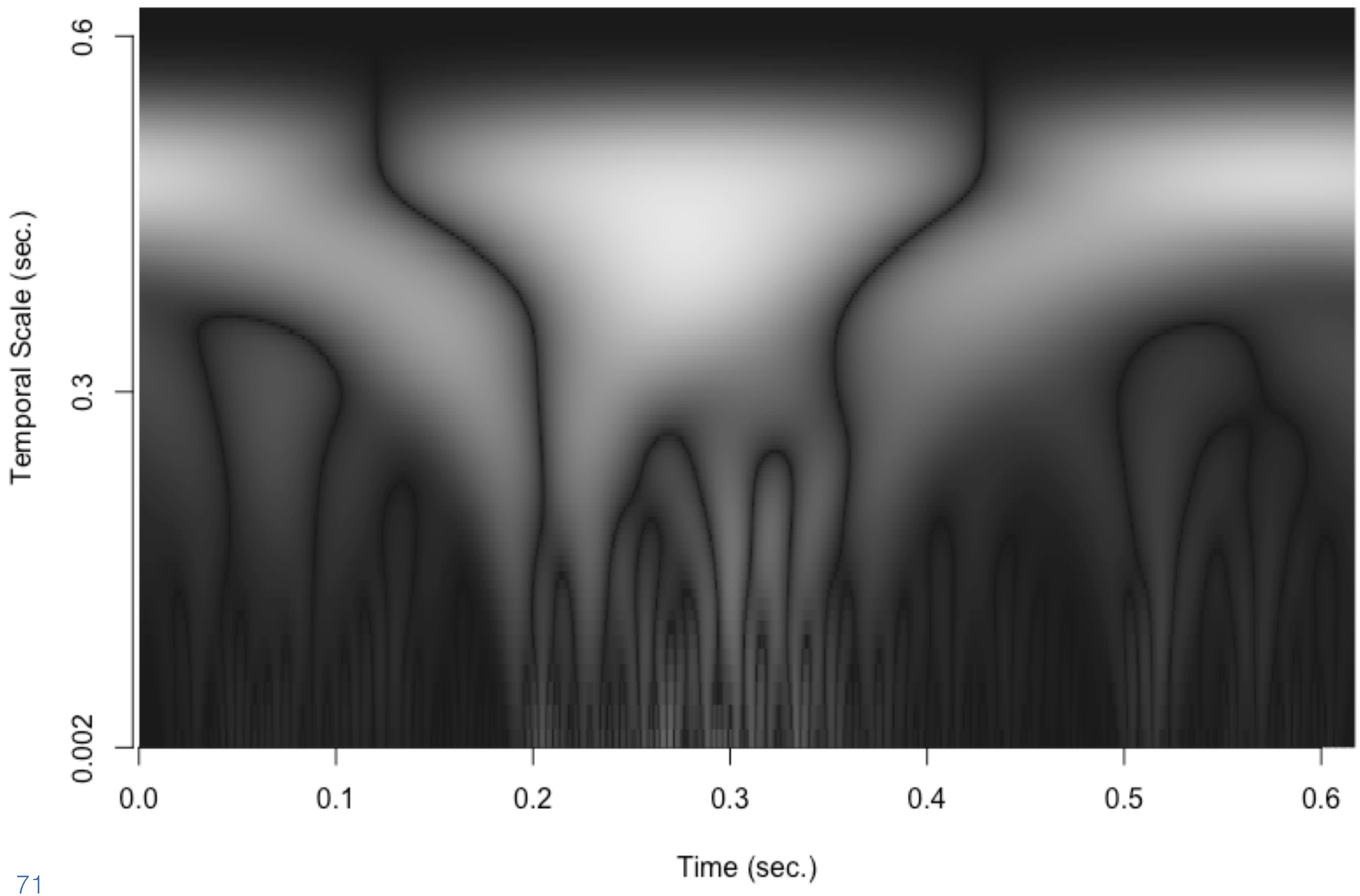
Center for the Ecological Study of Perception and Action, University of Connecticut



$$dx/dt=\sigma(y-x)$$
$$dy/dt=x(\rho-z)-y$$
$$dz/dt=xy-\beta z$$

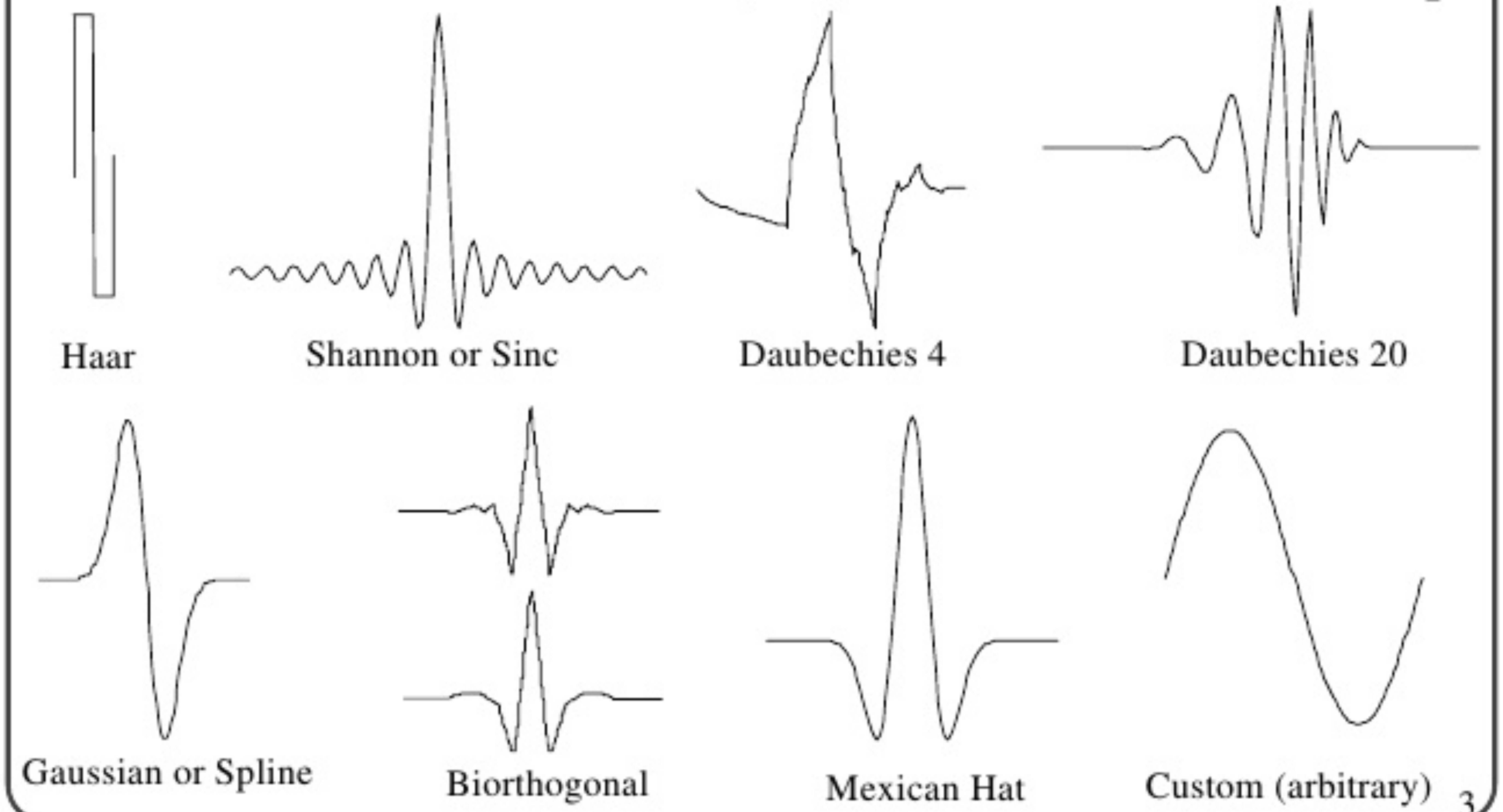


Scaleogram - Continuous Wavelet Transform

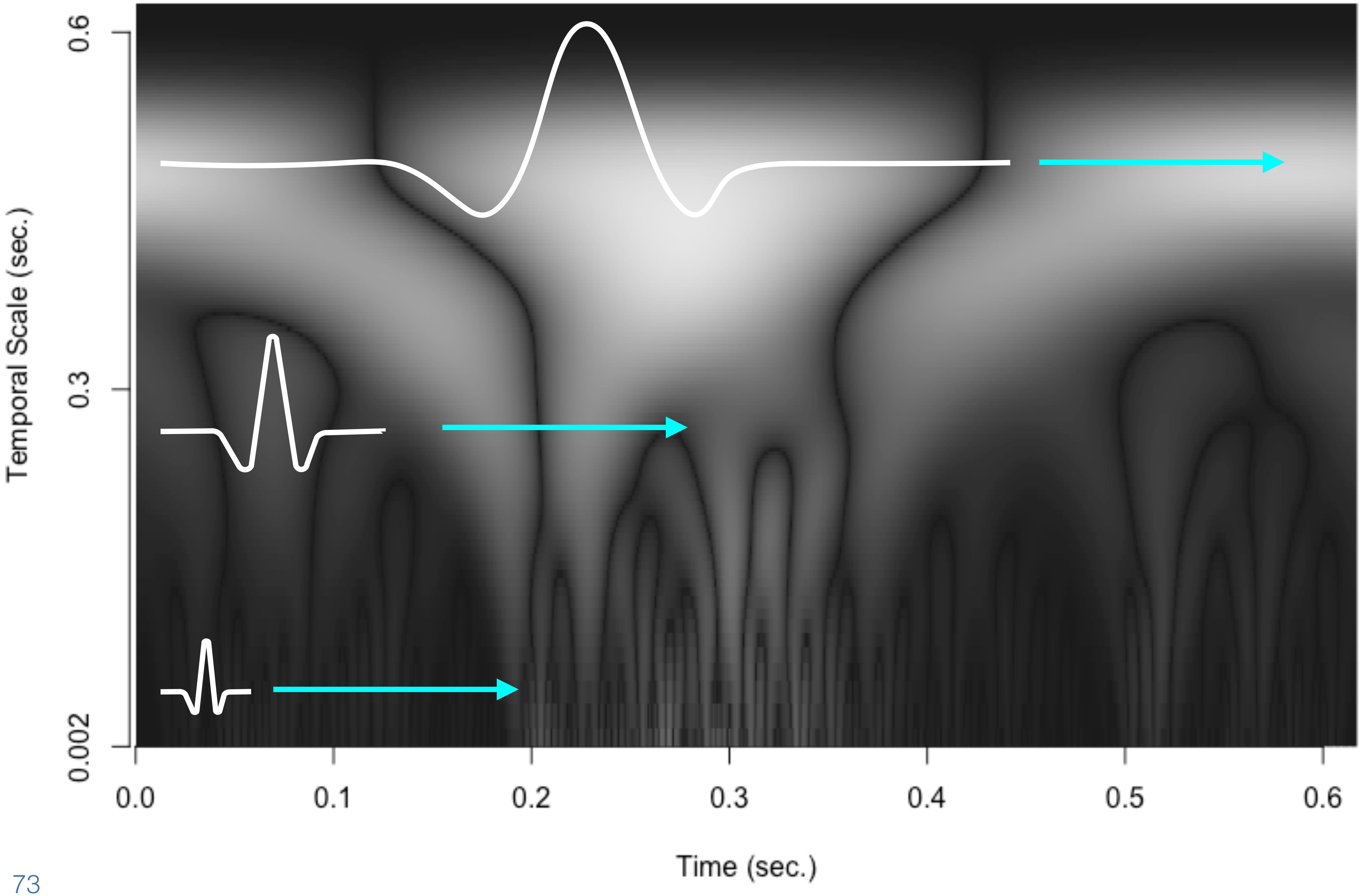


EXAMPLES OF WAVELETS

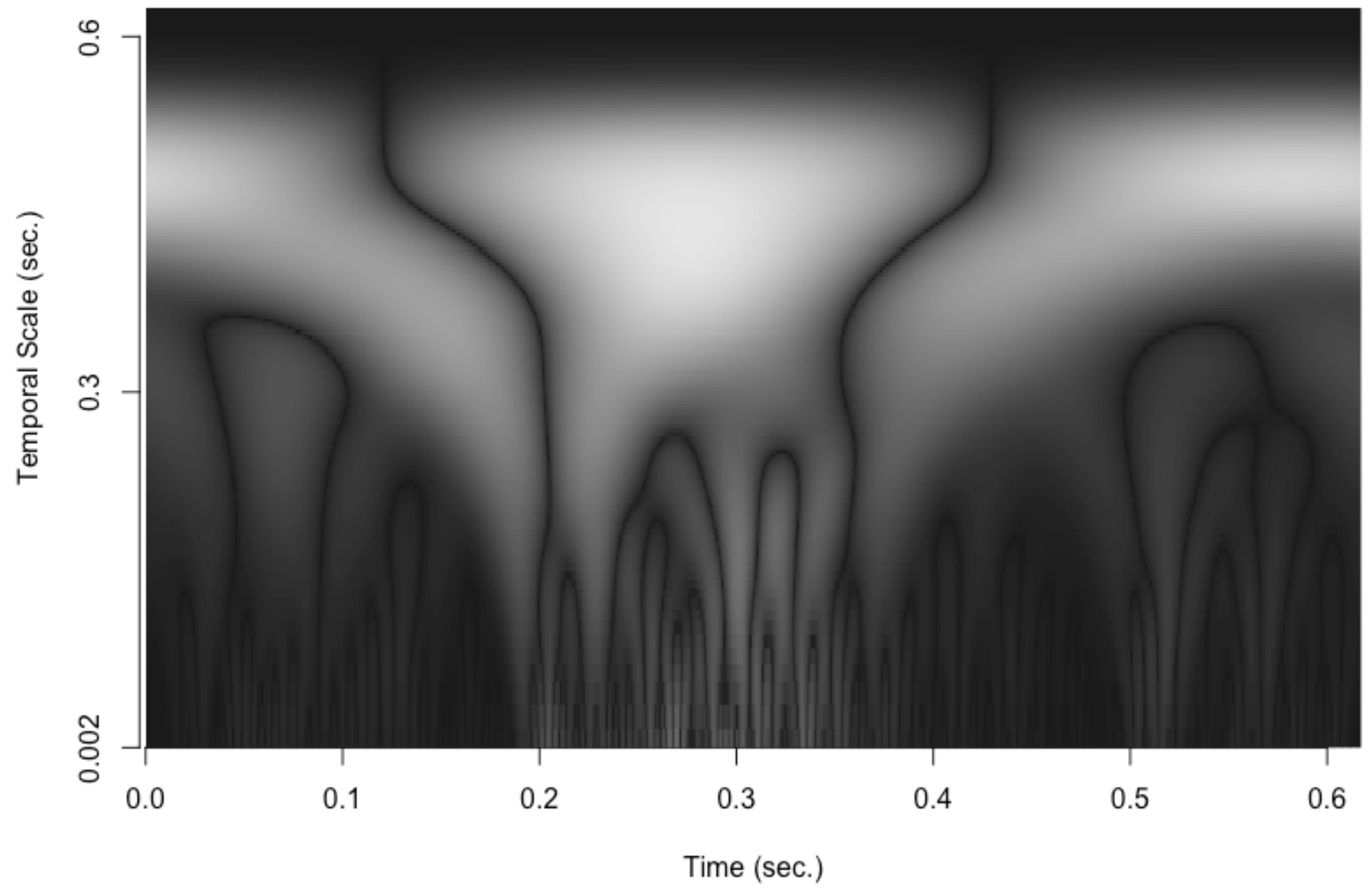
- WAVE for Frequency, LET indicates Compact Support.
- Jargon Alert*: Compact Support = having start & stop time
- Some more localized in time, some more localized in freq.

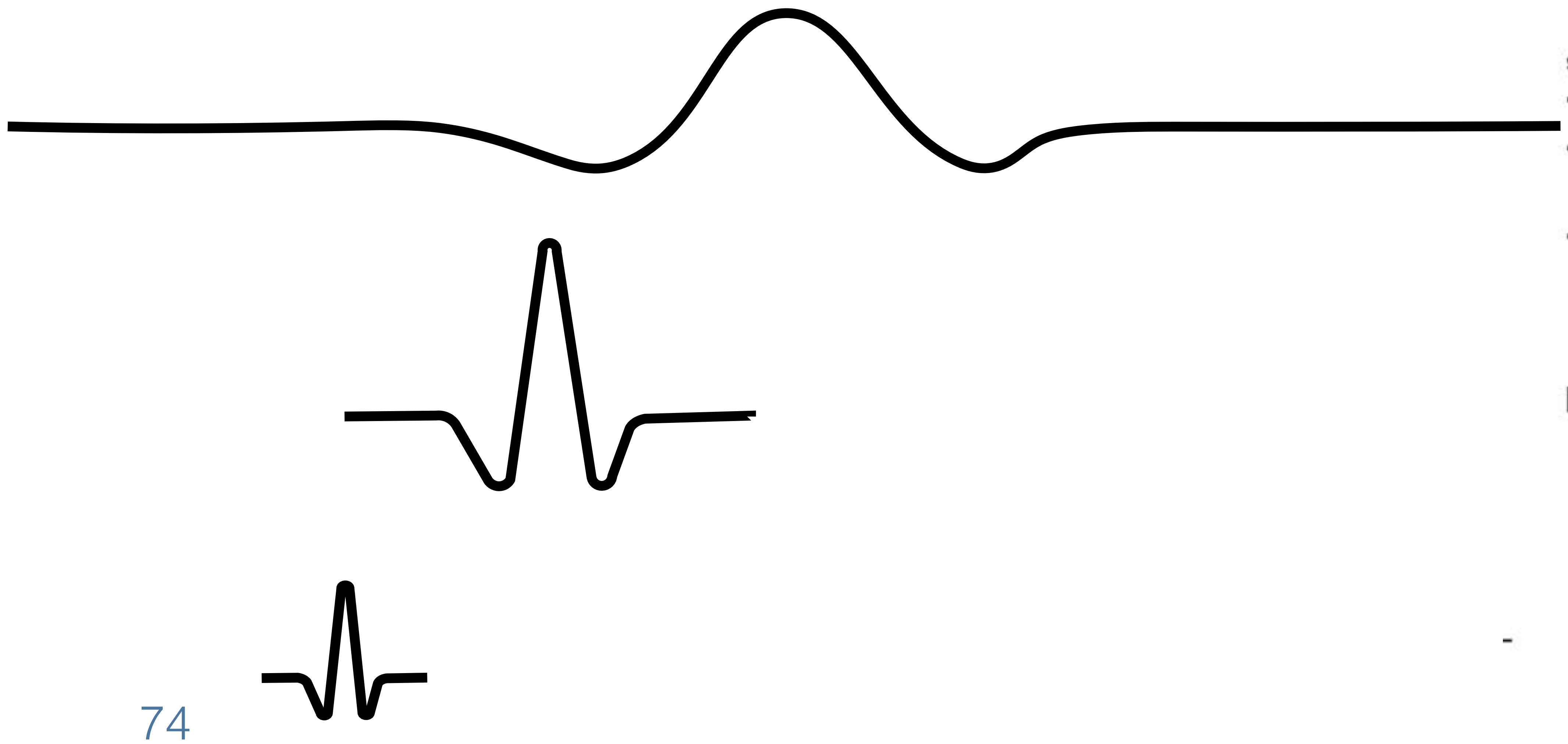


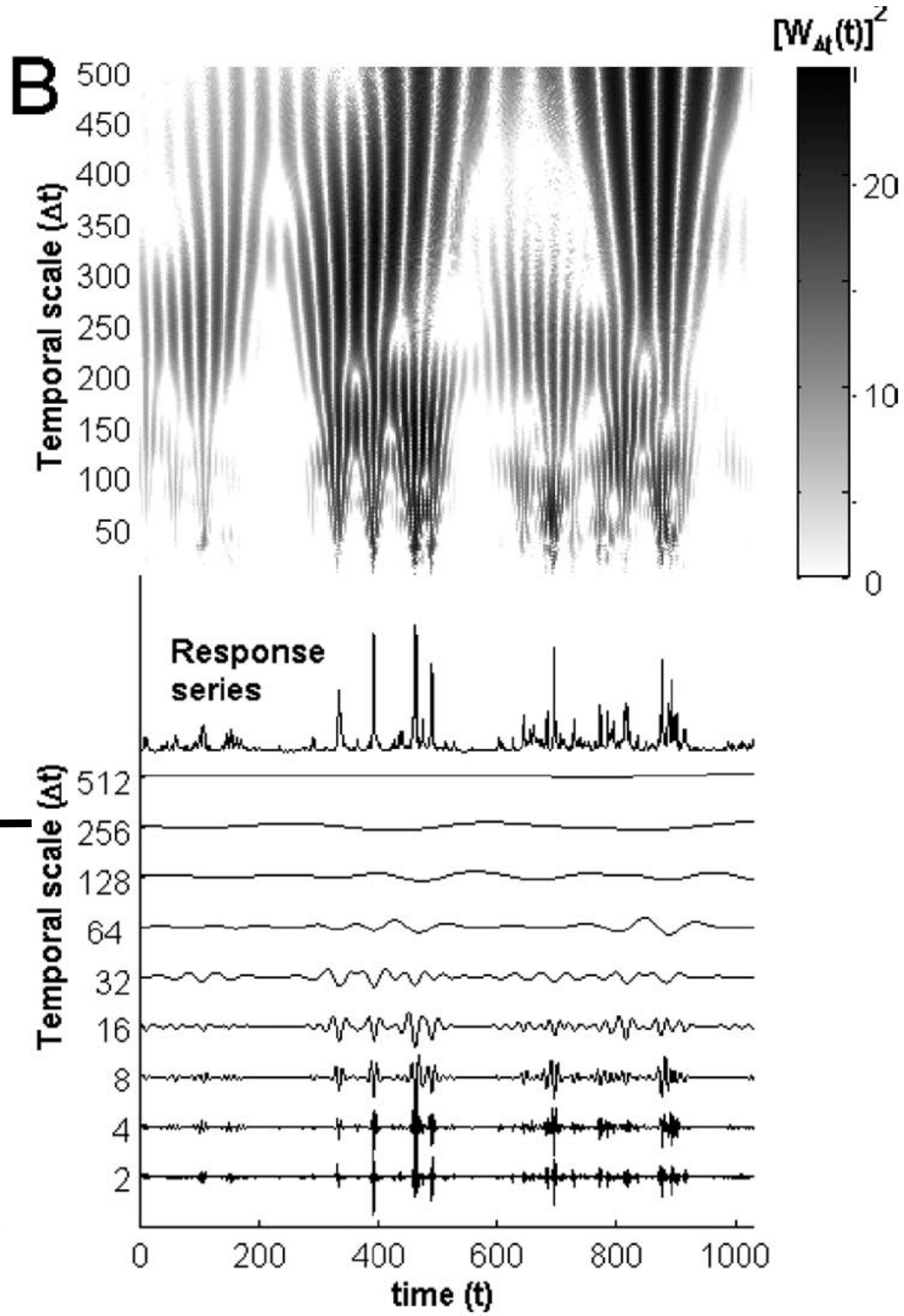
Scaleogram - Continuous Wavelet Transform

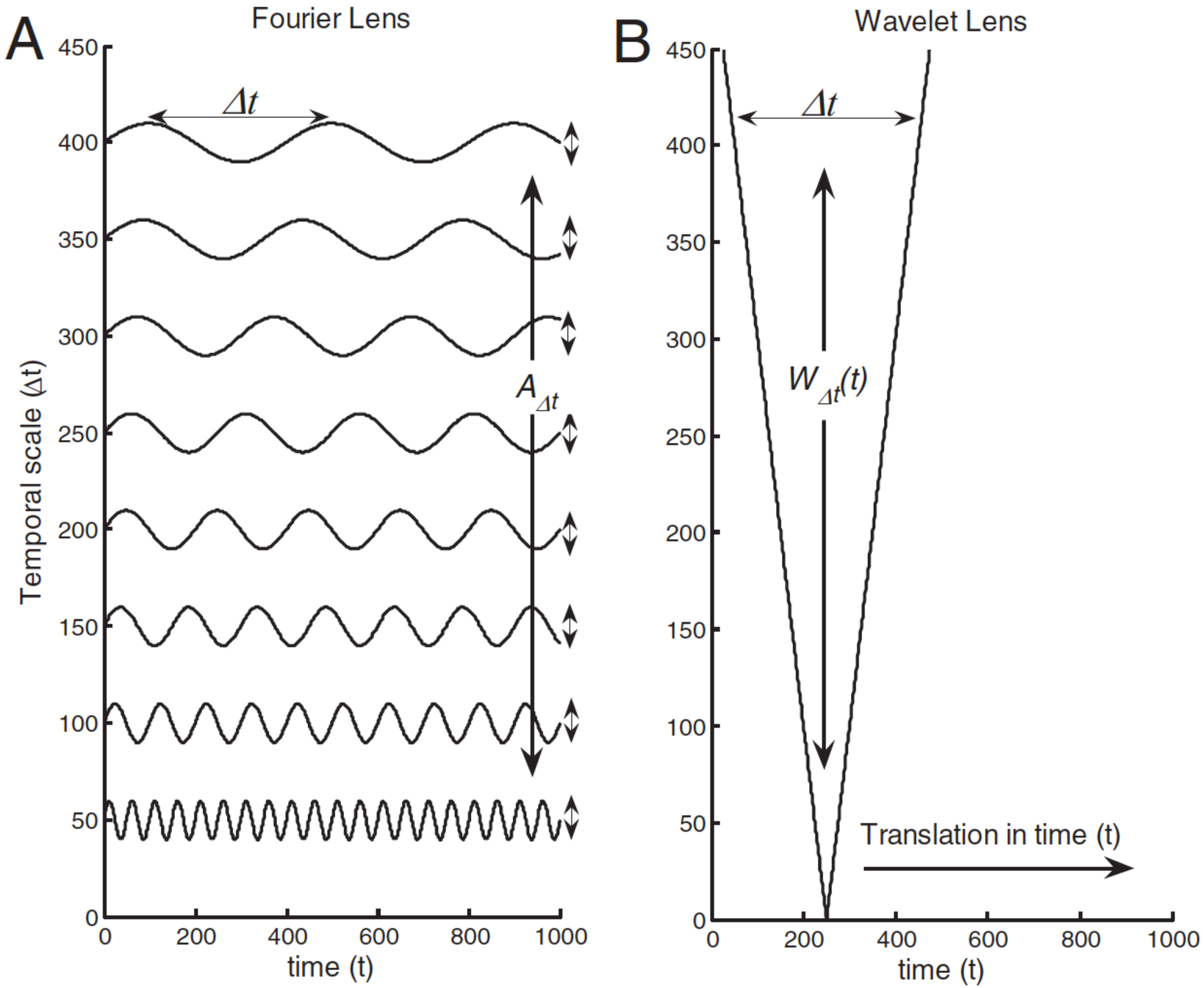


Scaleogram - Continuous Wavelet Transform








A
Fourier Lens
Δt
A_Δt
Temporal scale (Δt)
time (t)
0
200
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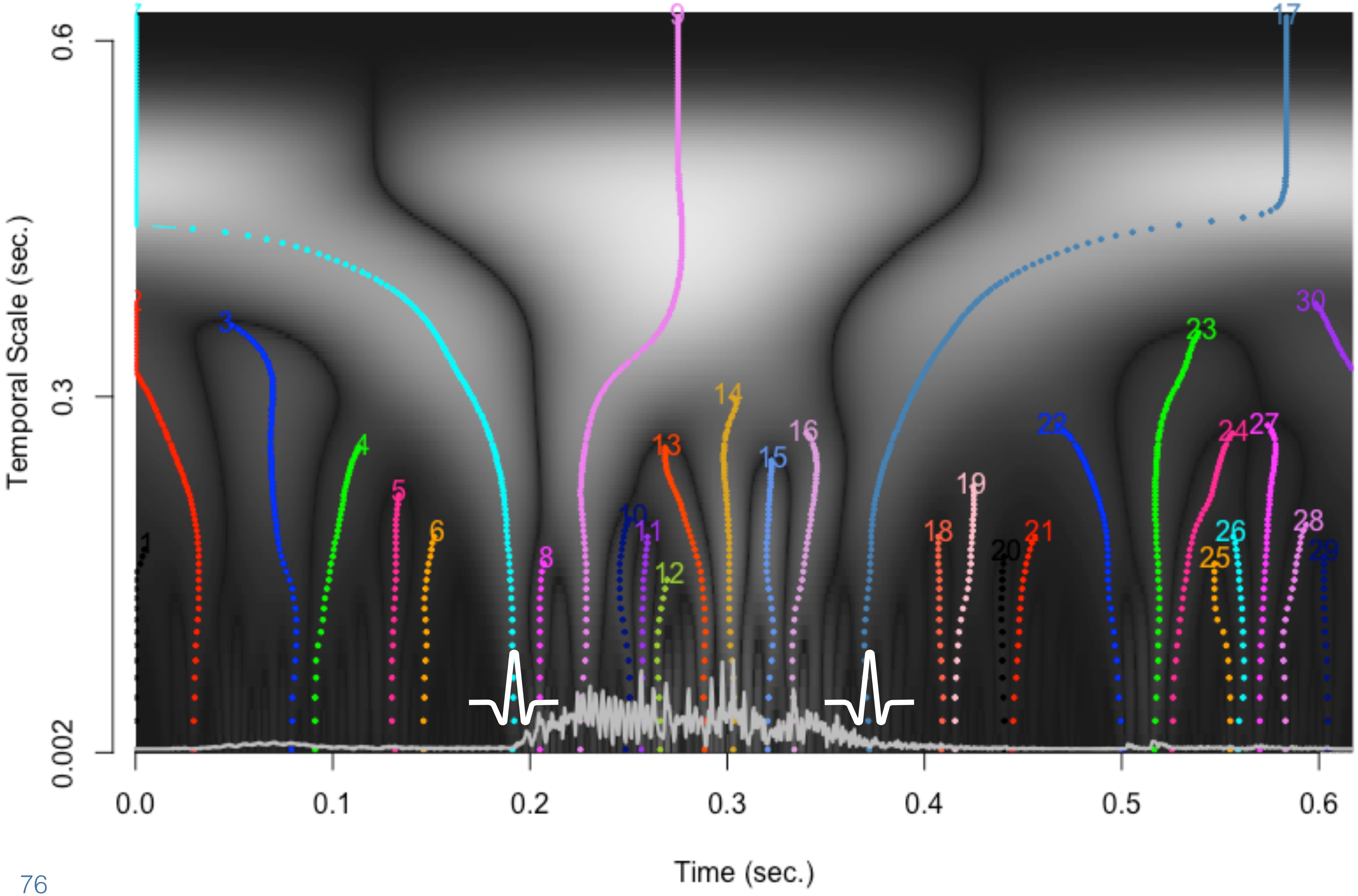
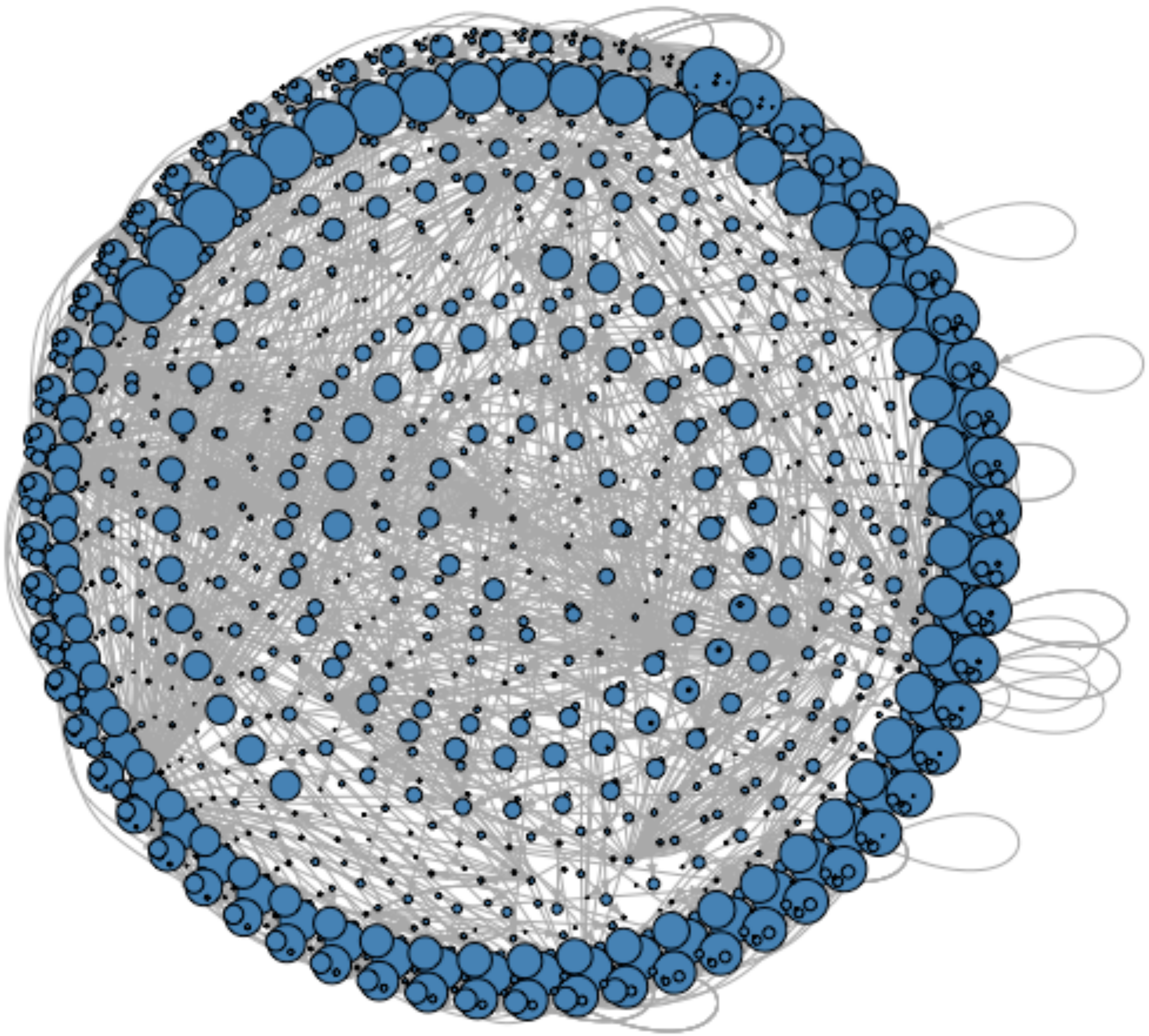
450
B
Wavelet Lens
Δt
W_Δt(t)
Translation in time (t)
time (t)

Self-Affine Resonance

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

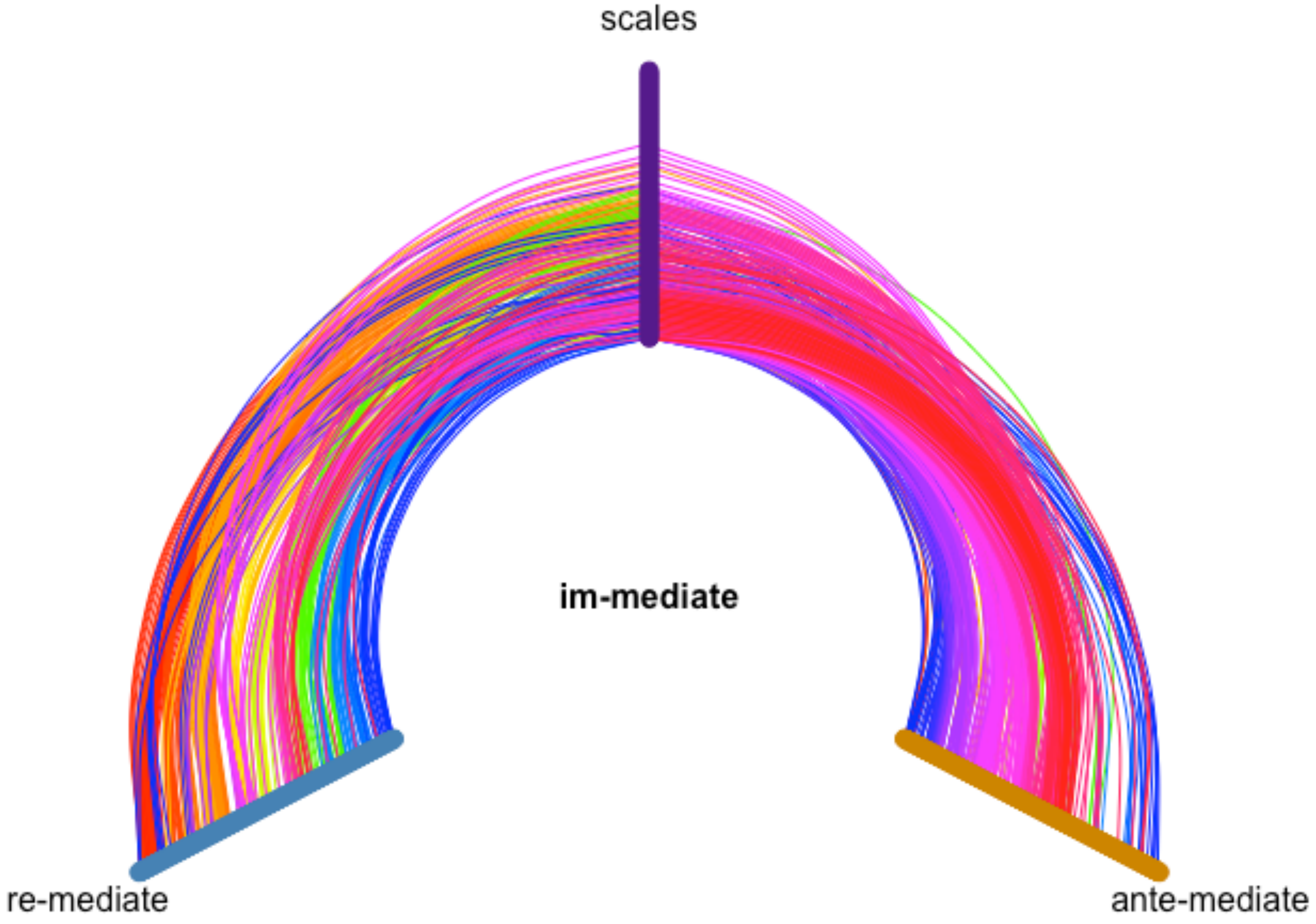


Network - Singularity Skeleton



Self-Affine Resonance

Network - Singularity Skeleton



reproduction of similarity by analogy

Complex networks: Do our current models suffice?

Neural network models:
Energy/potential functions for end-states
Recurrent networks

$$\xi_i := sign\left(\sum_j w_{ij}\xi_j\right) \qquad H = -\tfrac{1}{2}\sum_{ij} w_{ij} S_i S_j$$

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

Self-organizing maps

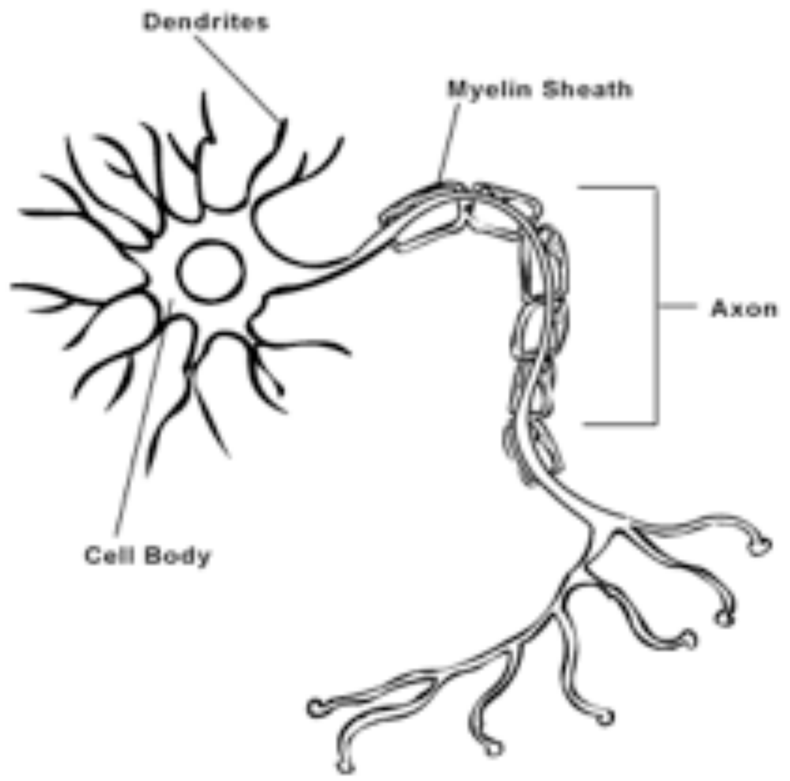
Two-neuron models:
adaptive resonance

Continuous single-neuron models:
dynamic field theory

Ising-spin models:
global, local and external forces

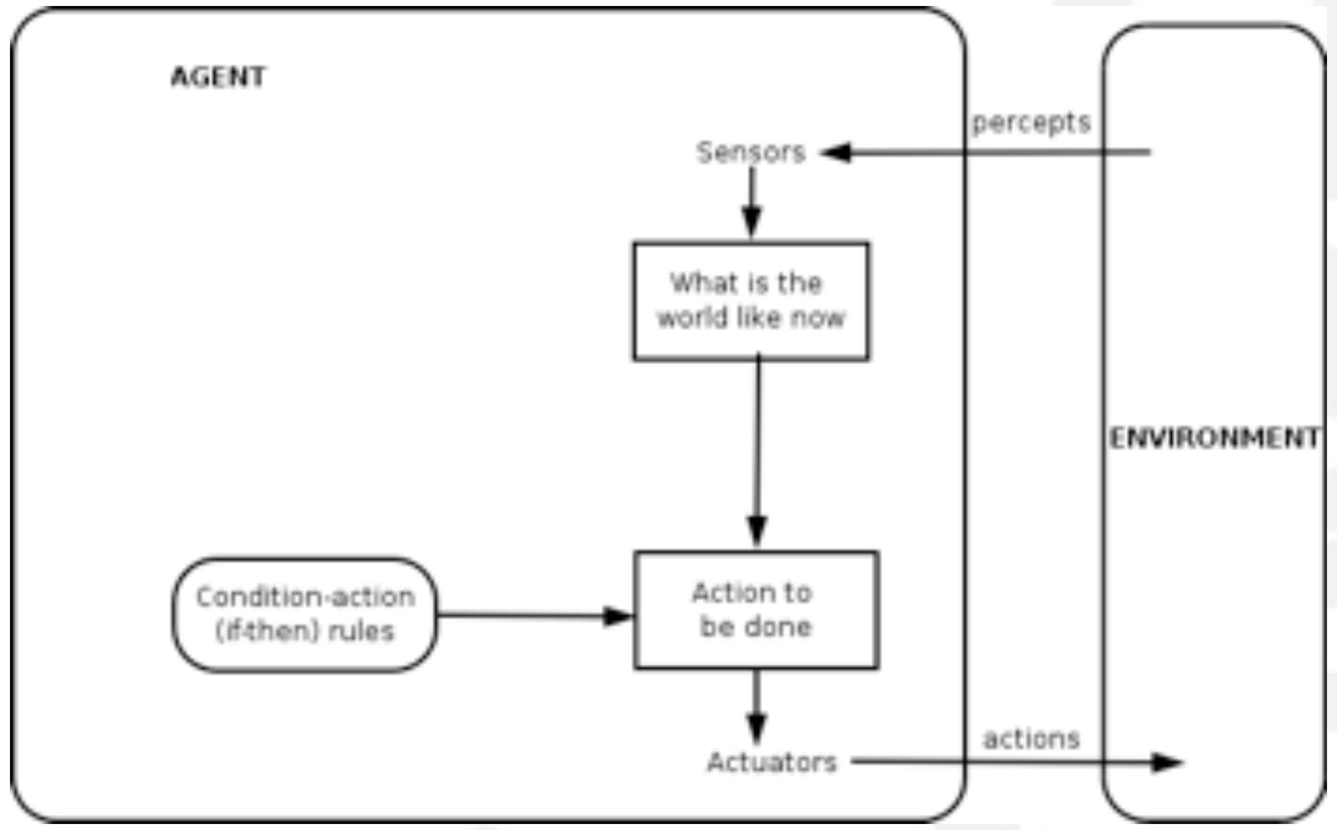
$$H_i = -\frac{J}{2}\sum_{\substack{neighbor\\atoms}} S_i S_{neighbor}$$

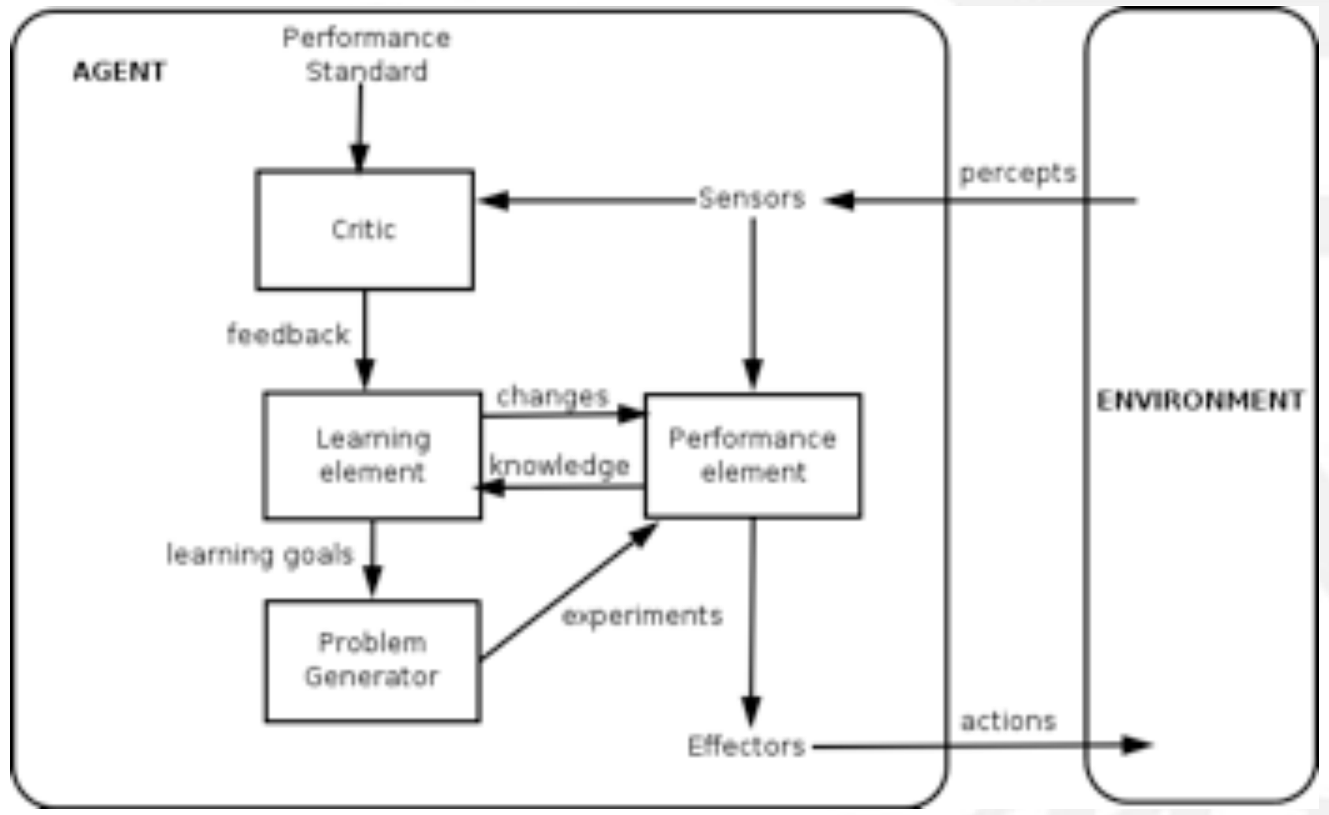
$$I_i = \sqrt{\sum_j^N \left(\frac{s_j}{d_{ij}^2}\right)^2}$$



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

Agent-based models





Evolving agent-based models

The wish list for a formal description of agent-environment systems...

- **Composition principle**
  (quasi-static structure: relation of wholes to parts)

  Holism?
  Neural networks / dynamical systems = Holistic systems?

- **Dynamic interaction principle**
  (time evolution: relation of the dynamic whole to dynamic parts)

  Strong emergence, novelty = SOC?
  SOC-system = adaptive agent-environment system?

- **A theory of measurement** for such systems...

"Life is a fractal in Hilbert space."

- Rudy Rucker, 1987

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