

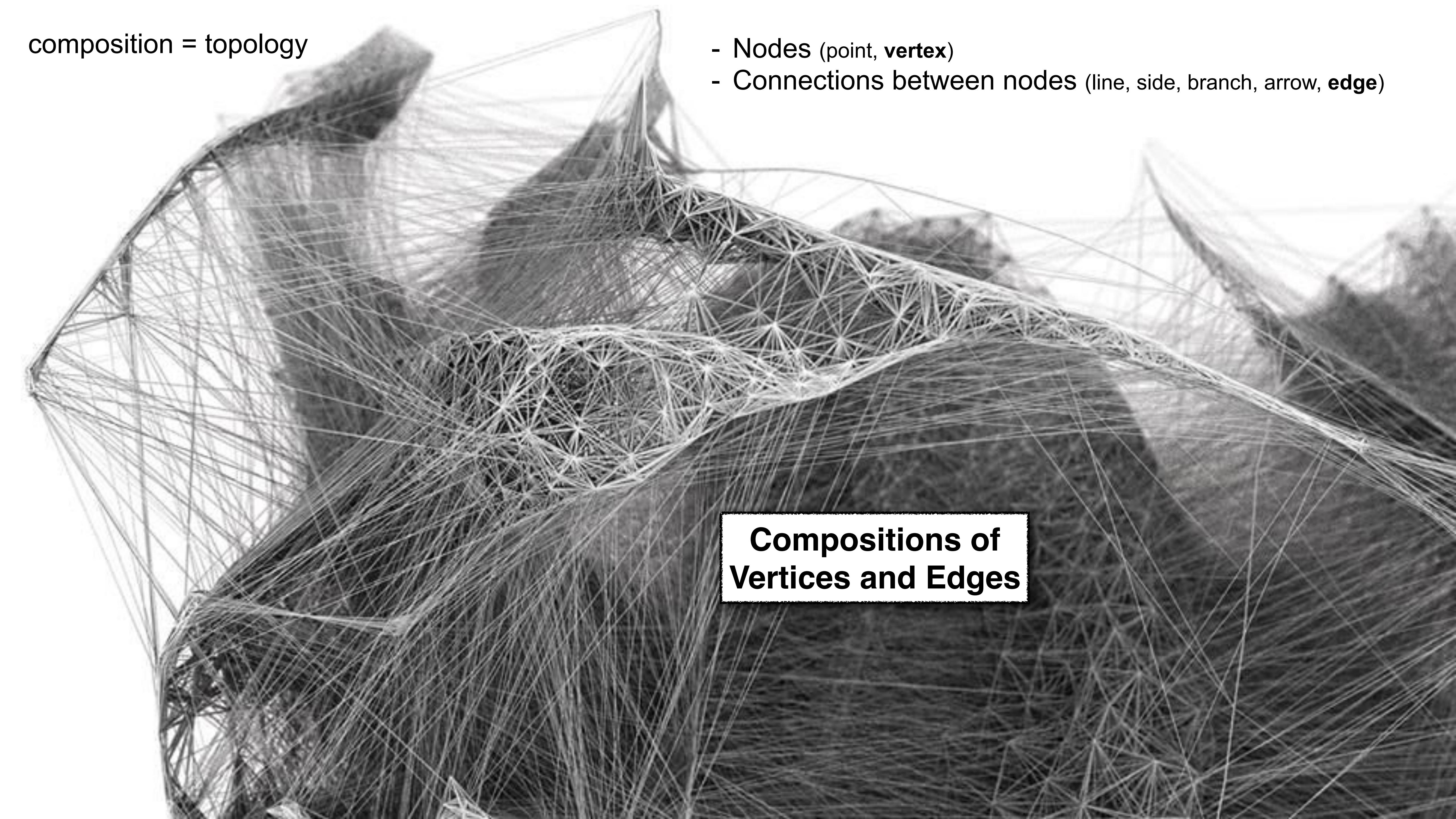
Complexity Methods For Behavioural Science

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**)

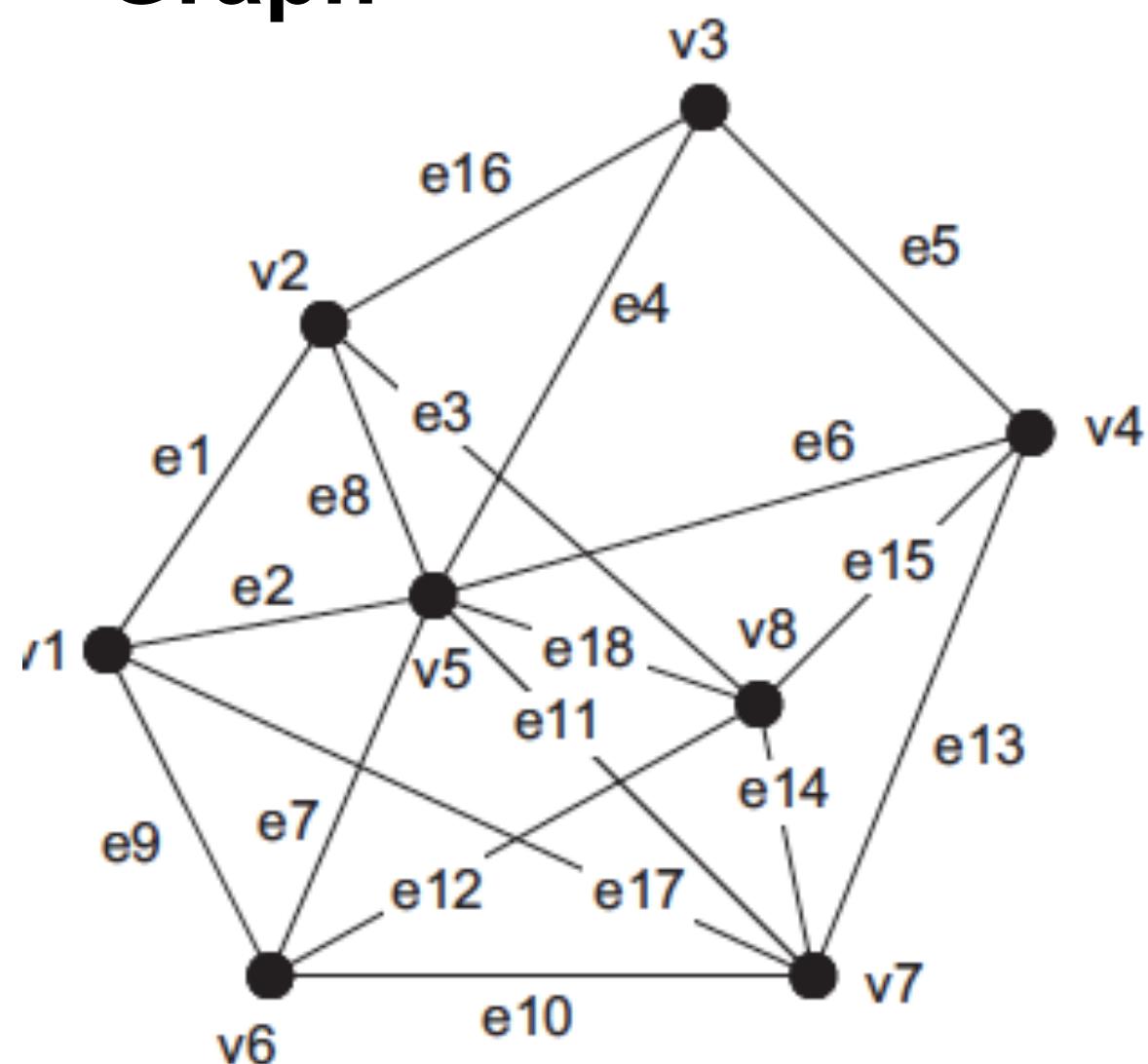


**Compositions of
Vertices and Edges**

Grafentheorie

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

Graph



Formal

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

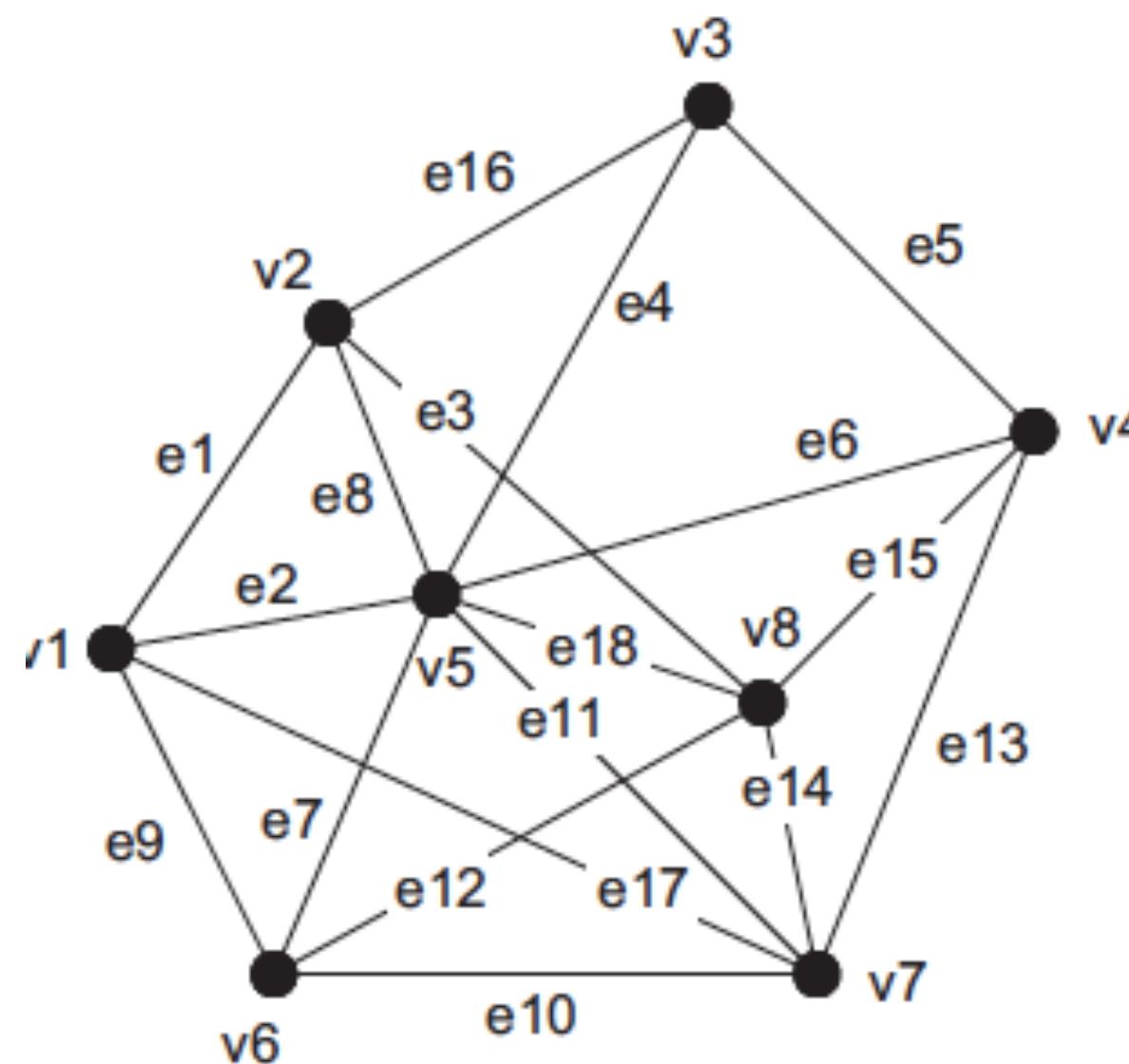
Figure 2.1: An example of a graph with eight vertices and 18 edges.

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

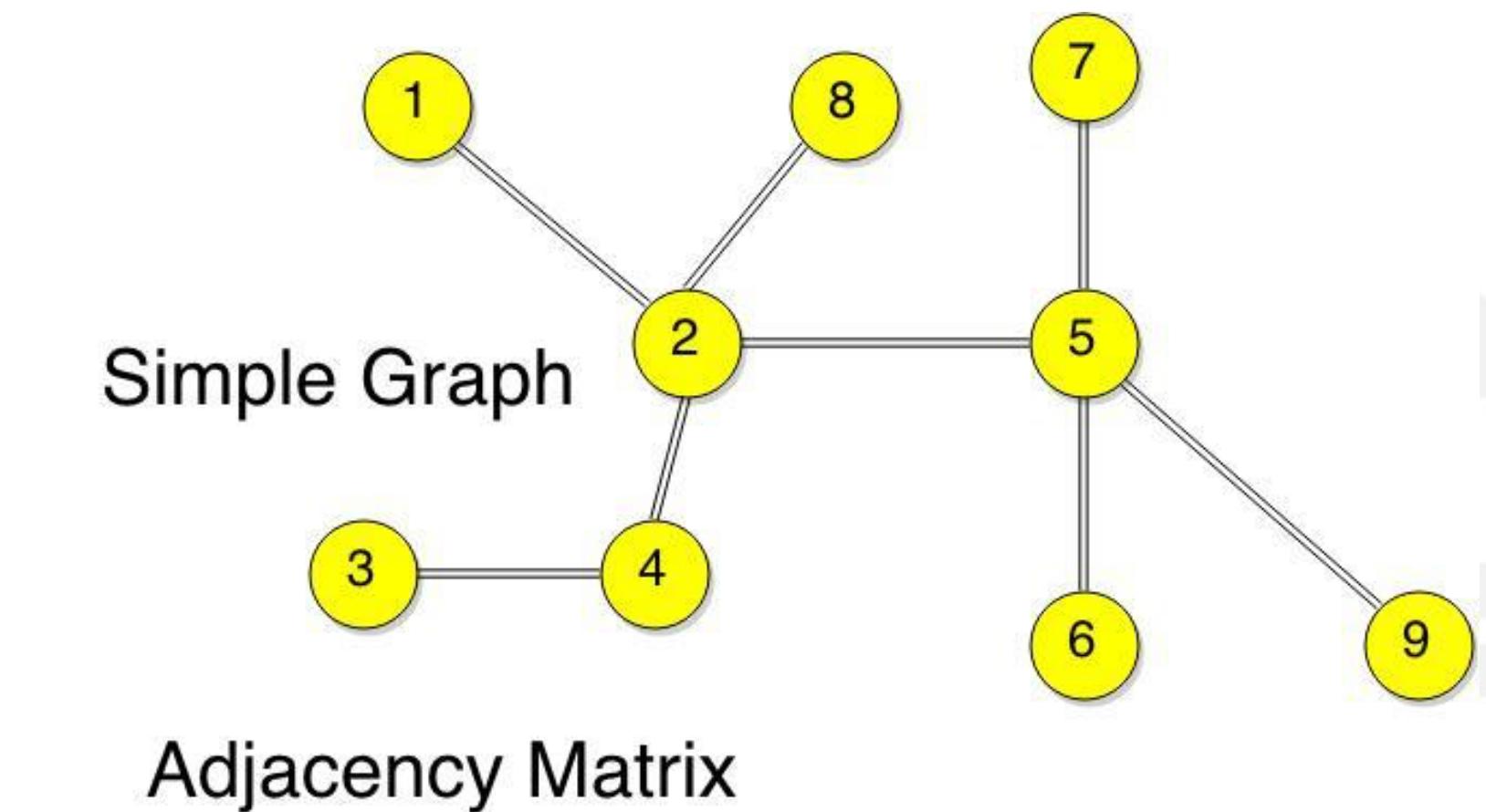
Graph theory

undirected graph



$V(G) = \{v_1, \dots, v_8\}$
 $E(G) = \{e_1, \dots, e_{18}\}$
 $e_1 = \langle v_1, v_2 \rangle \quad e_{10} = \langle v_6, v_7 \rangle$
 $e_2 = \langle v_1, v_5 \rangle \quad e_{11} = \langle v_5, v_7 \rangle$
 $e_3 = \langle v_2, v_8 \rangle \quad e_{12} = \langle v_6, v_8 \rangle$
 $e_4 = \langle v_3, v_5 \rangle \quad e_{13} = \langle v_4, v_7 \rangle$
 $e_5 = \langle v_3, v_4 \rangle \quad e_{14} = \langle v_7, v_8 \rangle$
 $e_6 = \langle v_4, v_5 \rangle \quad e_{15} = \langle v_4, v_8 \rangle$
 $e_7 = \langle v_5, v_6 \rangle \quad e_{16} = \langle v_2, v_3 \rangle$
 $e_8 = \langle v_2, v_5 \rangle \quad e_{17} = \langle v_1, v_7 \rangle$
 $e_9 = \langle v_1, v_6 \rangle \quad e_{18} = \langle v_5, v_8 \rangle$

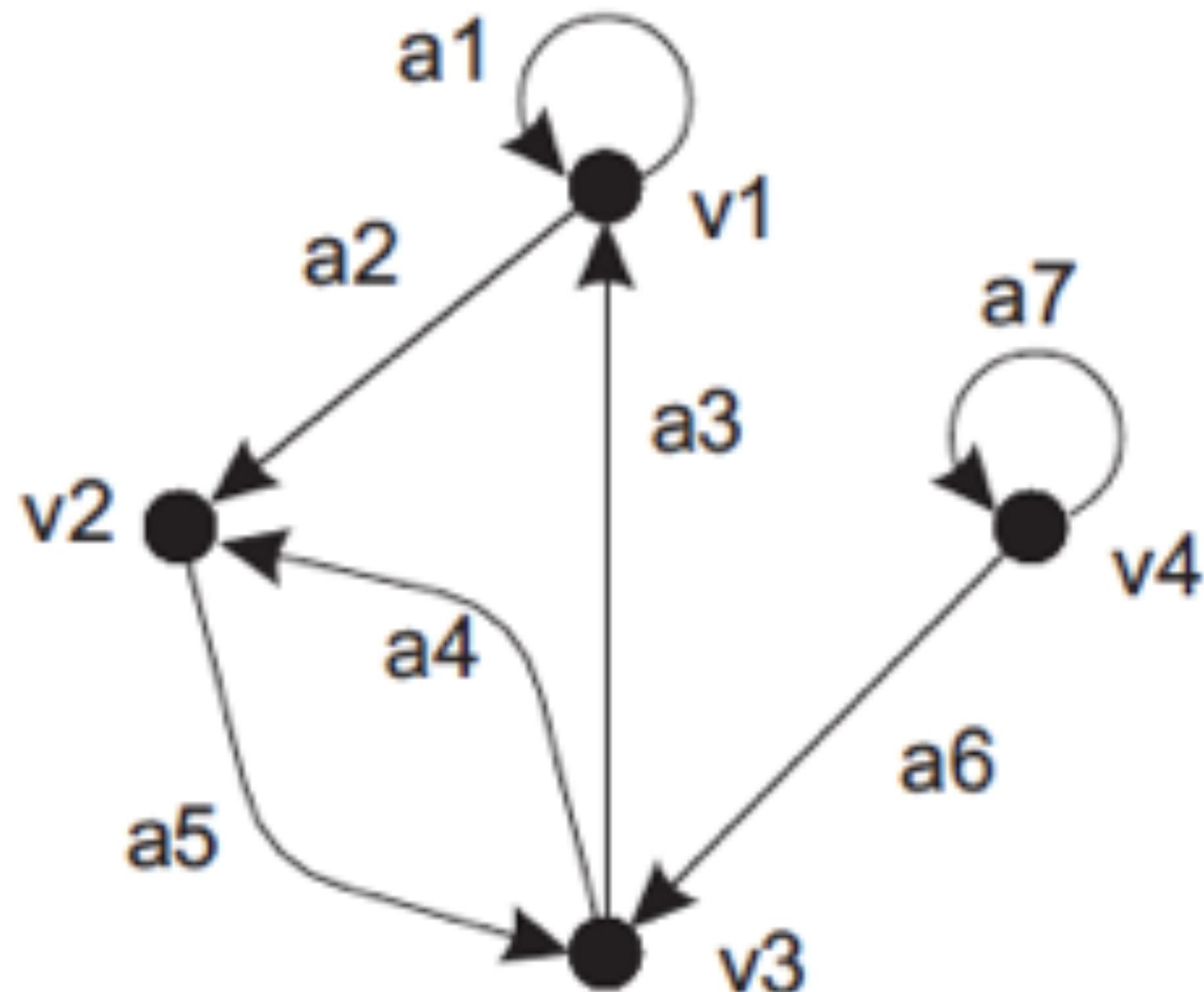
Figure 2.1: An example of a graph with eight vertices and 18 edges.



Graph theory

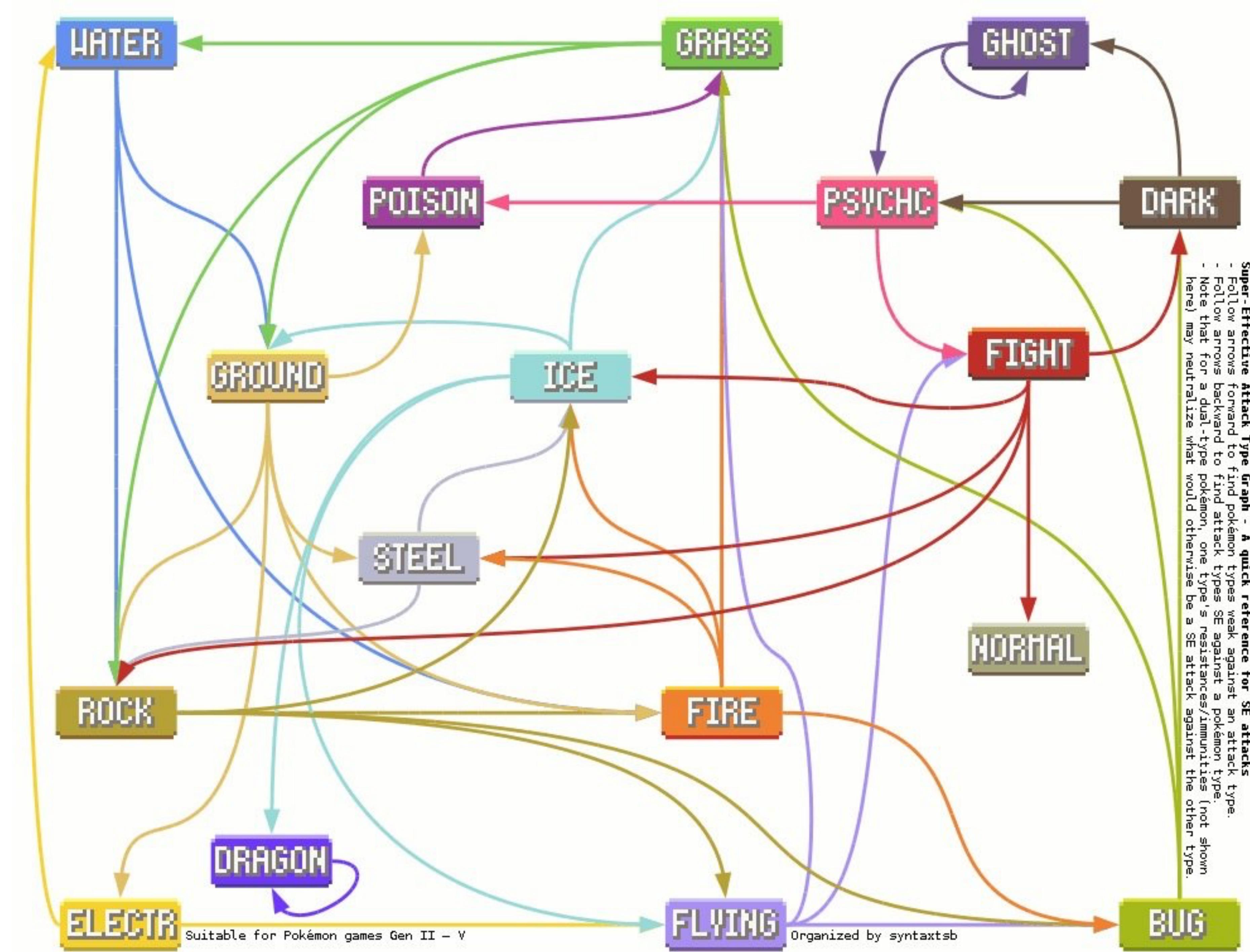
directed graph (digraph)

With *loops* en *arcs*



	v_1	v_2	v_3	v_4	OUT
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	2	2	2	1	7
Σ	2	2	2	1	7





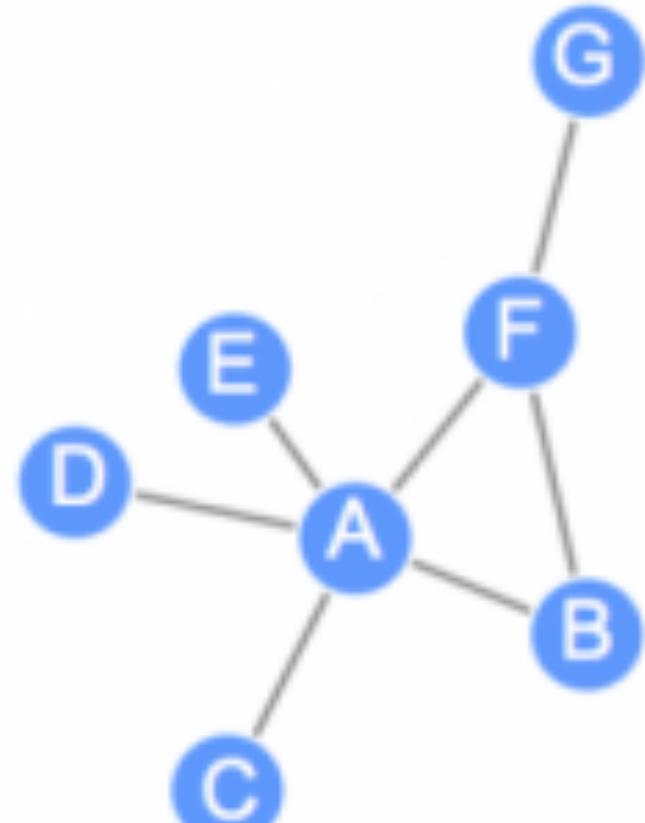
directed network

*Effectivity of
Pokemon attacks
By species*

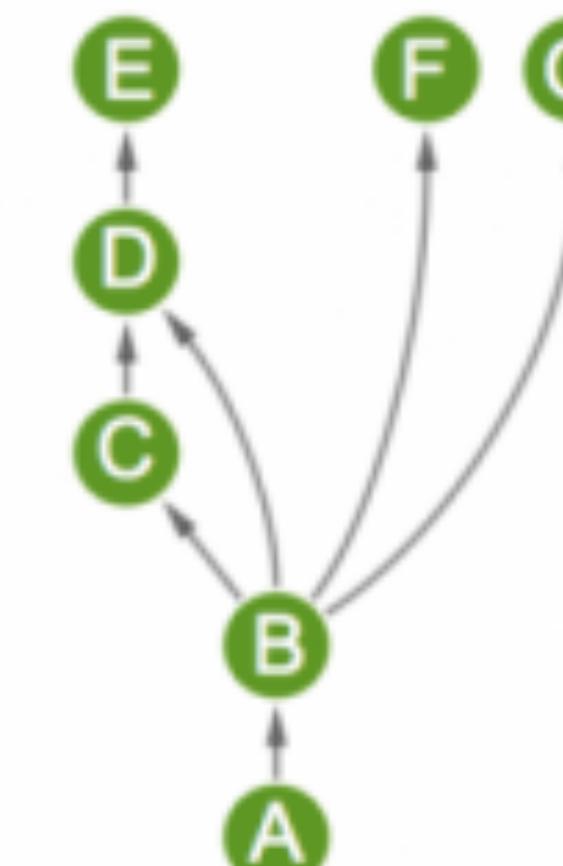
Graph theory

Degree:

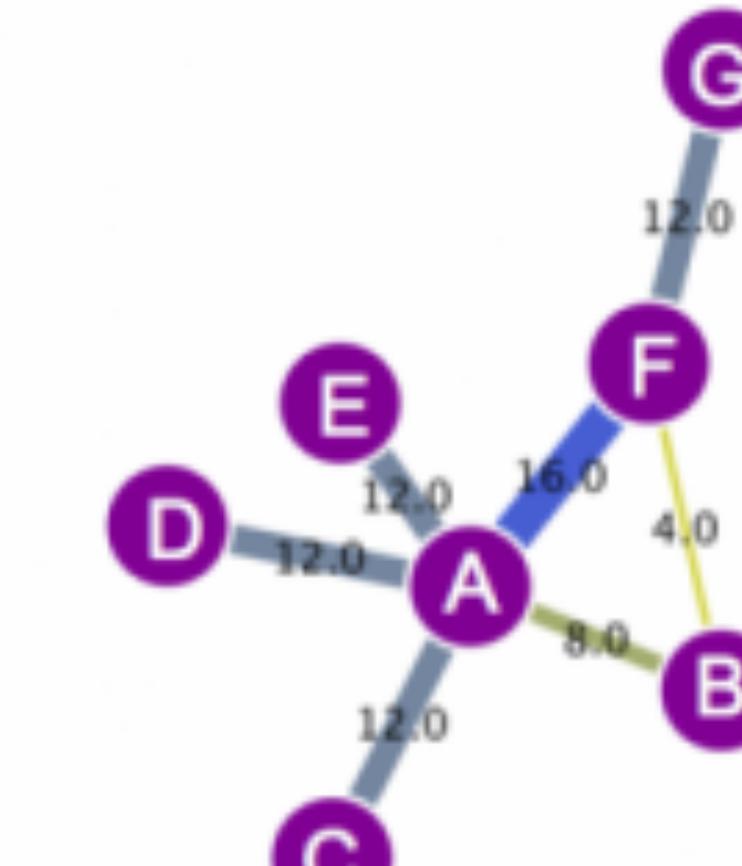
Undirected



Directed



Weighted



How many edges connect to a vertex/node

directed graphs:

in-degree, out-degree

	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

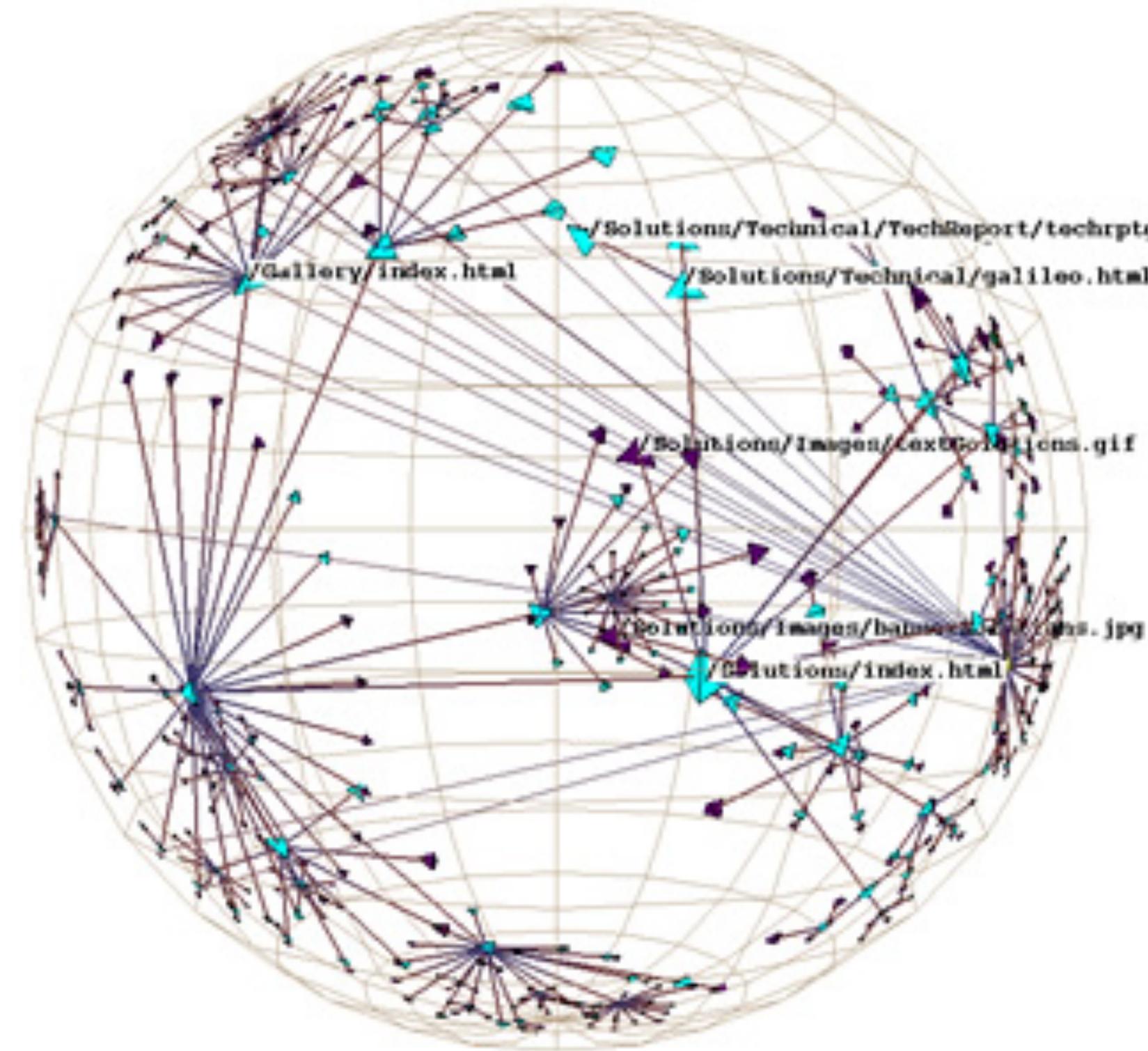
Adjacency matrices

	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

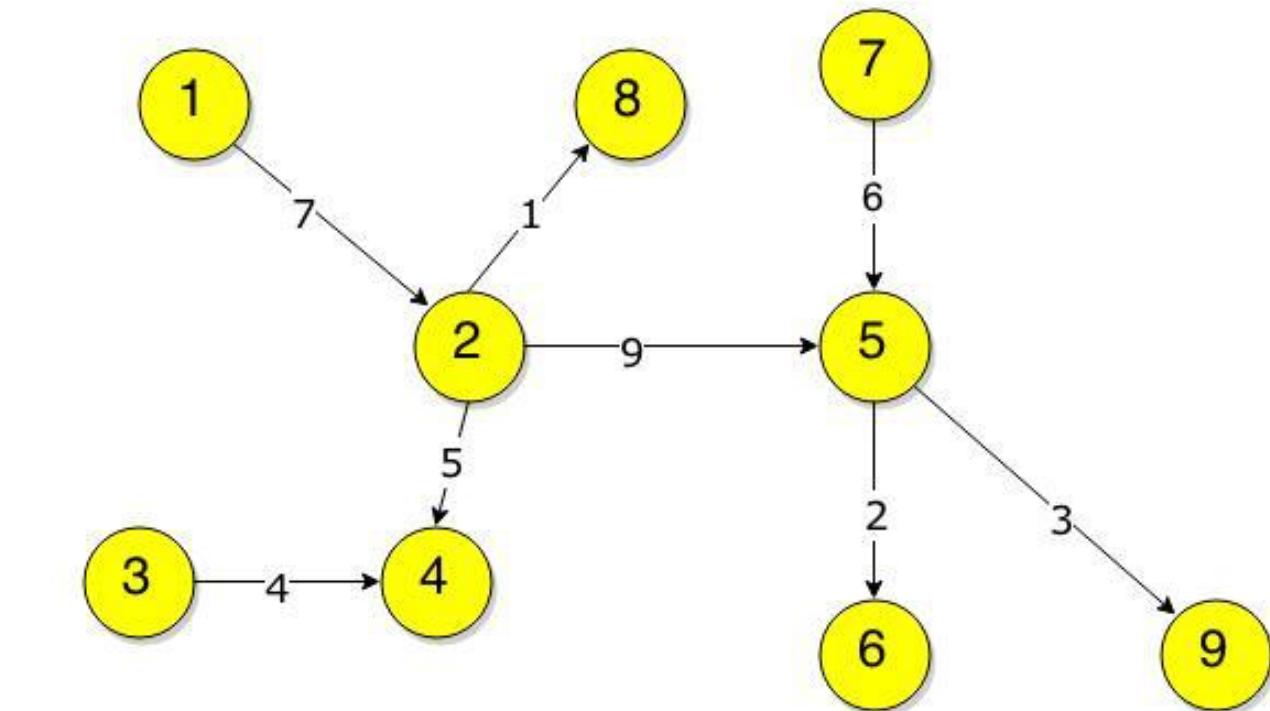
	A	B	C	D	E	F	G	Degree
A	0	8	12	12	12	16	12	72
B	8	0	0	0	0	4	0	12
C	12	0	0	0	0	0	0	12
D	12	0	0	0	0	0	0	12
E	12	0	0	0	0	0	0	12
F	16	4	0	0	0	0	12	32
G	12	0	0	0	0	12	0	24

Graph theory

weighted directed graph



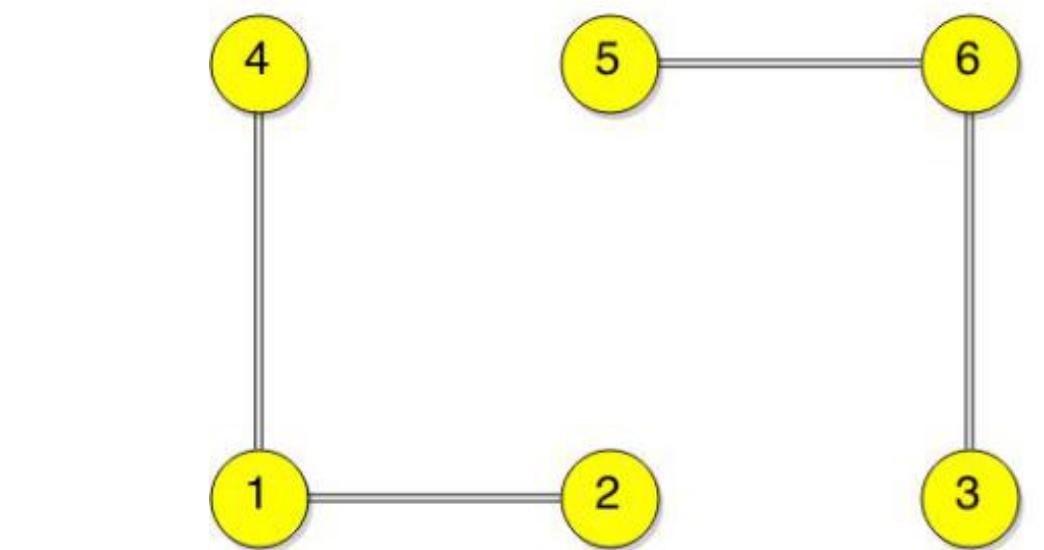
Weighted Directed Graph



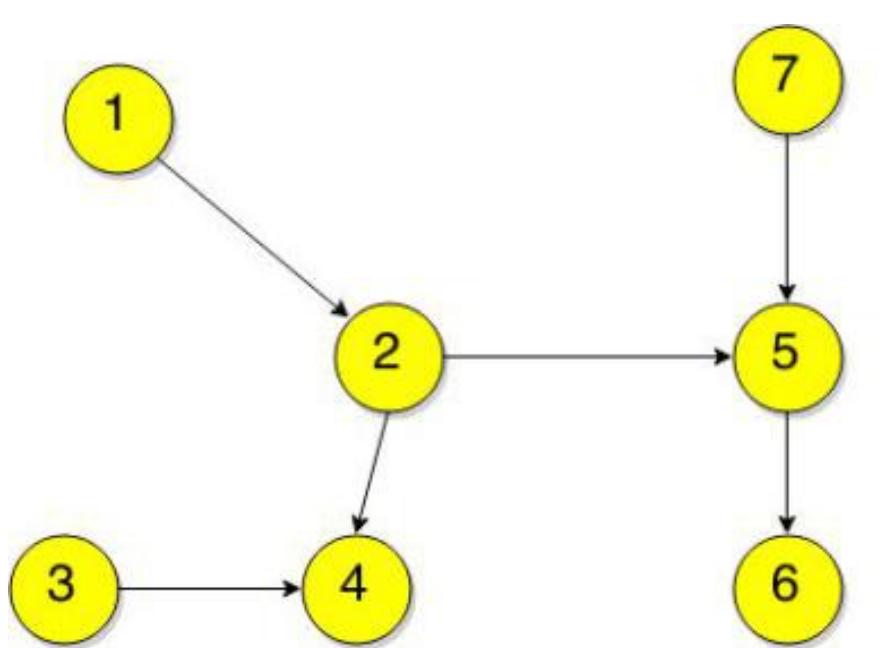
Adjacency Matrix

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

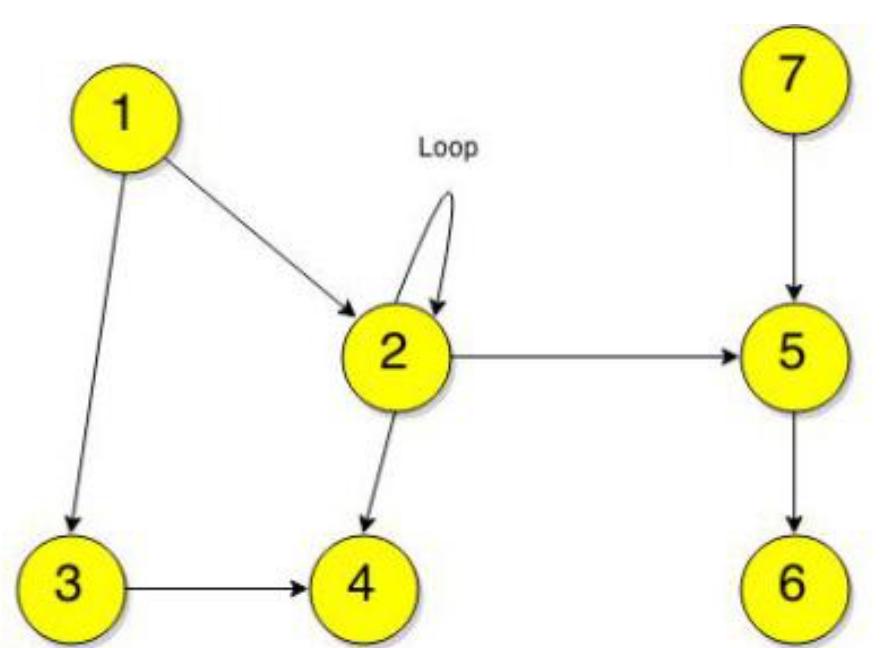




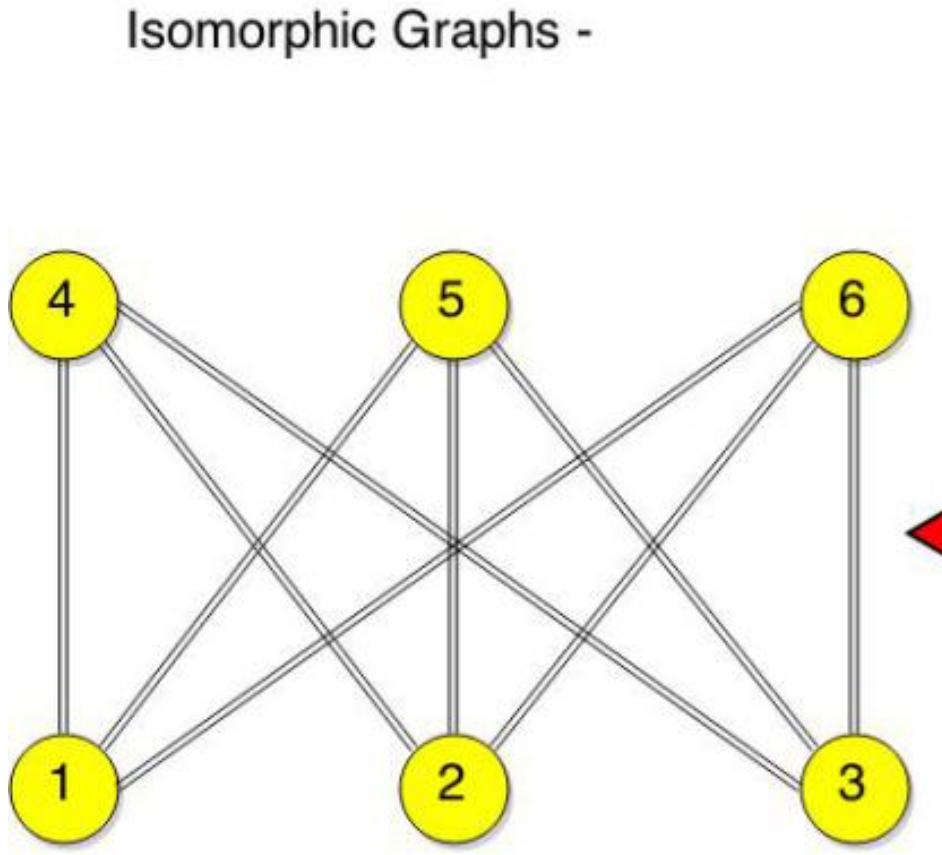
Disconnected Graph



Simple Graph

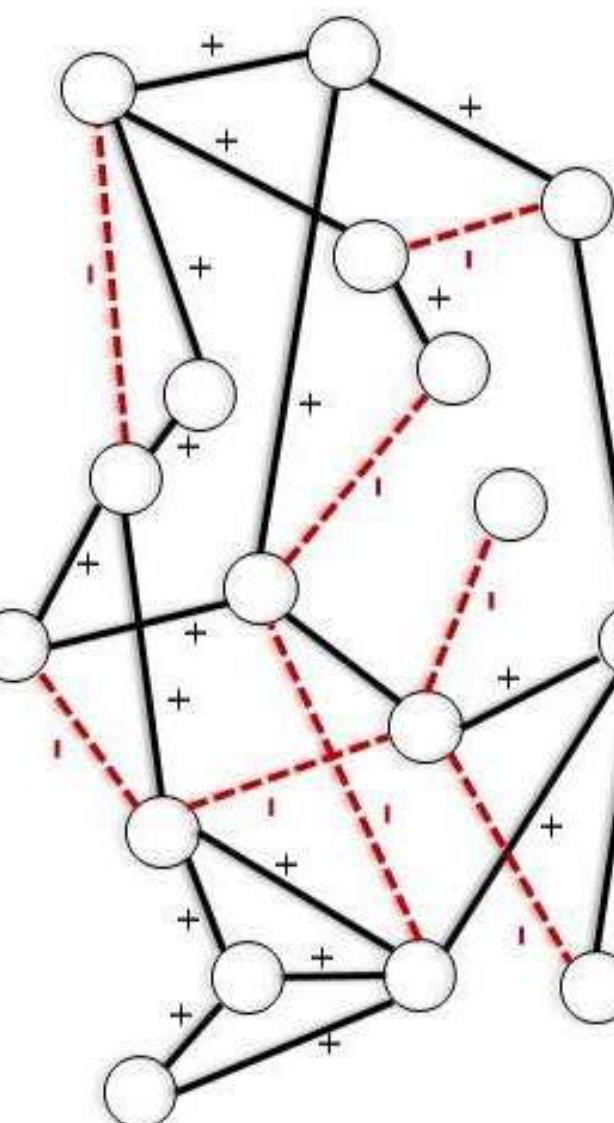


Non - Simple Graph

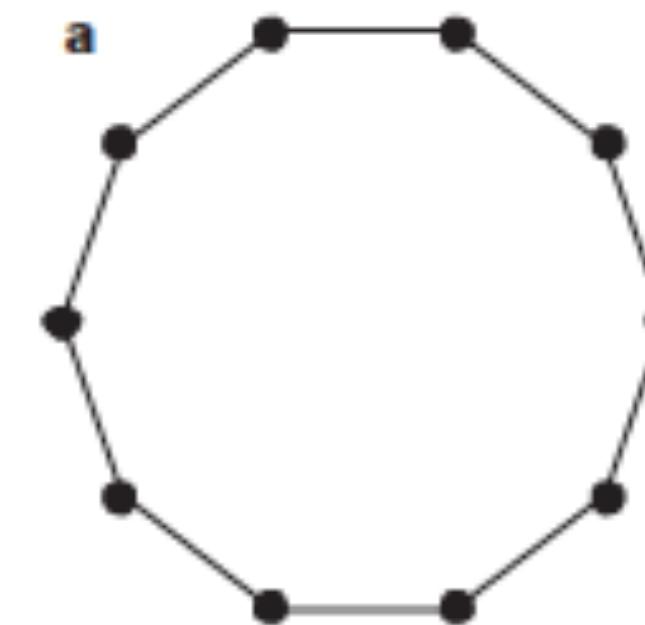


<http://theoryofprogramming.com/tag/adjacency-matrix/>

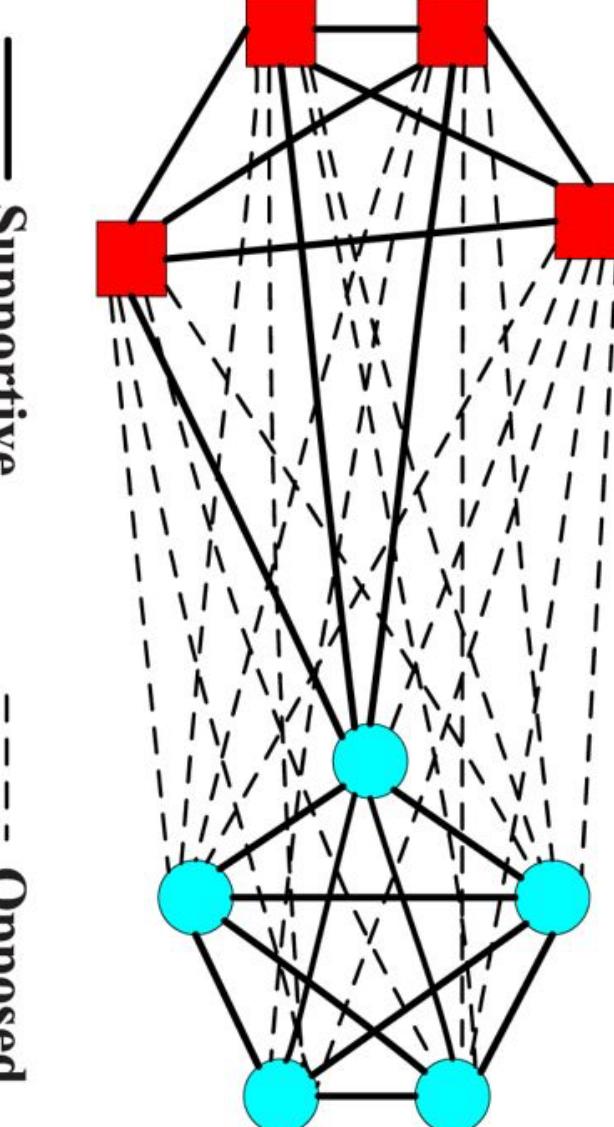
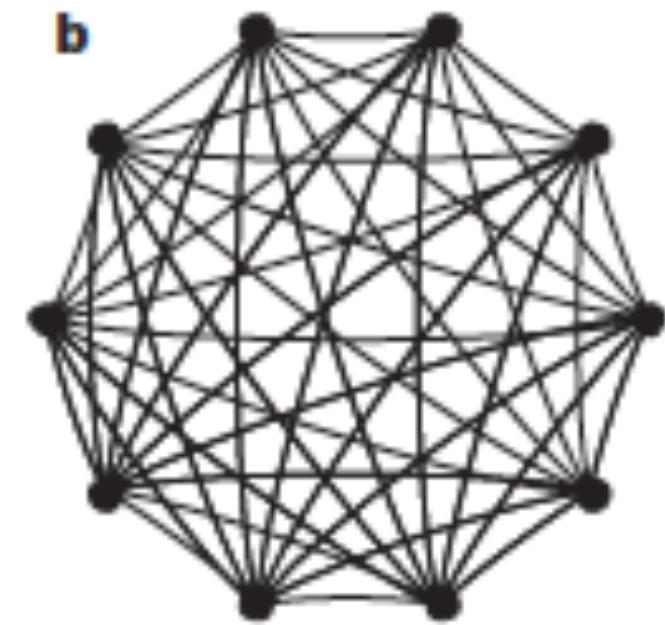
signed graphs



nearest
neighbour ring



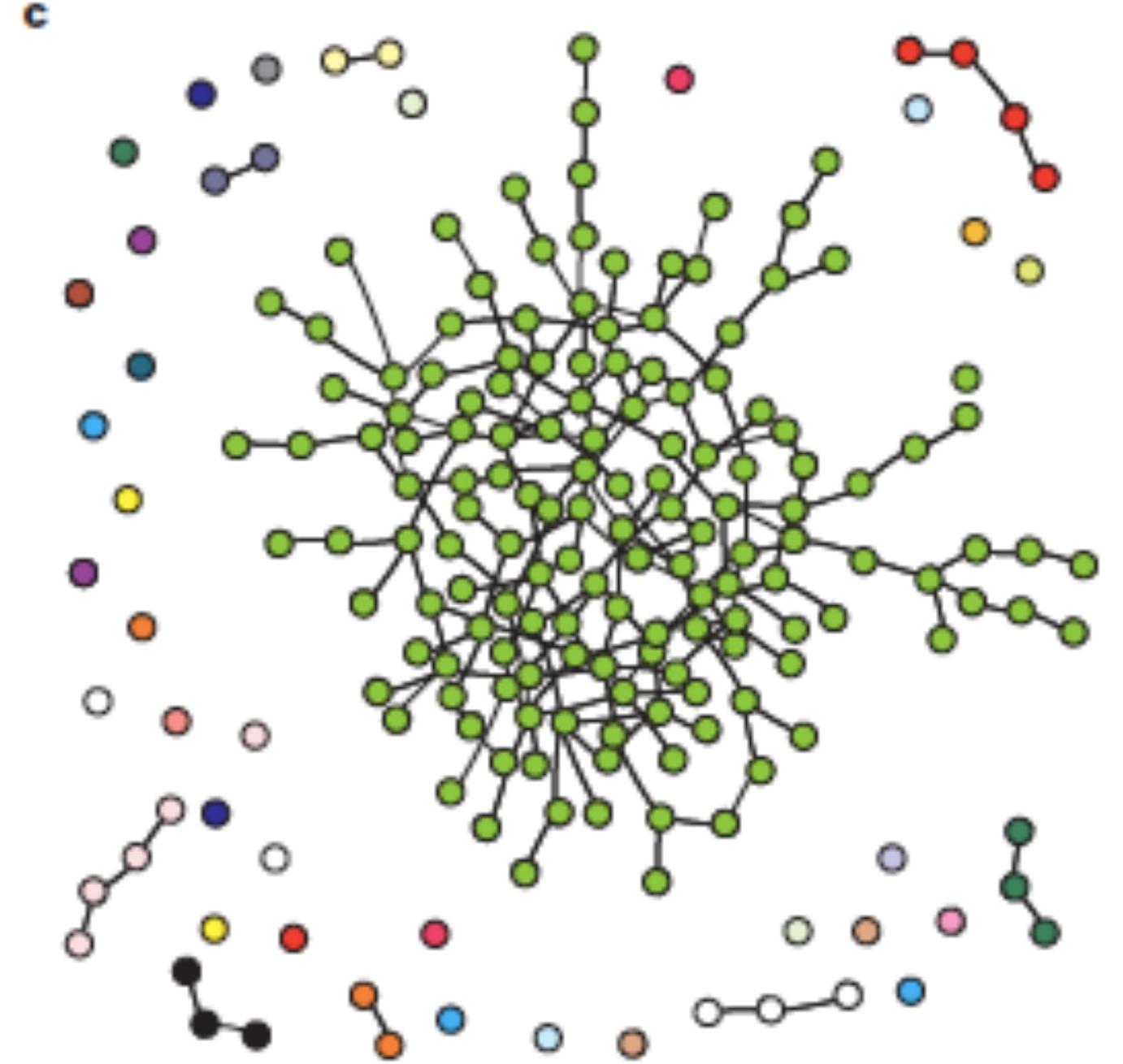
complete
network



— Supportive
- - Opposed

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

random
network
(random
edges)

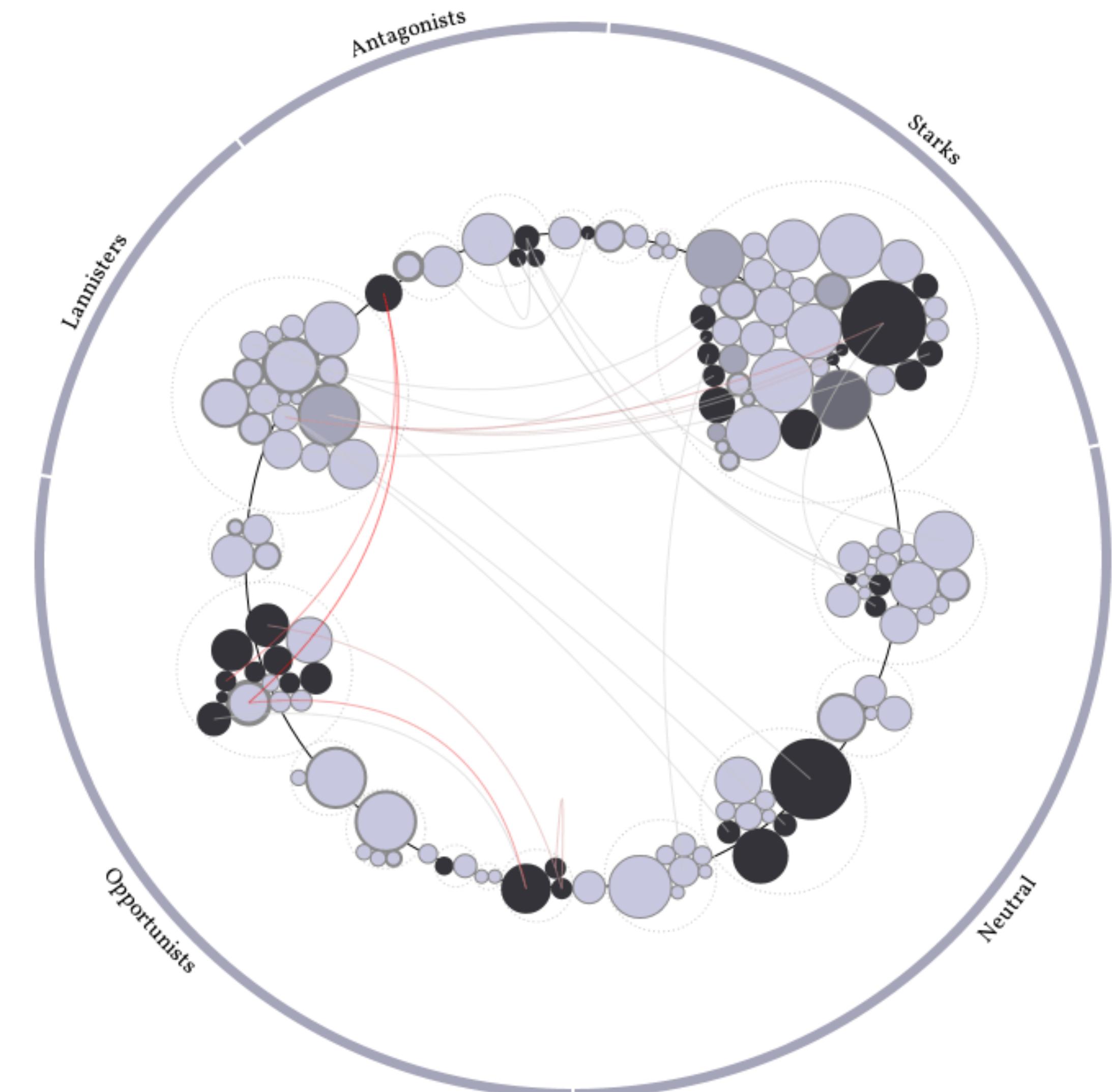
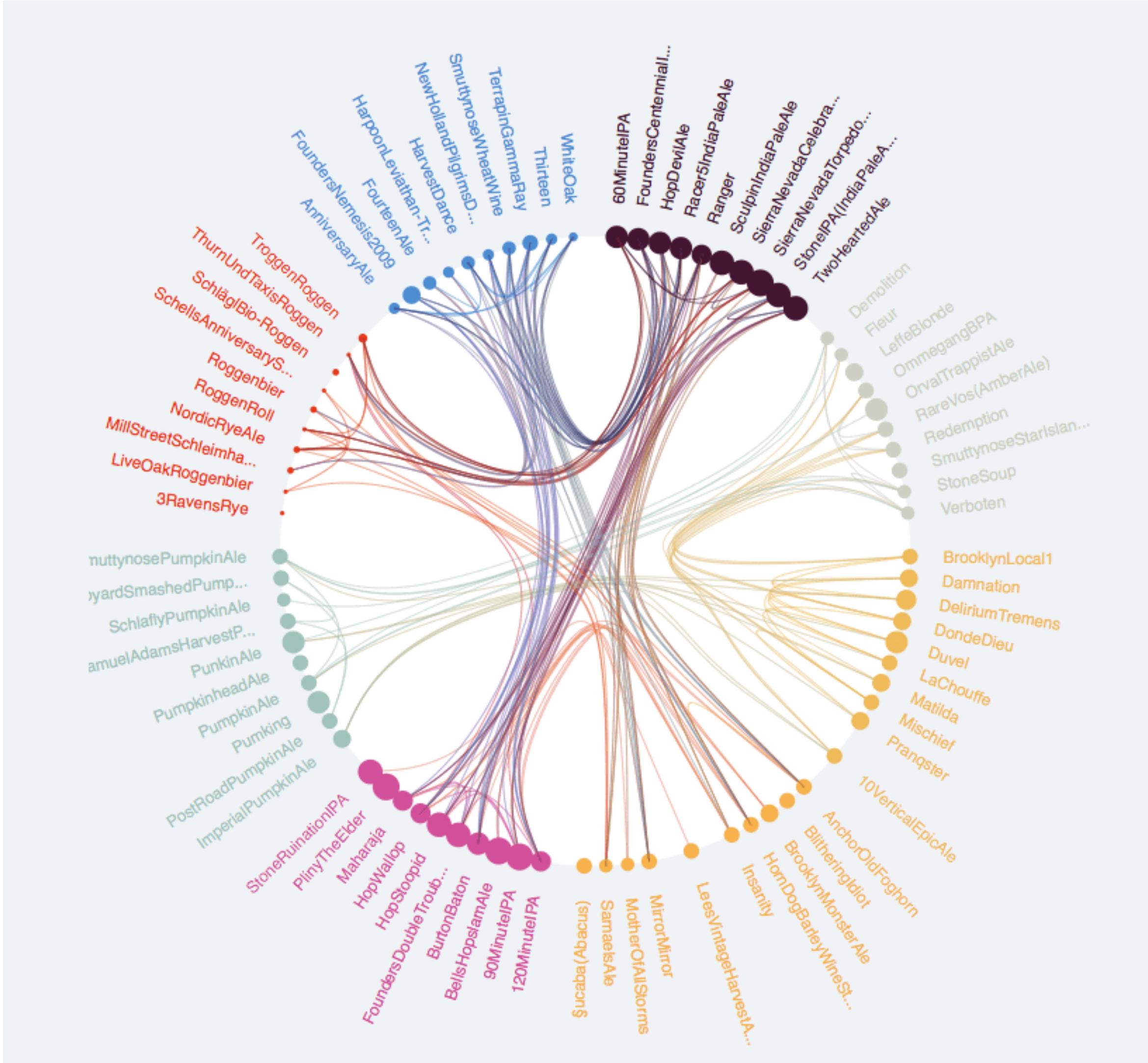


Graph theory

Network 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>

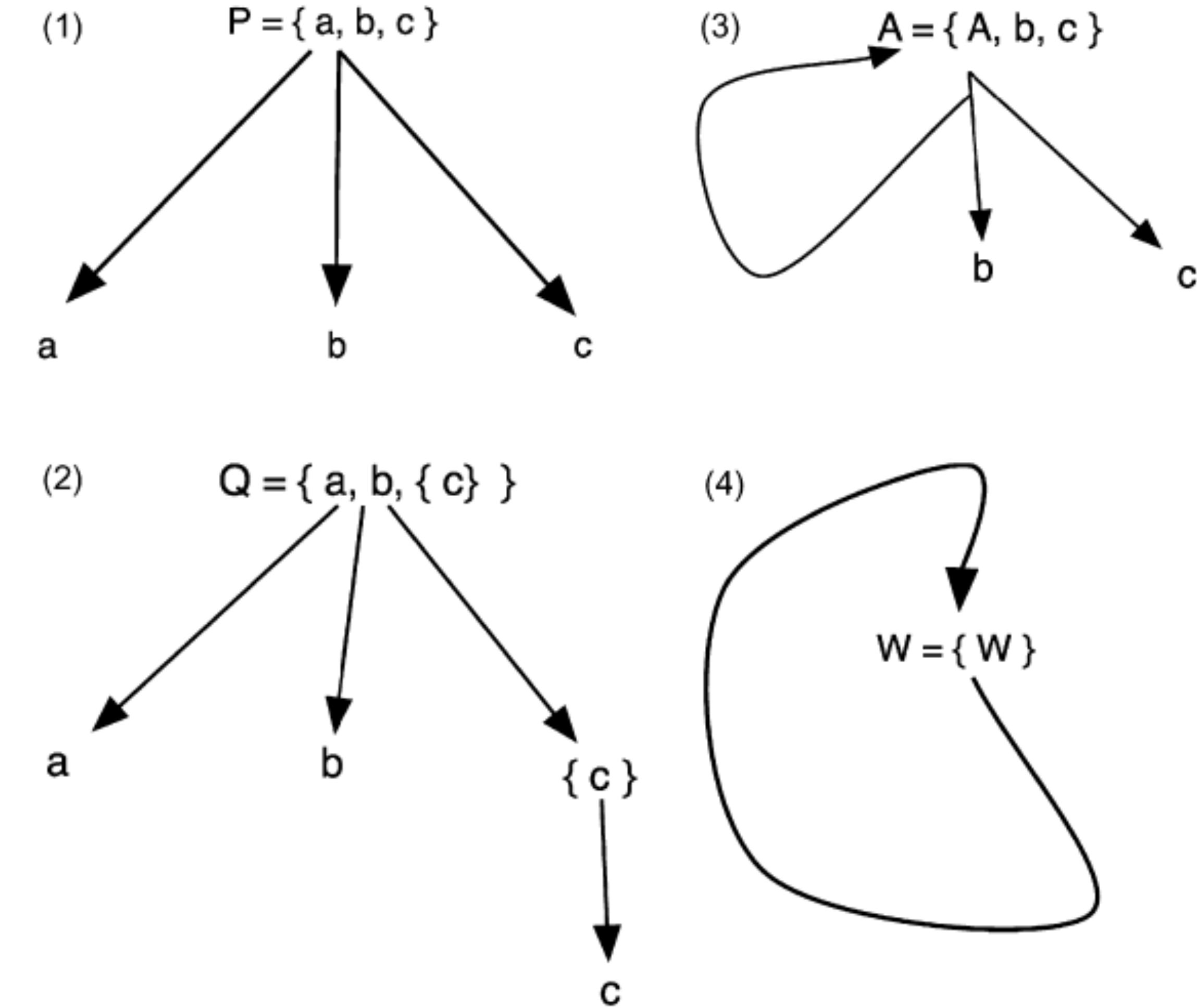


Hyperset theory + Graph theory = Hyperset Graphs (Impredicative Logic)

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

Non well-founded sets:

Definition of a set can
contain itself



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

Impredicative loop

Hyperset loop

Rosen's definition of
a living system
(metabolism-repair-system)

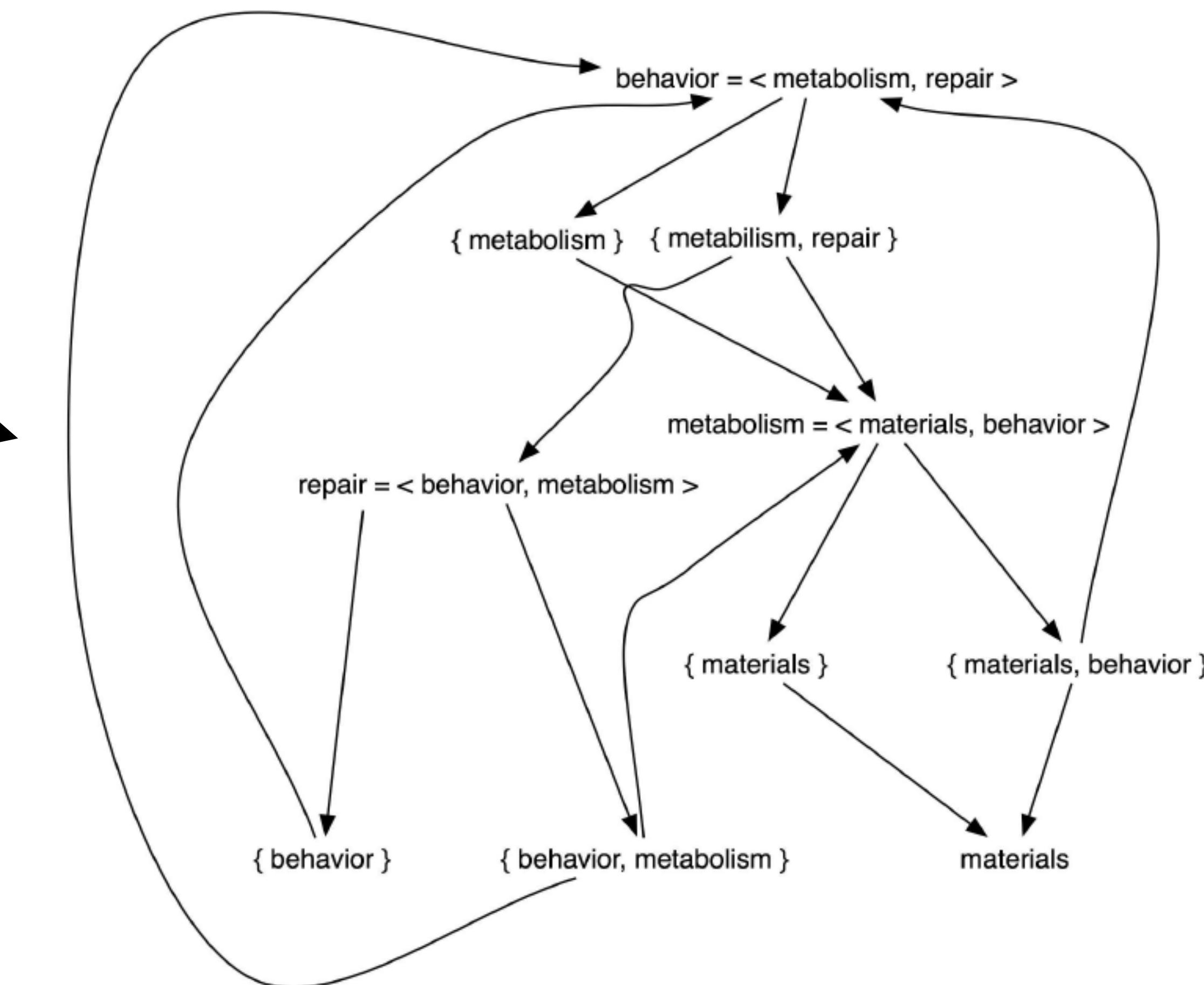


Fig. 6. Hyperset diagram of Rosen's metabolism-repair system. Functions are represented as ordered pairs containing their domain and range. So $f(a) = b$ is represented as $f = \langle a, b \rangle$.

Social networks

Moreno, 1930

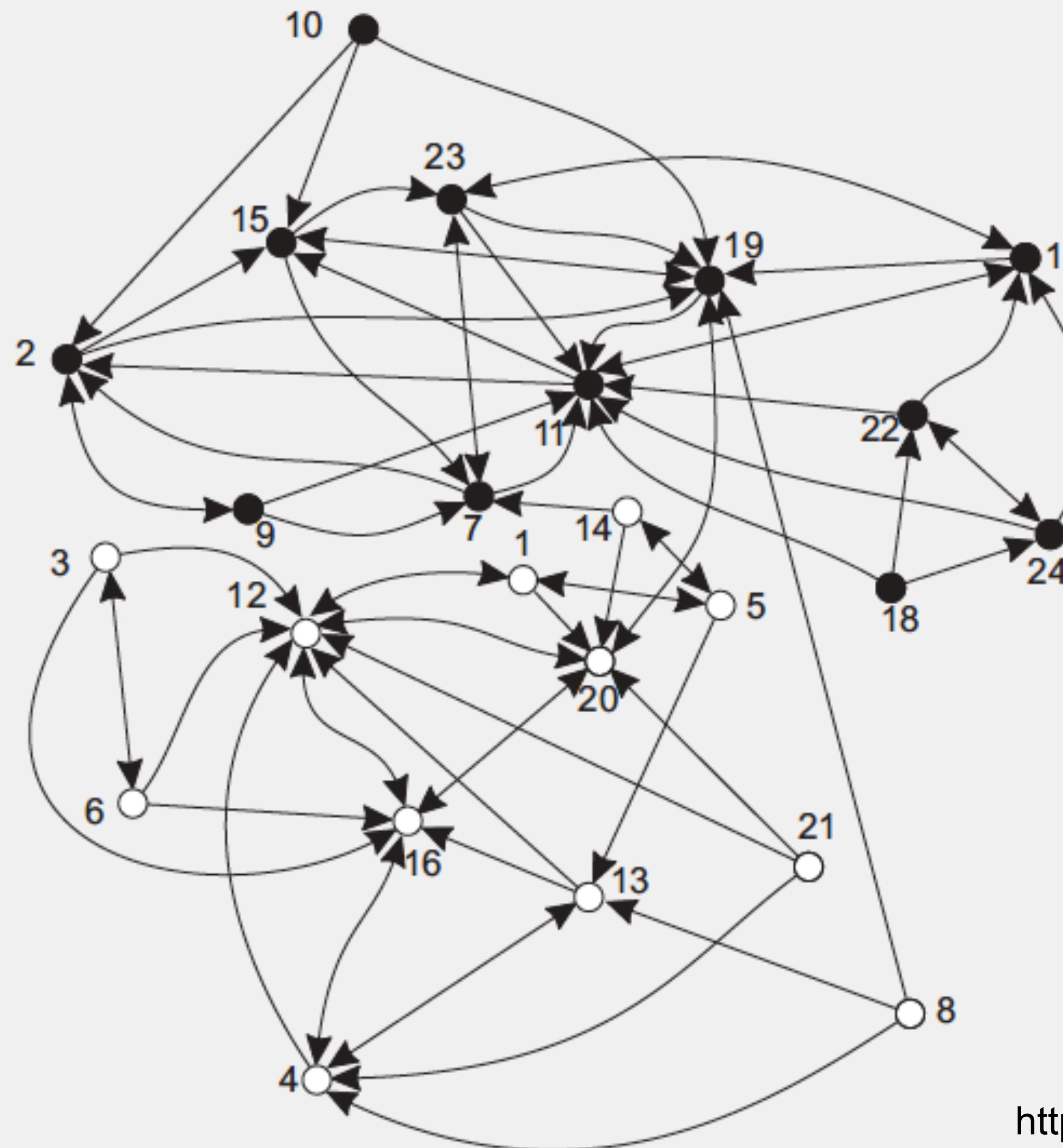
sociogram

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	



Classroom example - positive nominations



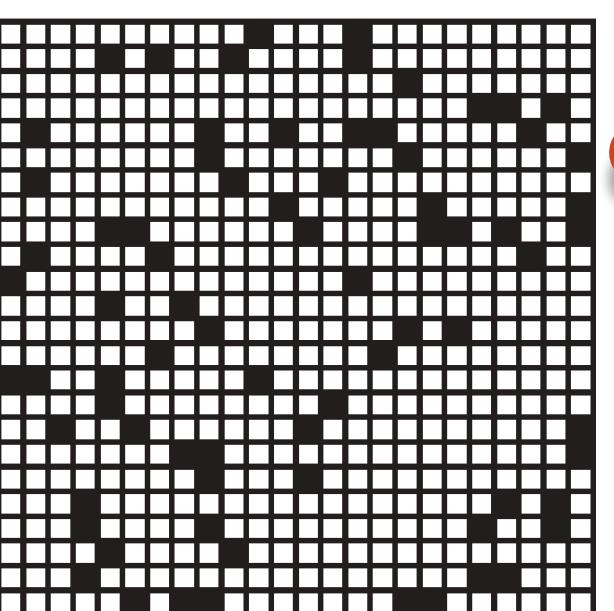
- Clear distinction between boys ("•") and girls ("○")
- Relation between 19 and 20 is important
- There are a few "isolated" children (8 & 10)

Issue

Can we discover these properties **mathematically**?

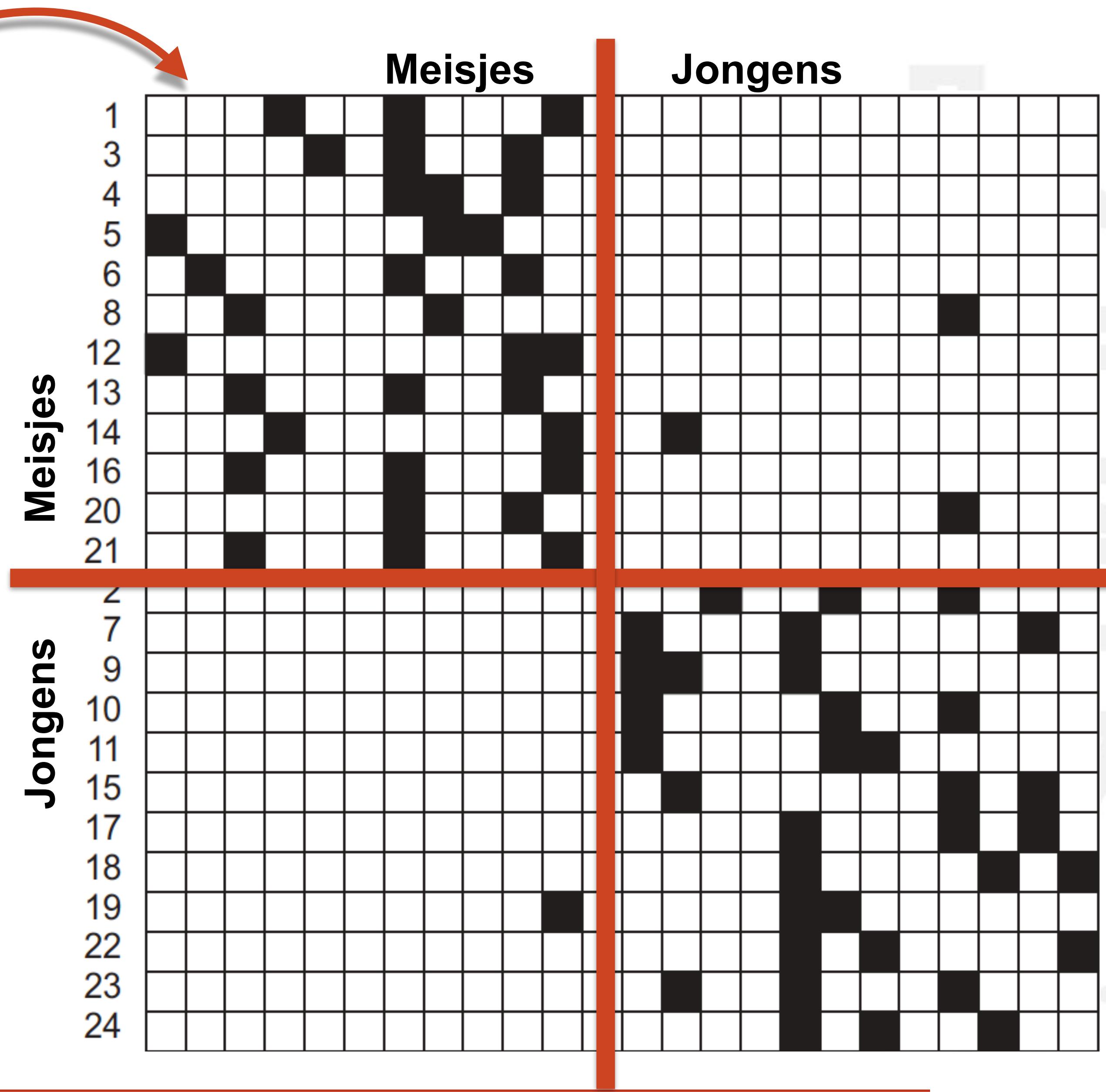
Degree, Centrality, Closeness,
Eccentricity, Betweenness,

Sociale networks



Clusters (communities, subgraphs, modules)

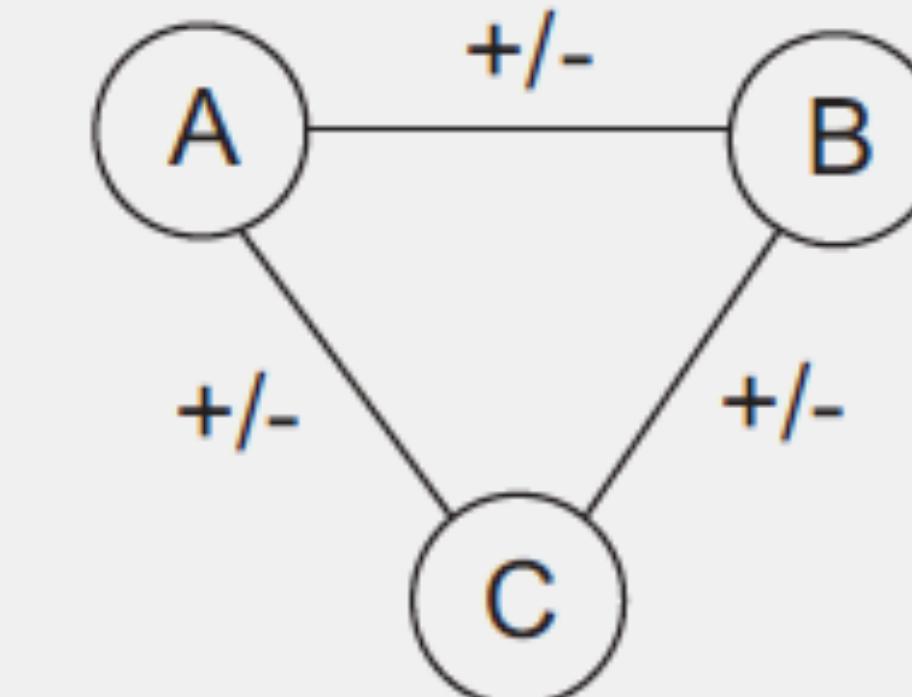
“hubs”



Motifs (signed) Motieven

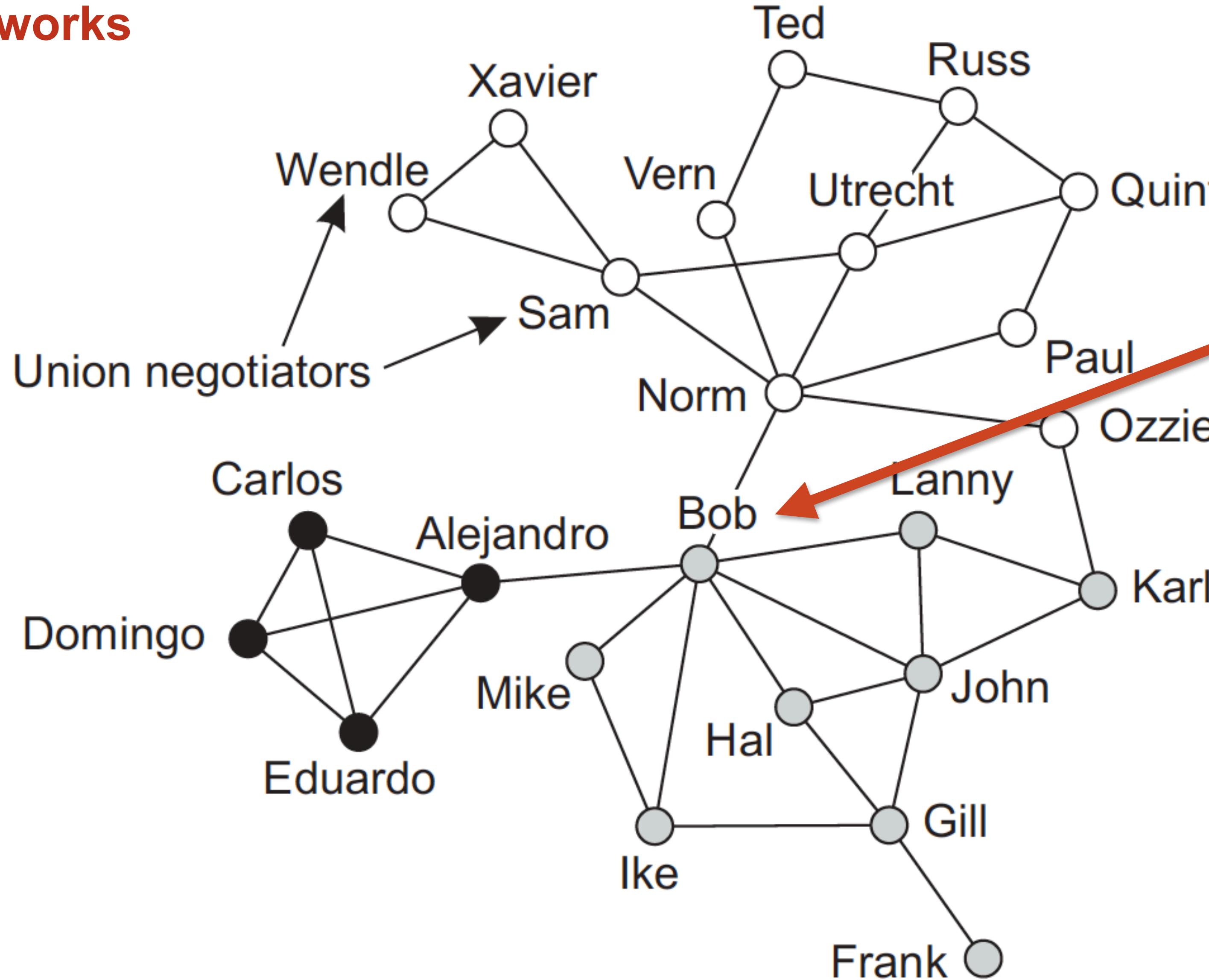
Basic idea

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

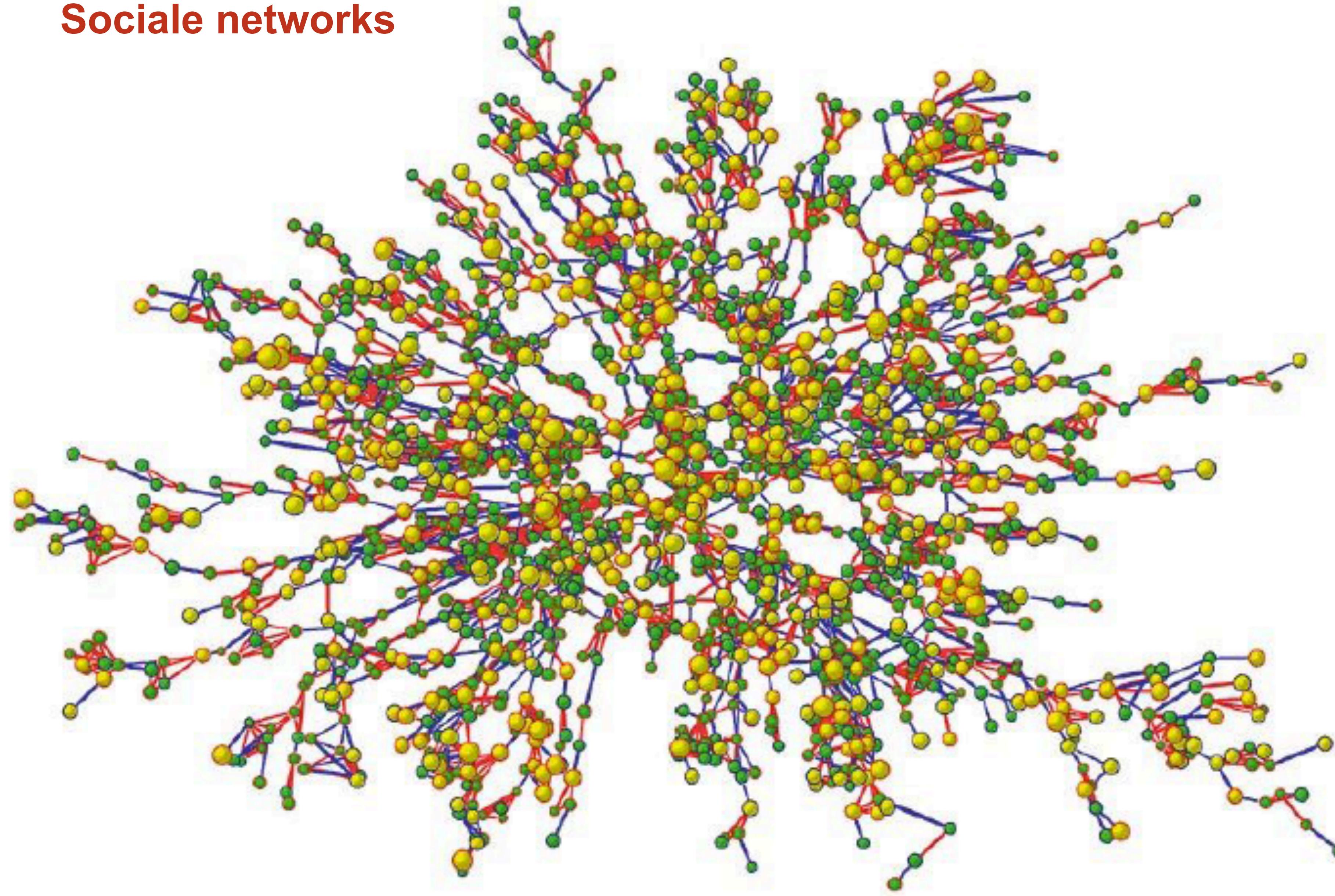


Bob is a ‘connector hub

For 3 clusters



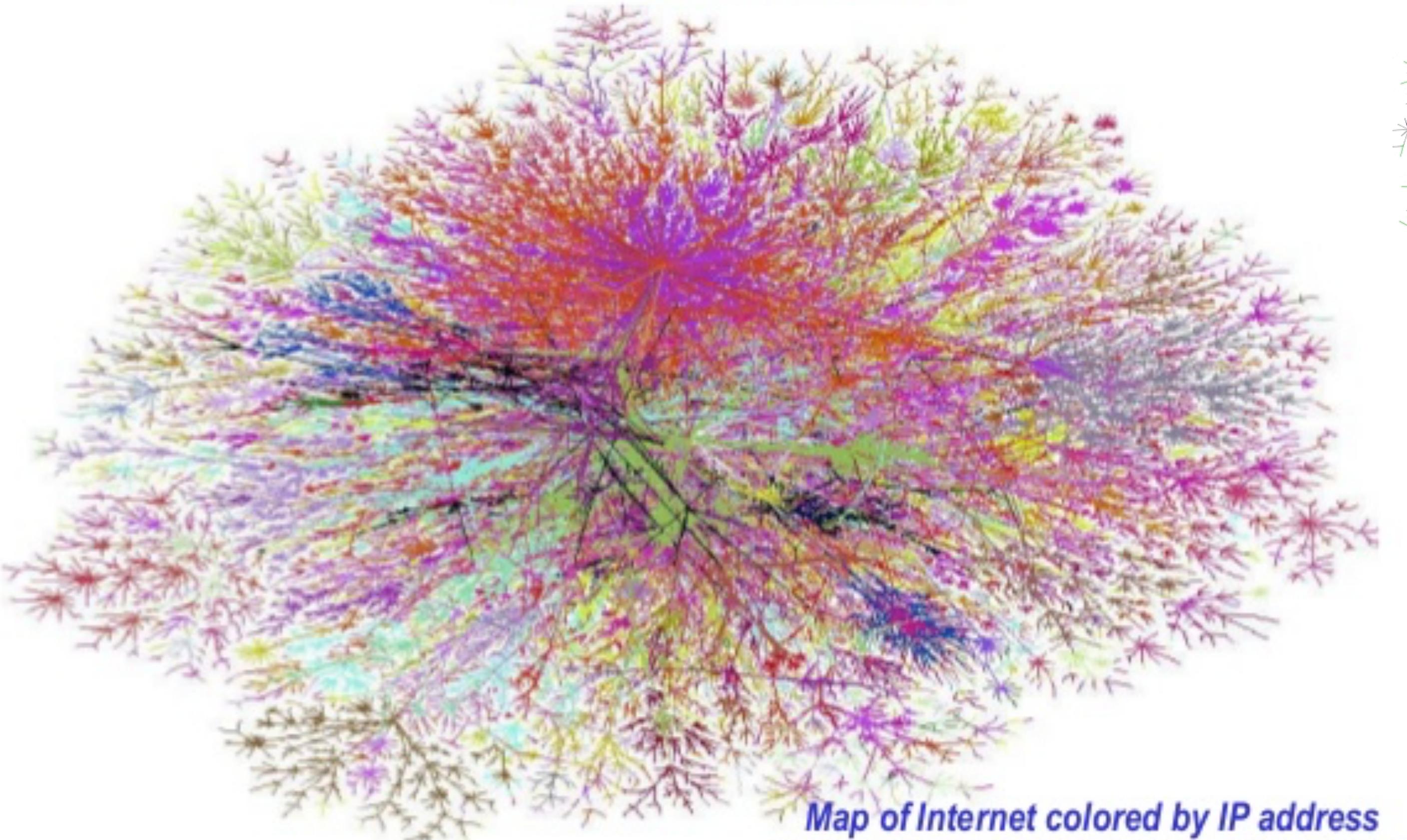
Sociale networks



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

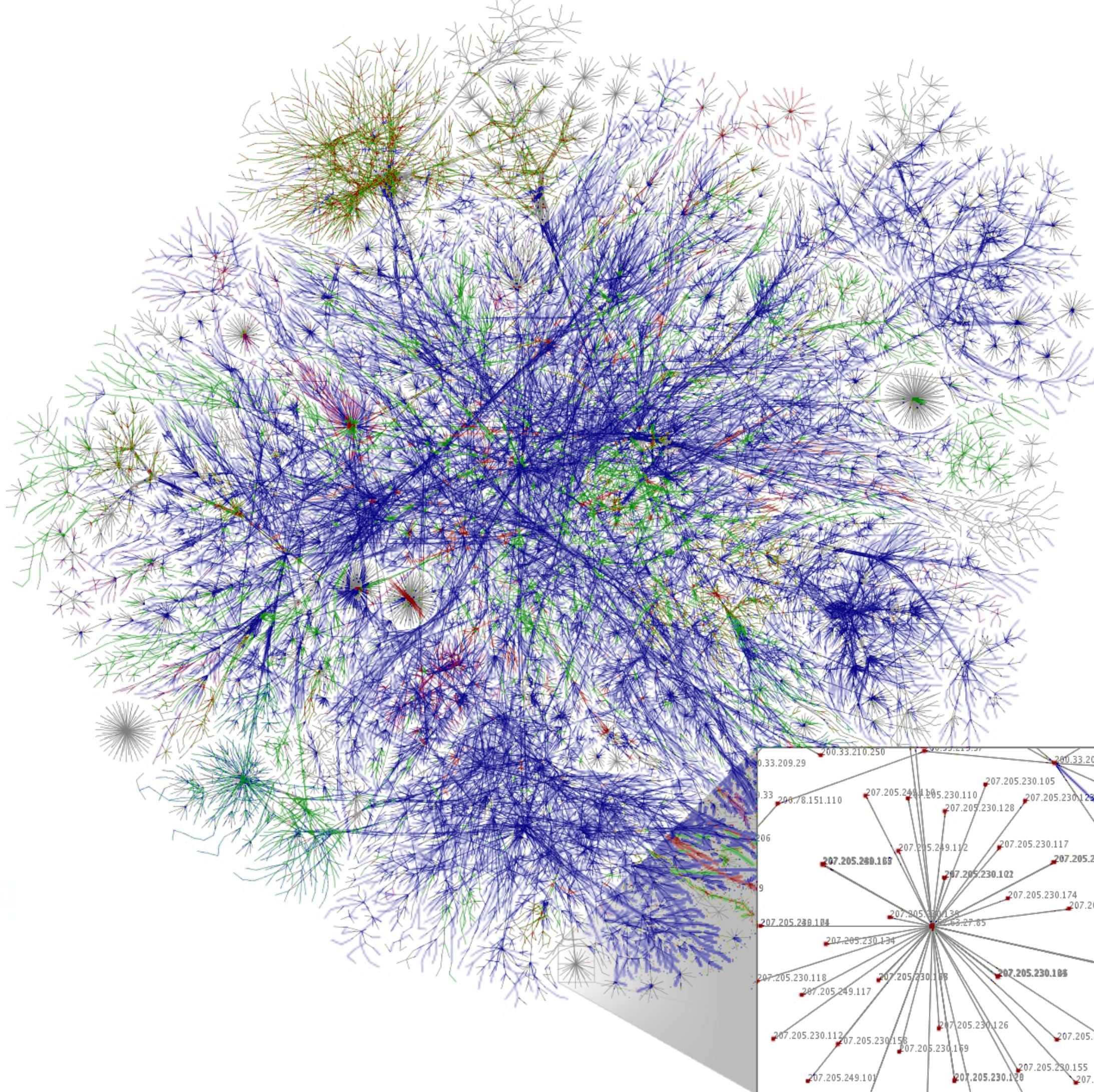
Complexe 'sociale' networks

Complex networks Case studies: Internet



Map of Internet colored by IP address

(Bill Cheswick & Hal Burch, <http://research.lumeta.com/ches/map>)



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

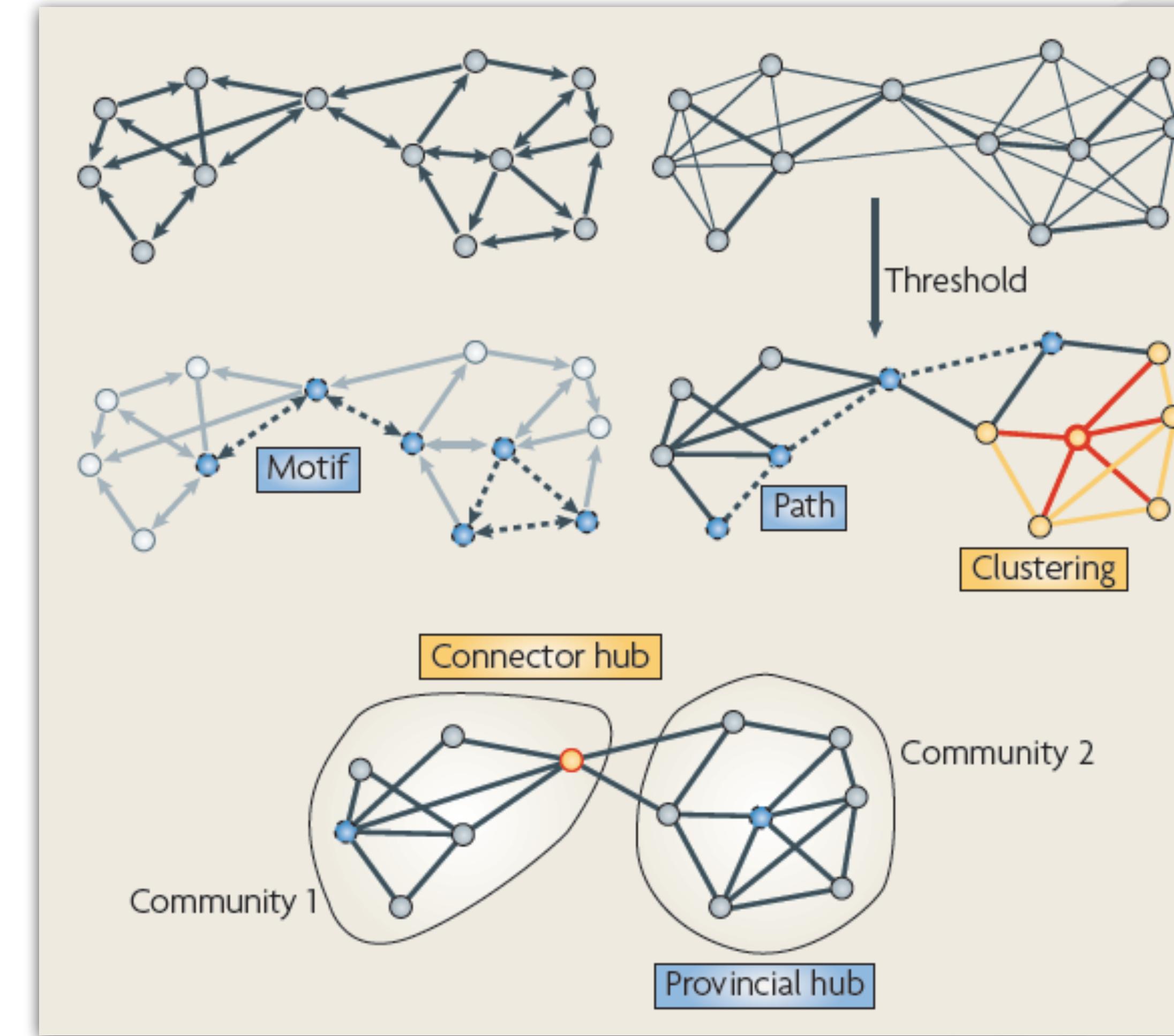
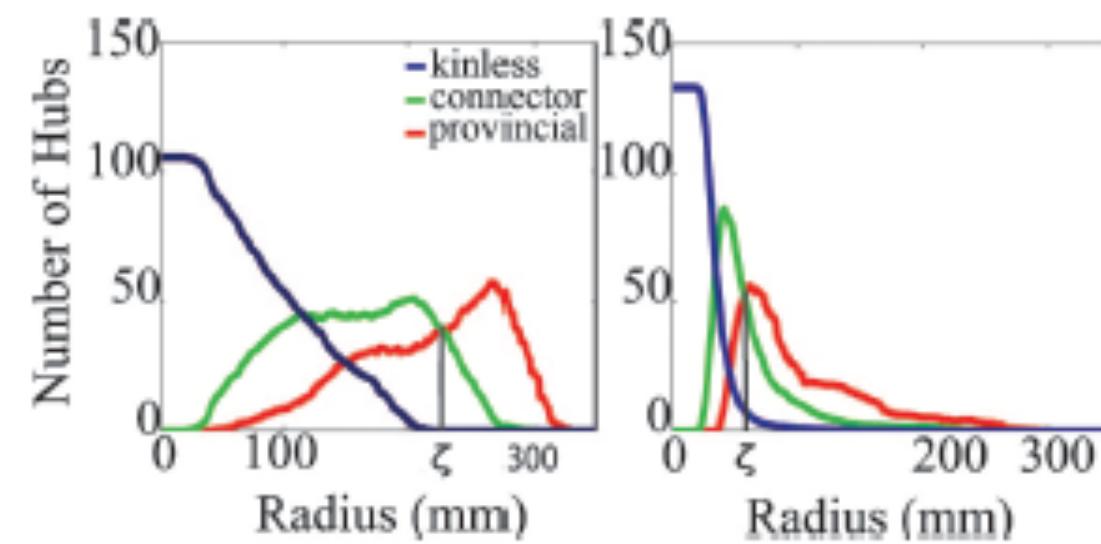


Table A1 (continued)

Measure	Binary and undirected definitions	Weighted and directed definitions
Modularity	<p>Modularity of the network (Newman, 2004b),</p> $Q = \sum_{u \in M} \left[e_{uu} - \left(\sum_{v \in M} e_{uv} \right)^2 \right],$ <p>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.</p> <p>An equivalent alternative formulation of the modularity (Newman, 2006) is given by $Q = \frac{1}{T} \sum_{i,j \in N} \left(a_{ij} - \frac{k_i k_j}{T} \right) \delta_{m_i, m_j}$, where m_i is the module containing node i, and $\delta_{m_i, m_j} = 1$ if $m_i = m_j$, and 0 otherwise.</p>	<p>Weighted modularity (Newman, 2004),</p> $Q^w = \frac{1}{W} \sum_{i,j \in N} \left[w_{ij} - \frac{k_i^w k_j^w}{W} \right] \delta_{m_i, m_j}.$ <p>Directed modularity (Leicht and Newman, 2008),</p> $Q^\rightarrow = \frac{1}{l} \sum_{i,j \in N} \left[a_{ij} - \frac{k_i^{\text{out}} k_j^{\text{in}}}{l} \right] \delta_{m_i, m_j}.$
Measures of centrality		
Closeness centrality	<p>Closeness centrality of node i (e.g. Freeman, 1978),</p> $L_i^{-1} = \frac{n-1}{\sum_{j \in N, j \neq i} d_{ij}}.$	<p>Weighted closeness centrality, $(L_i^w)^{-1} = \frac{n-1}{\sum_{j \in N, j \neq i} d_{ij}^w}$.</p> <p>Directed closeness centrality, $(L_i^\rightarrow)^{-1} = \frac{n-1}{\sum_{j \in N, j \neq i} d_{ij}^\rightarrow}$.</p>
Betweenness centrality	<p>Betweenness centrality of node i (e.g., Freeman, 1978),</p> $b_i = \frac{1}{(n-1)(n-2)} \sum_{\substack{h,j \in N \\ h \neq j, h \neq i, j \neq i}} \frac{\rho_{hj}(i)}{\rho_{hj}},$ <p>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.</p>	<p>Betweenness centrality is computed equivalently on weighted and directed networks, provided that path lengths are computed on respective weighted or directed paths.</p>
Within-module degree z-score	<p>Within-module degree z-score of node i (Guimera and Amaral, 2005),</p> $z_i = \frac{k_i(m_i) - \bar{k}(m_i)}{\sigma^{k(m_i)}},$ <p>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.</p>	<p>Weighted within-module degree z-score, $z_i^w = \frac{k_i^w(m_i) - \bar{k}^w(m_i)}{\sigma^{k^w(m_i)}}$.</p> <p>Within-module out-degree z-score, $z_i^{\text{out}} = \frac{k_i^{\text{out}}(m_i) - \bar{k}^{\text{out}}(m_i)}{\sigma^{k^{\text{out}}(m_i)}}$.</p> <p>Within-module in-degree z-score, $z_i^{\text{in}} = \frac{k_i^{\text{in}}(m_i) - \bar{k}^{\text{in}}(m_i)}{\sigma^{k^{\text{in}}(m_i)}}$.</p>

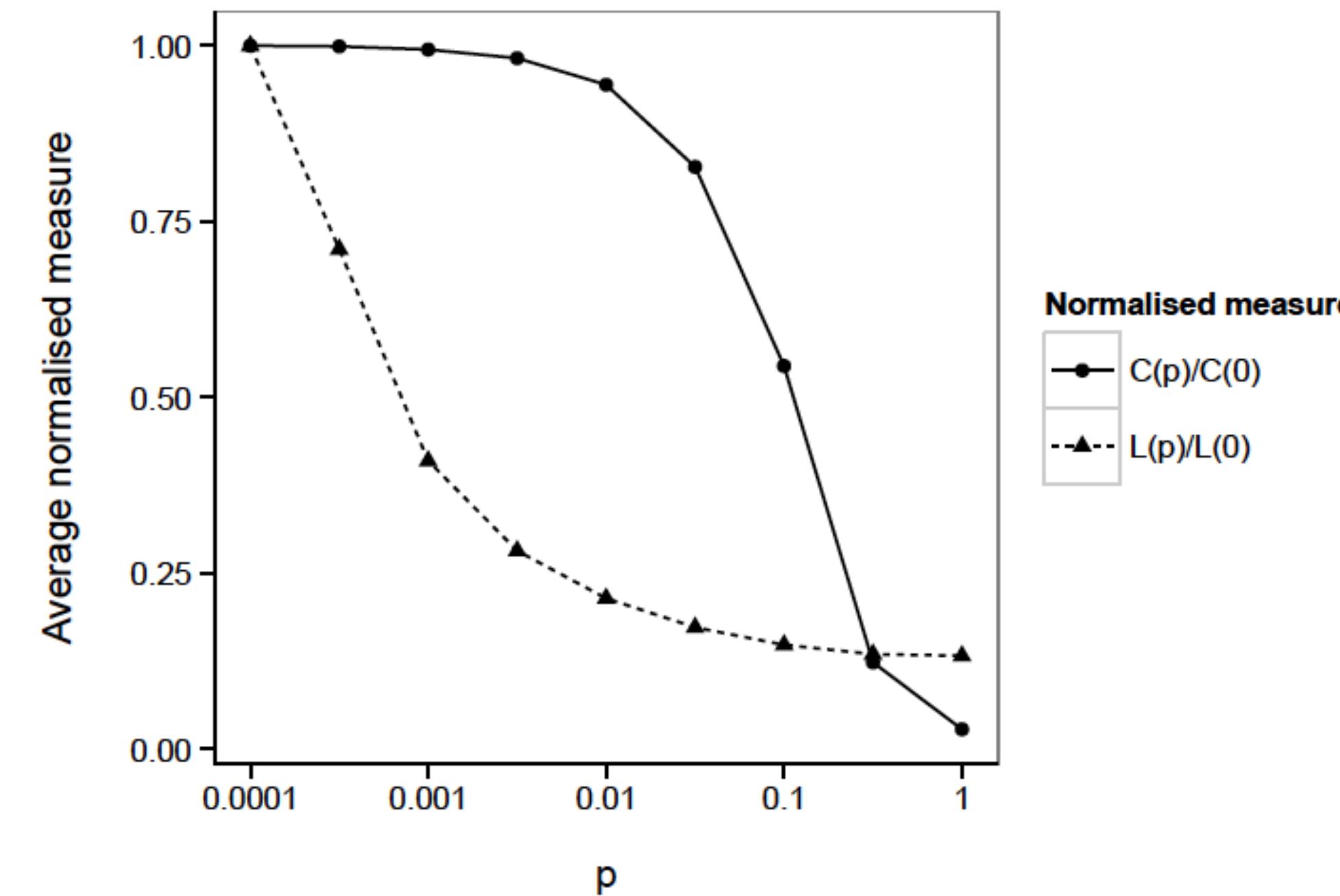
Network / Graph topology: It's a Small World After All

“small-world” test:

Average path length (L)

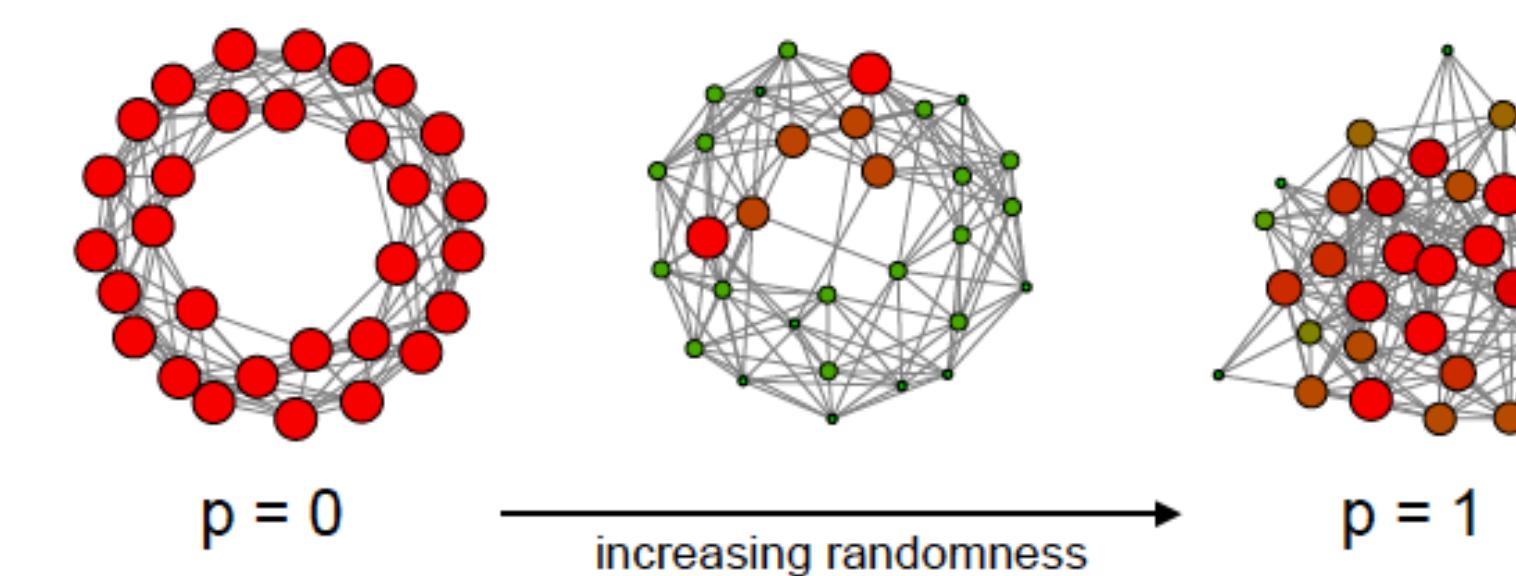
Clustering coefficient (C)

Compare to randomly
rewired version

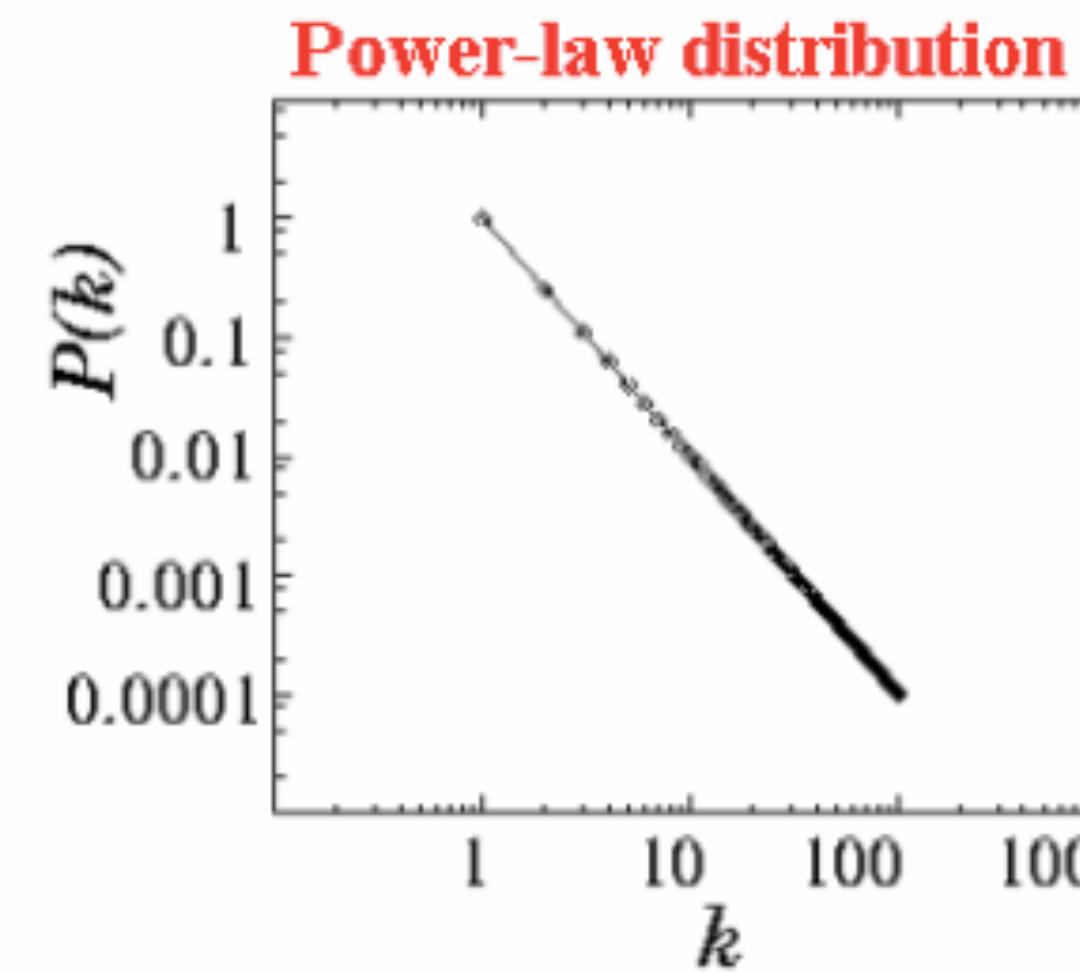
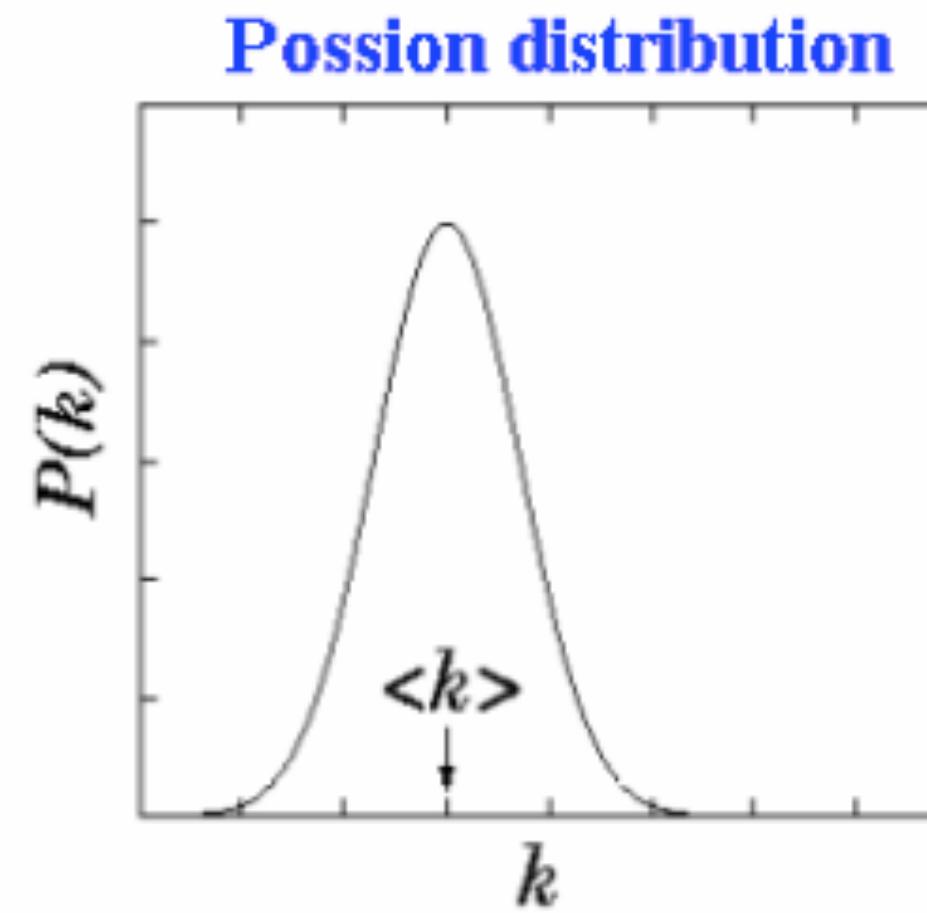


Sound familiar?

In between
fully ordered
&
completely random
=
optimal



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



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

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

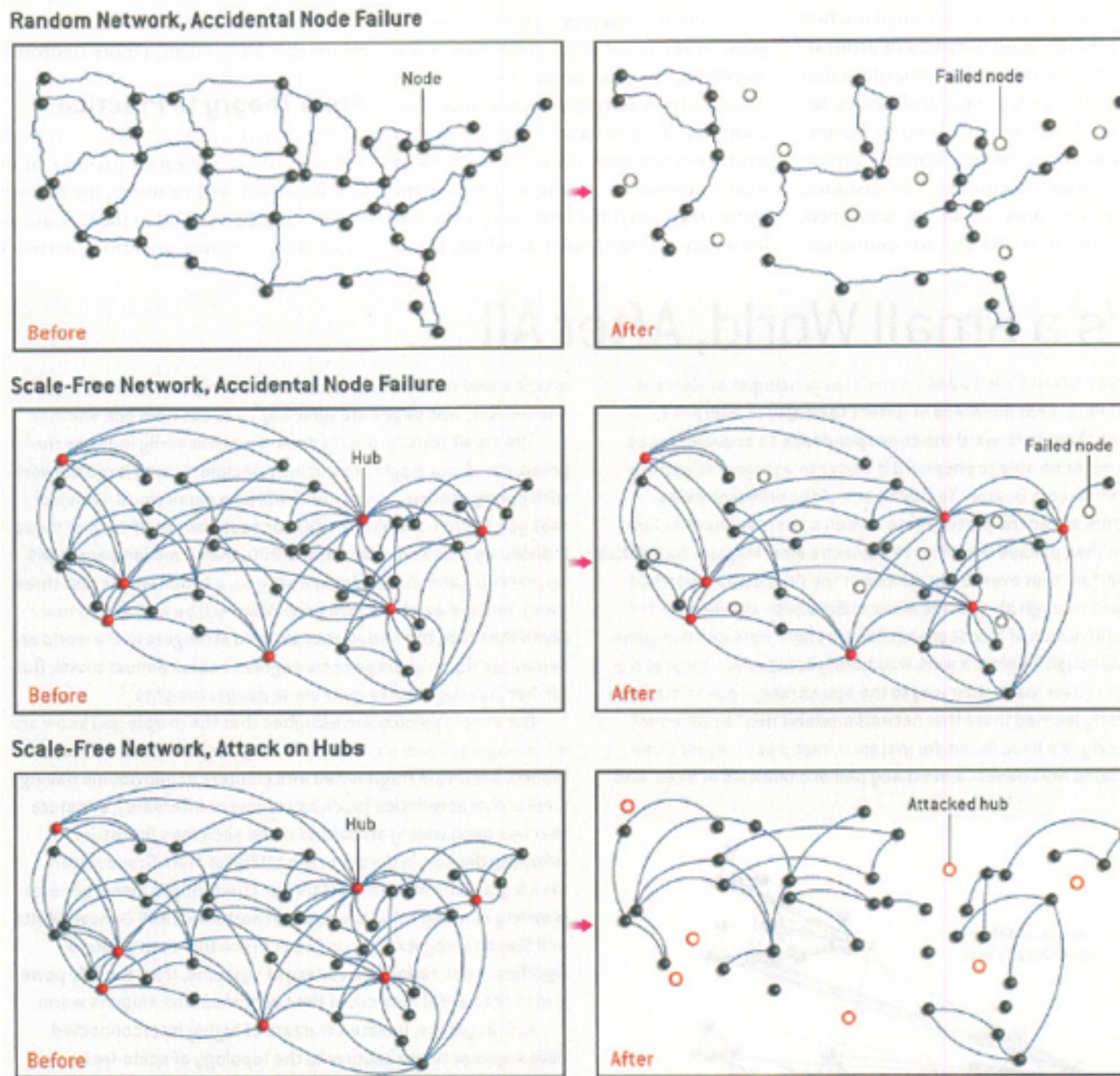


Scale free networks
are resilient to
random attacks on
nodes or node
failures

(cf. internet on 9/11)

when more hub nodes
fail though....

targeted attack!



Effectiveness / Connectivity: 6 degrees of separation

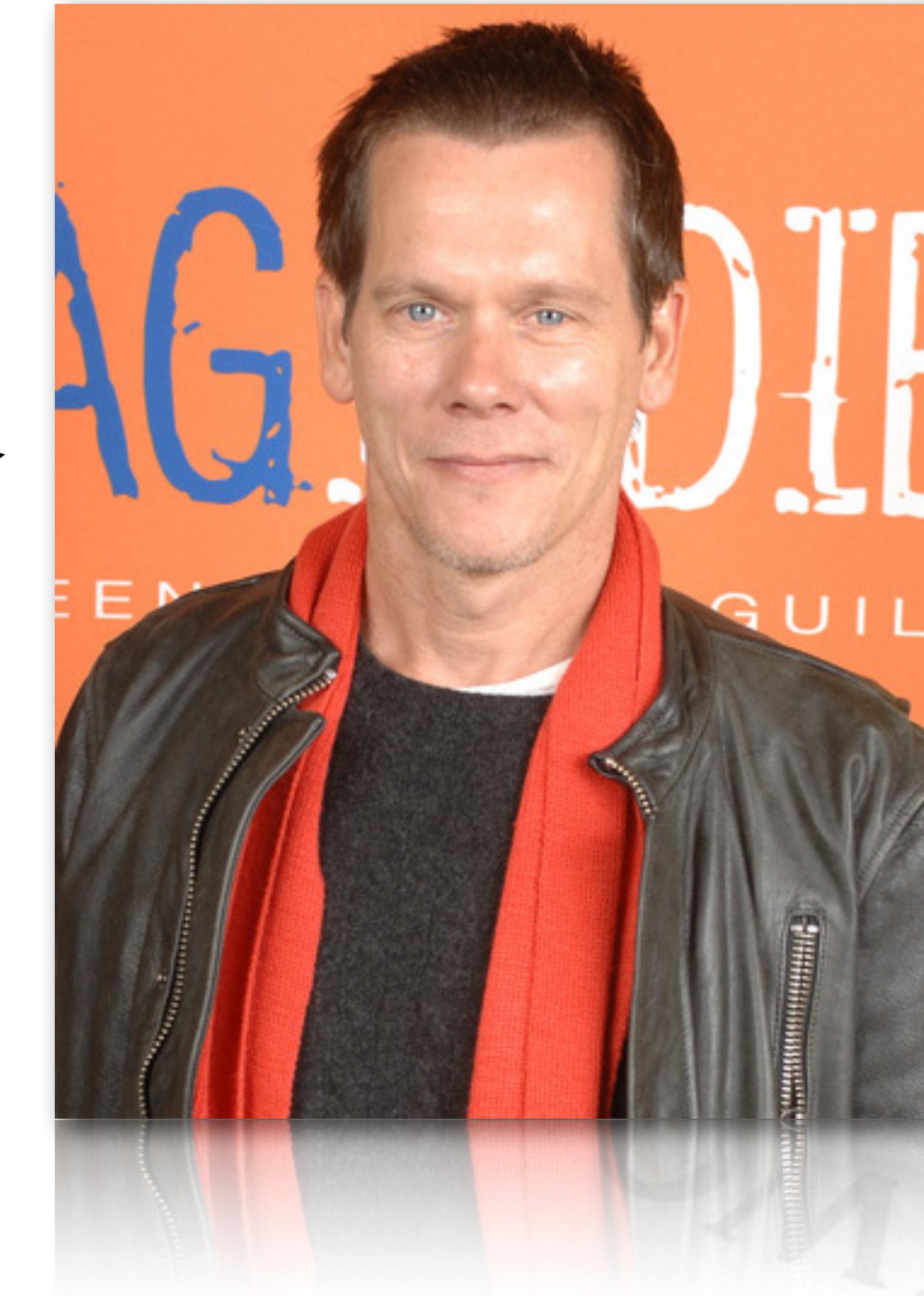
Kevin Bacon number (Erdős number)

- 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)



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Effectiveness / Connectivity: 6 degrees of separation

Your degree of separation from:

Nobel Laureate **1/2**

Pharrell Williams

Hillary Clinton
Donald Trump

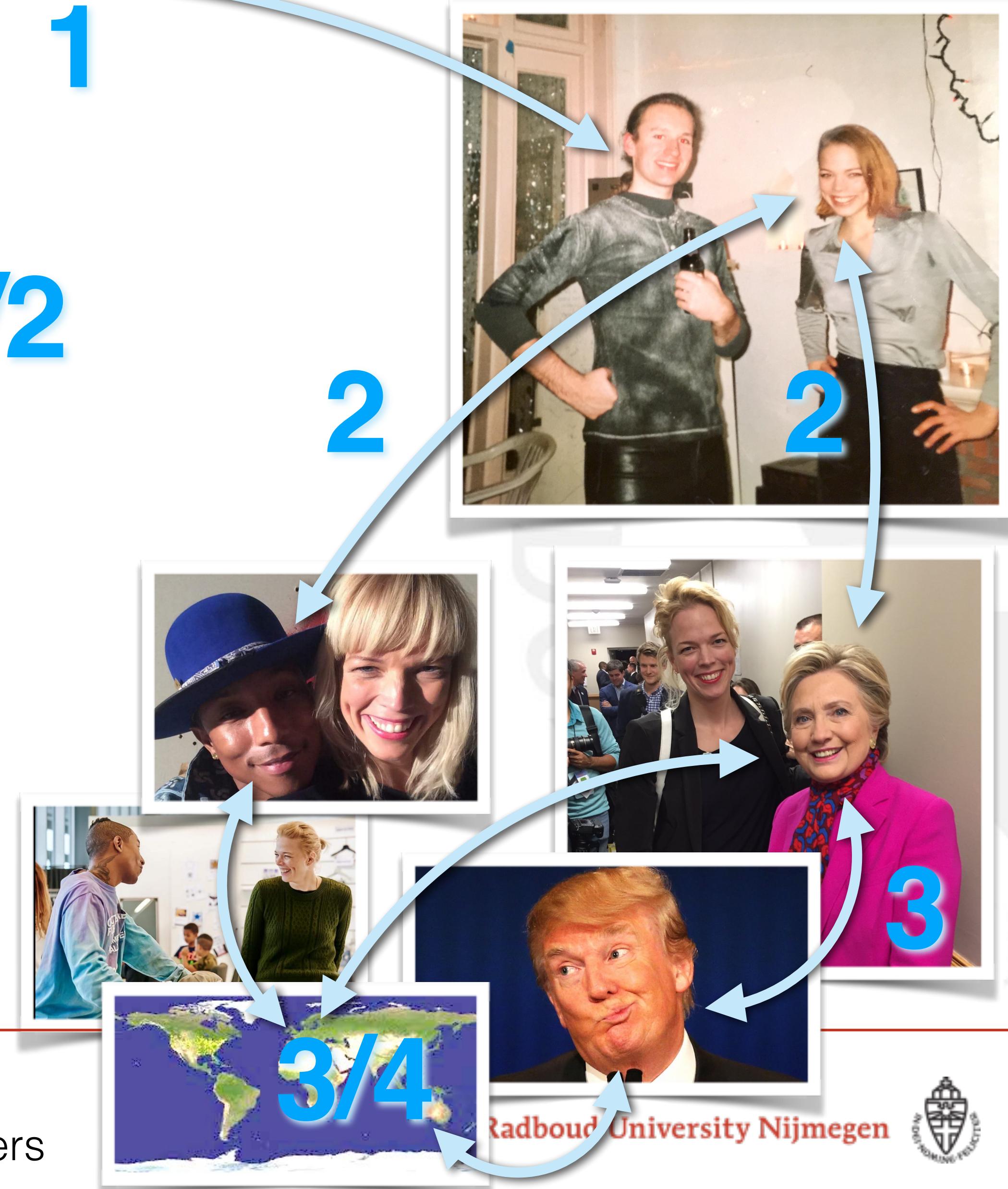
1

2

2

3

3/4



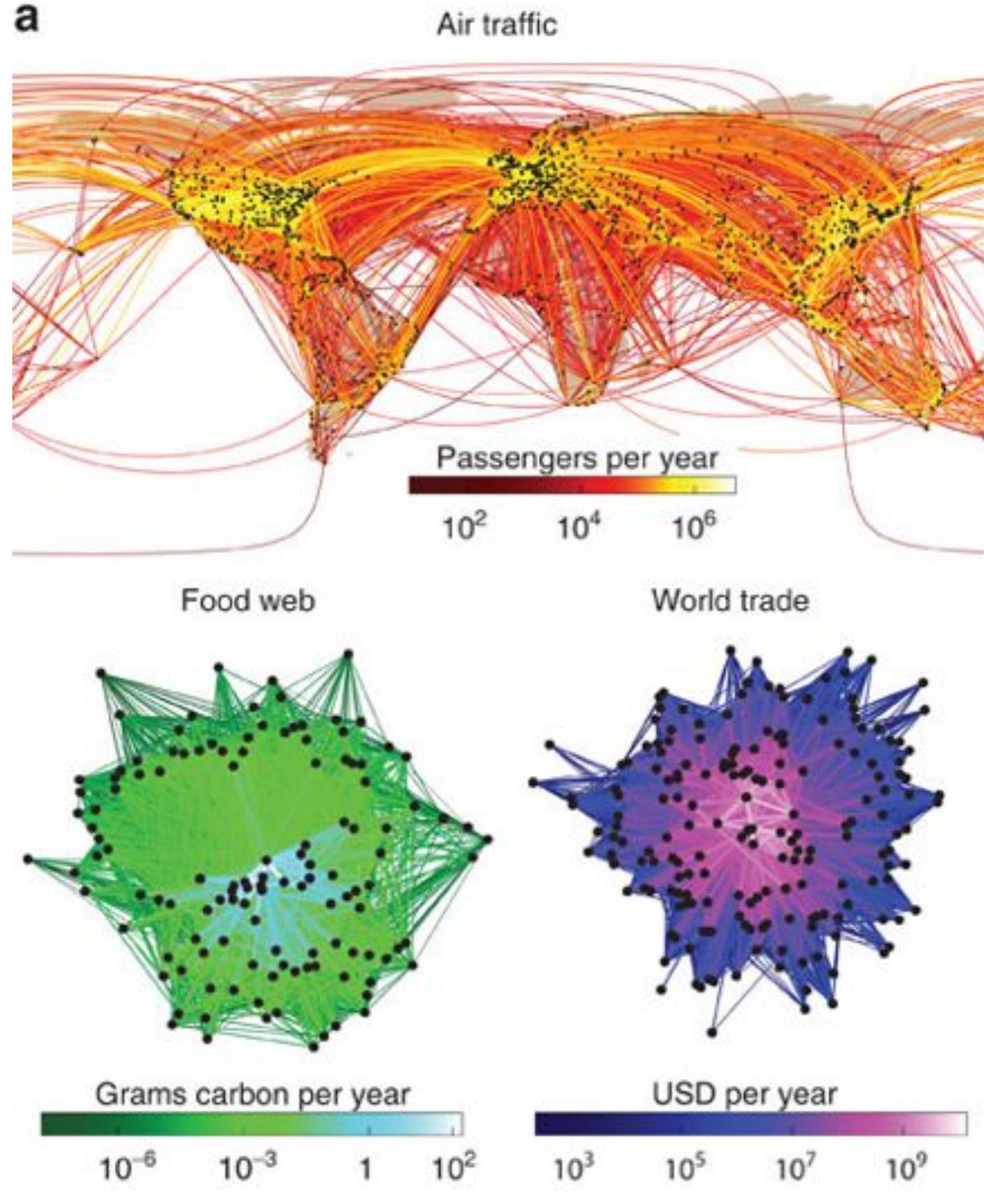
[http://en.wikipedia.org/wiki/
Bacon_number#Bacon_numbers](http://en.wikipedia.org/wiki/Bacon_number#Bacon_numbers)

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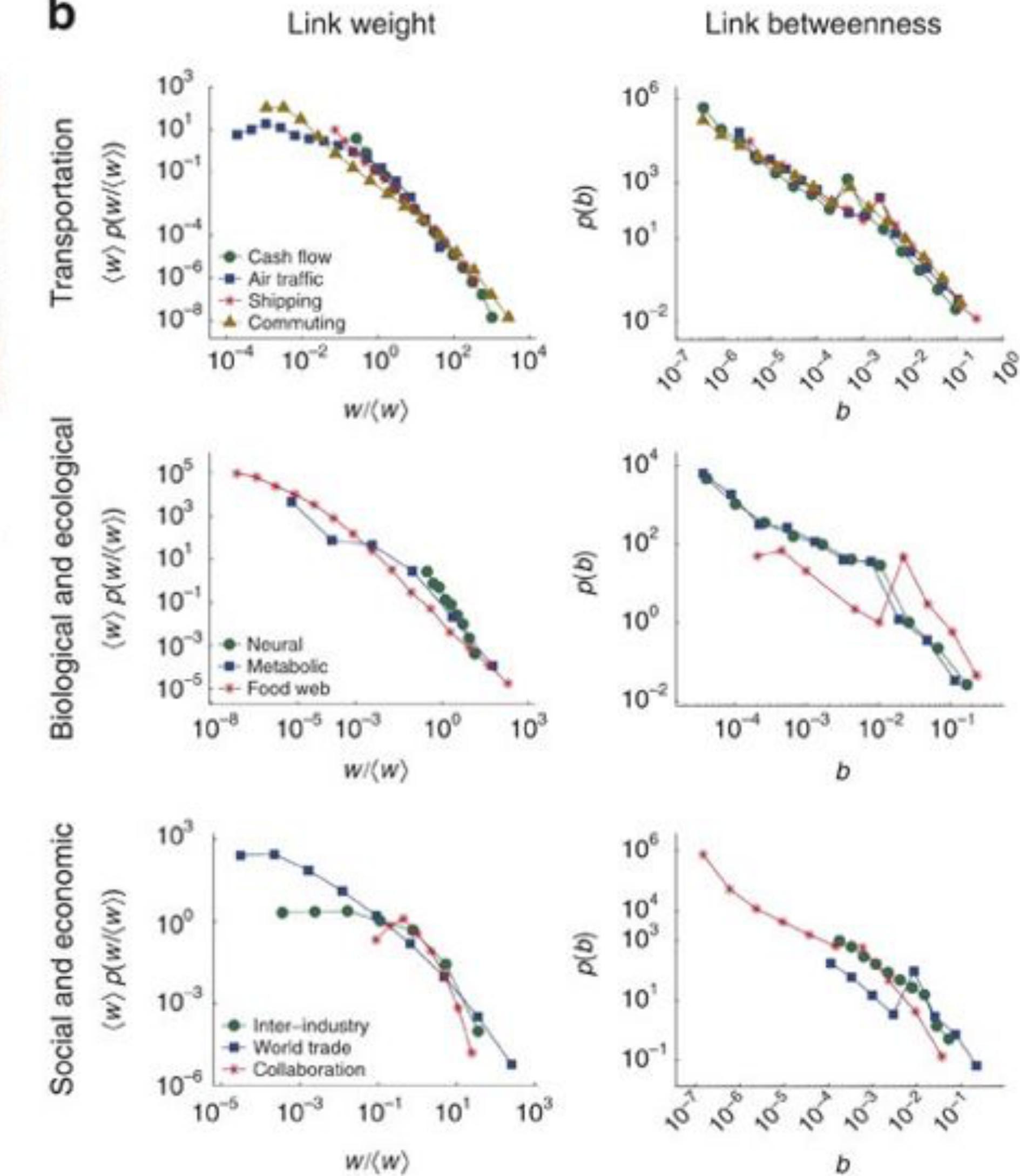


Scale-free structure

a



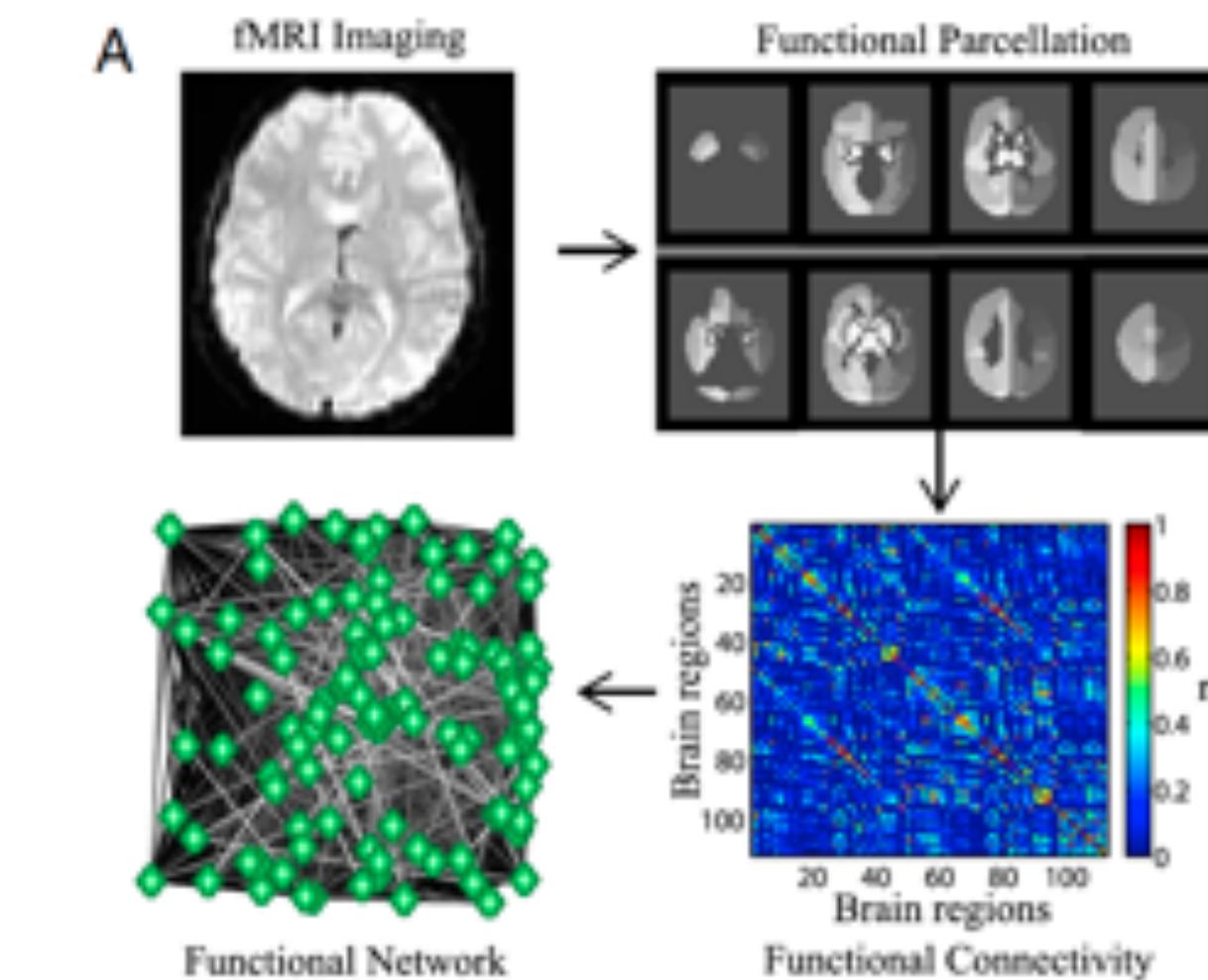
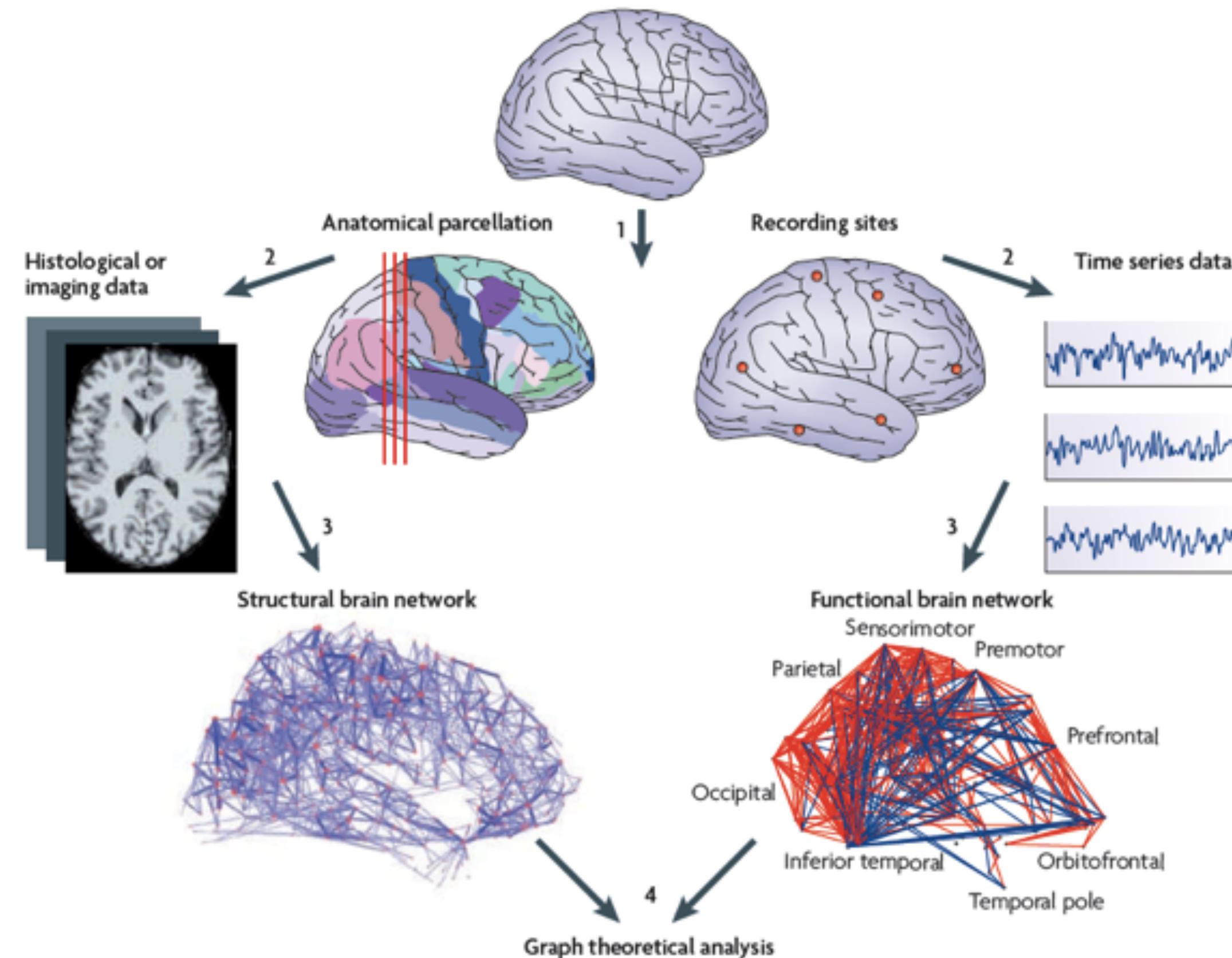
b



Network / Graph topology

Functional vs. Structural networks

Box 1 | Structural and functional brain networks



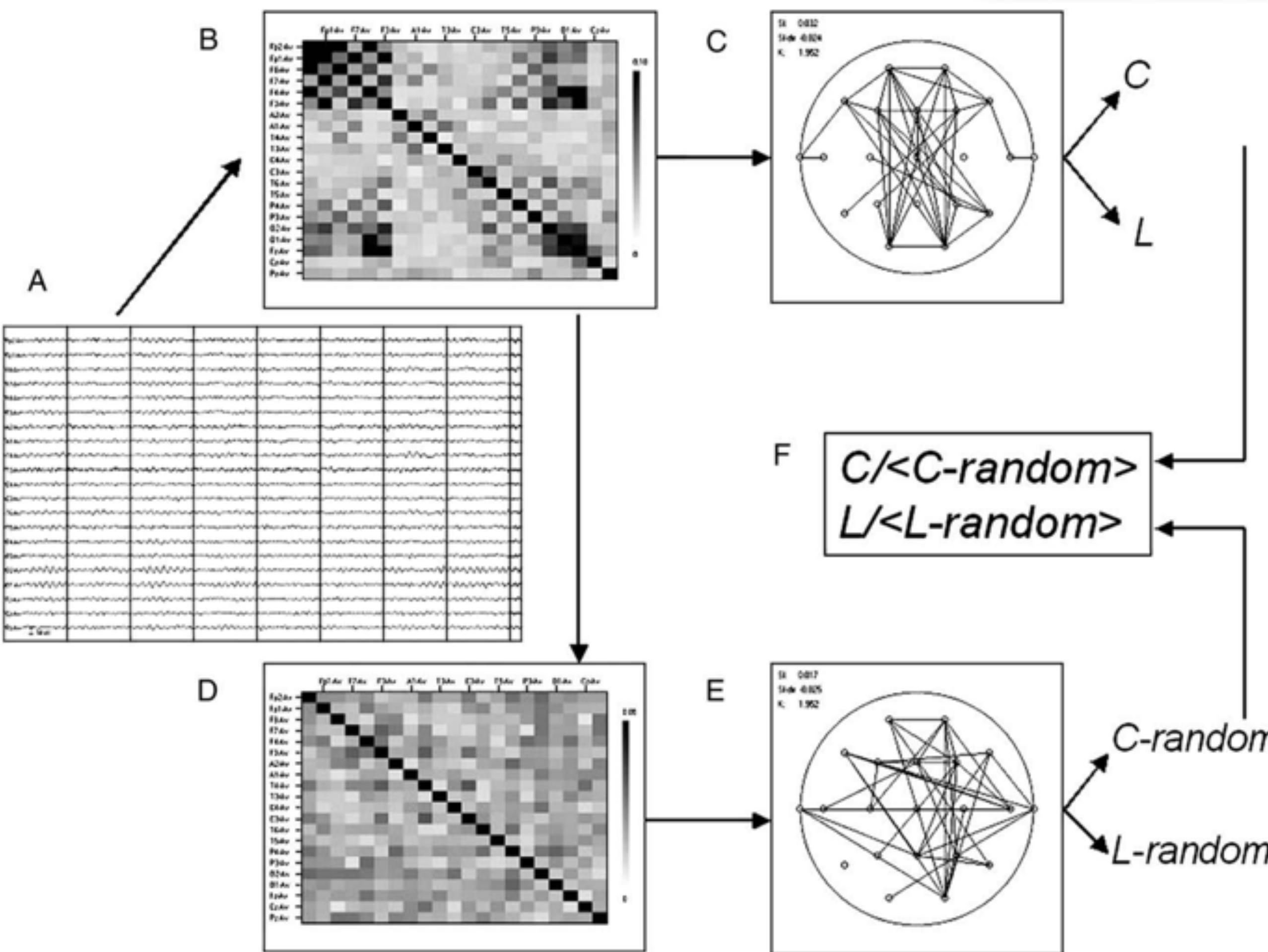
Bullmore, E., & Sporns, O. (2009). Complex brain networks: graph theoretical analysis of structural and functional systems. *Nature reviews. Neuroscience*, 10(3), 186-98. doi: 10.1038/nrn2575.

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Network / Graph topology

How to get the matrices



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

5 min. eyes closed

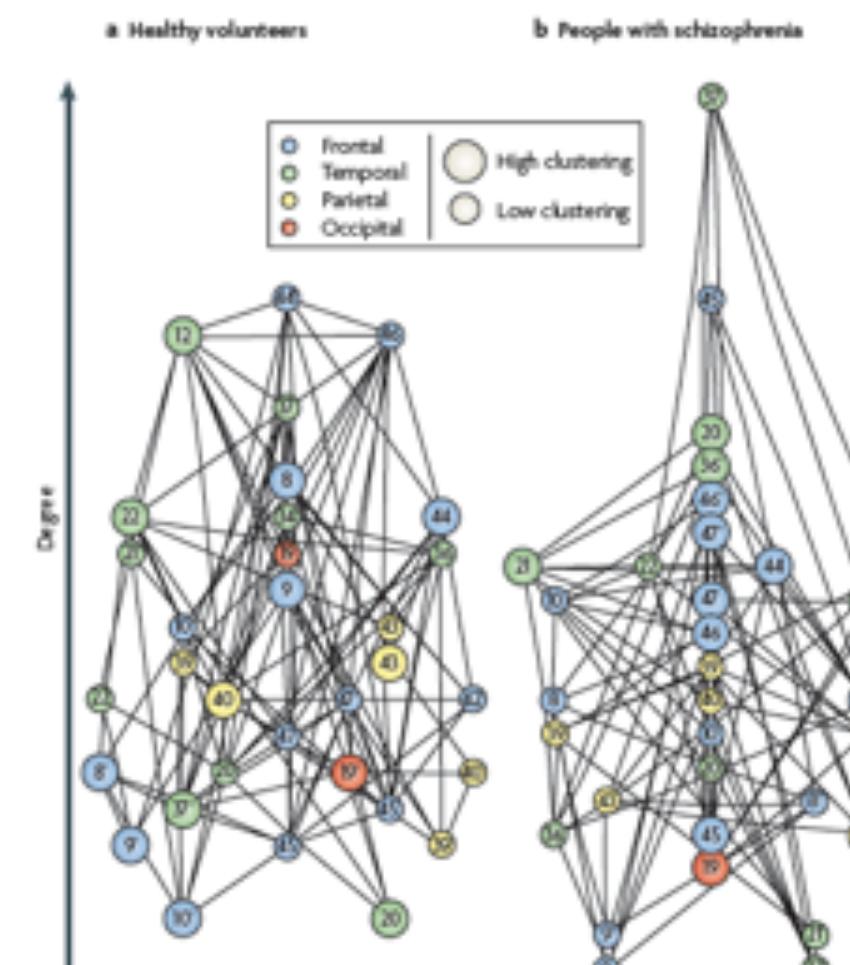
find 4096 samples
without artefacts

That's about 6-7
seconds!

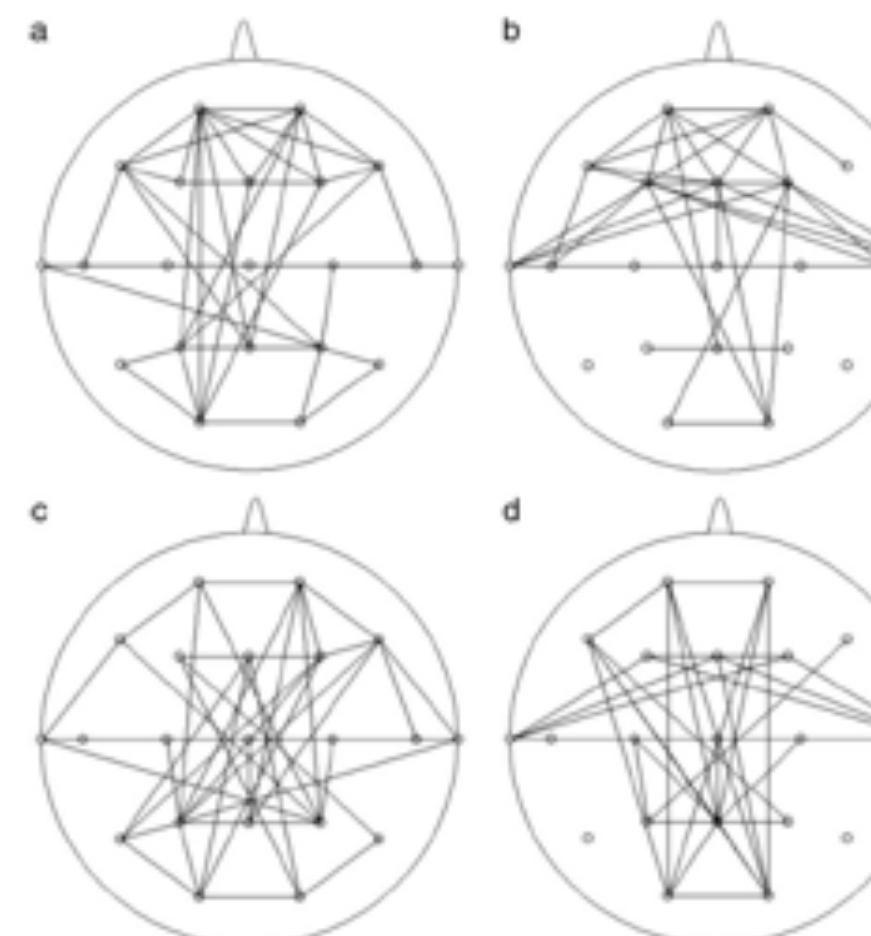
Network / Graph topology

Pathology studies

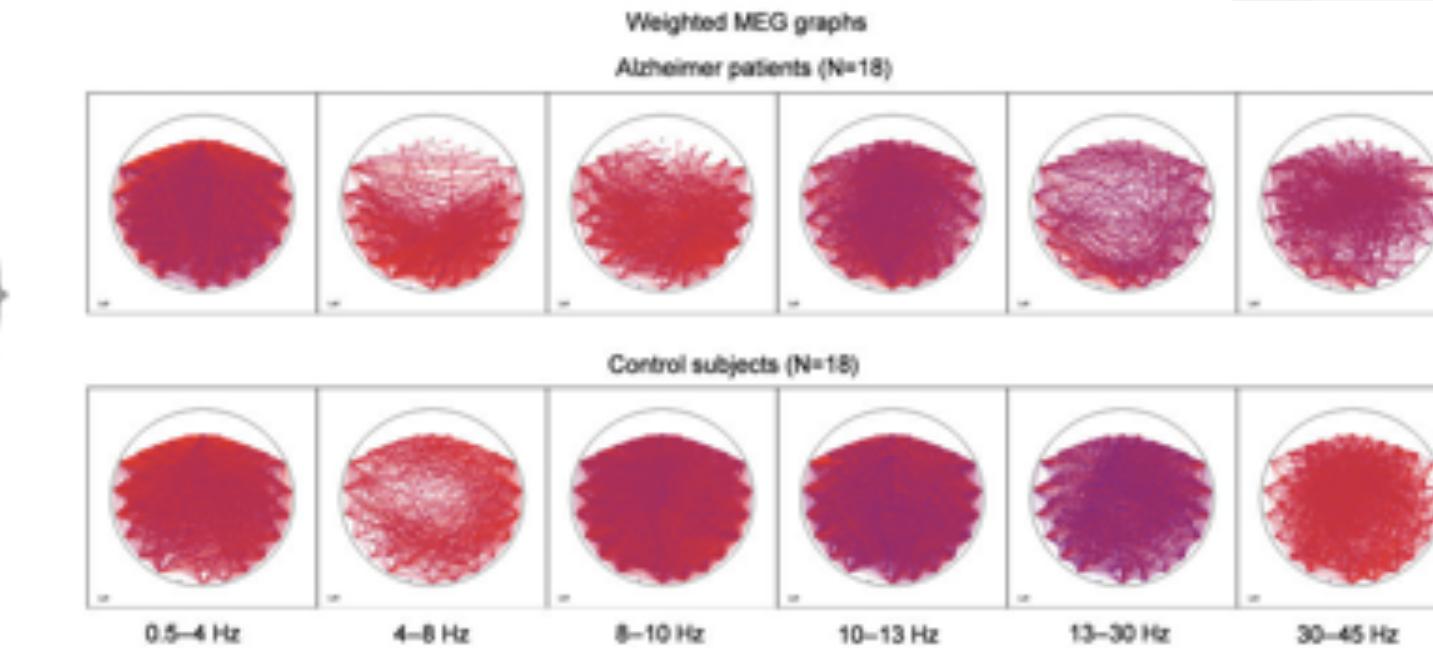
Based on a few samples we can distinguish healthy subjects from patients:



Schizophrenia



Absence seizure

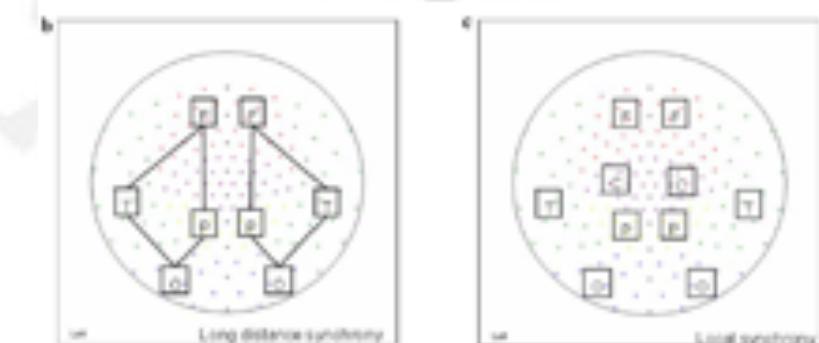


Alzheimer's disease: Targeted attack on hubs!

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.

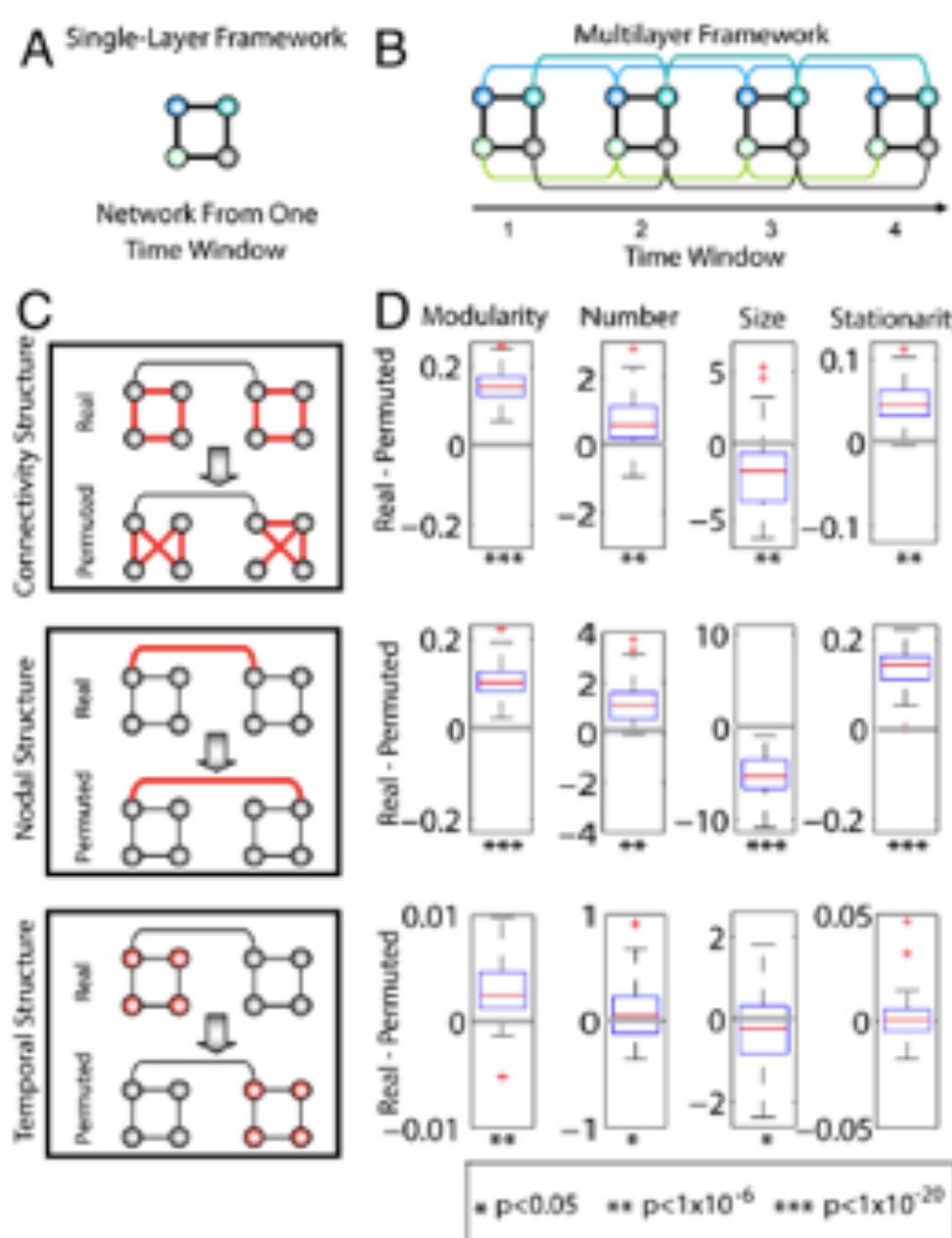
Stam, C. J., Haan, W. de, Daffertshofer, a, Jones, B. F., Manshanden, I., Cappellen van Walsum, a M. van, et al. (2009). Graph theoretical analysis of magnetoencephalographic functional connectivity in Alzheimer's disease. *Brain : a journal of neurology*, 132(Pt 1), 213-24. doi: 10.1093/brain/awn262.

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

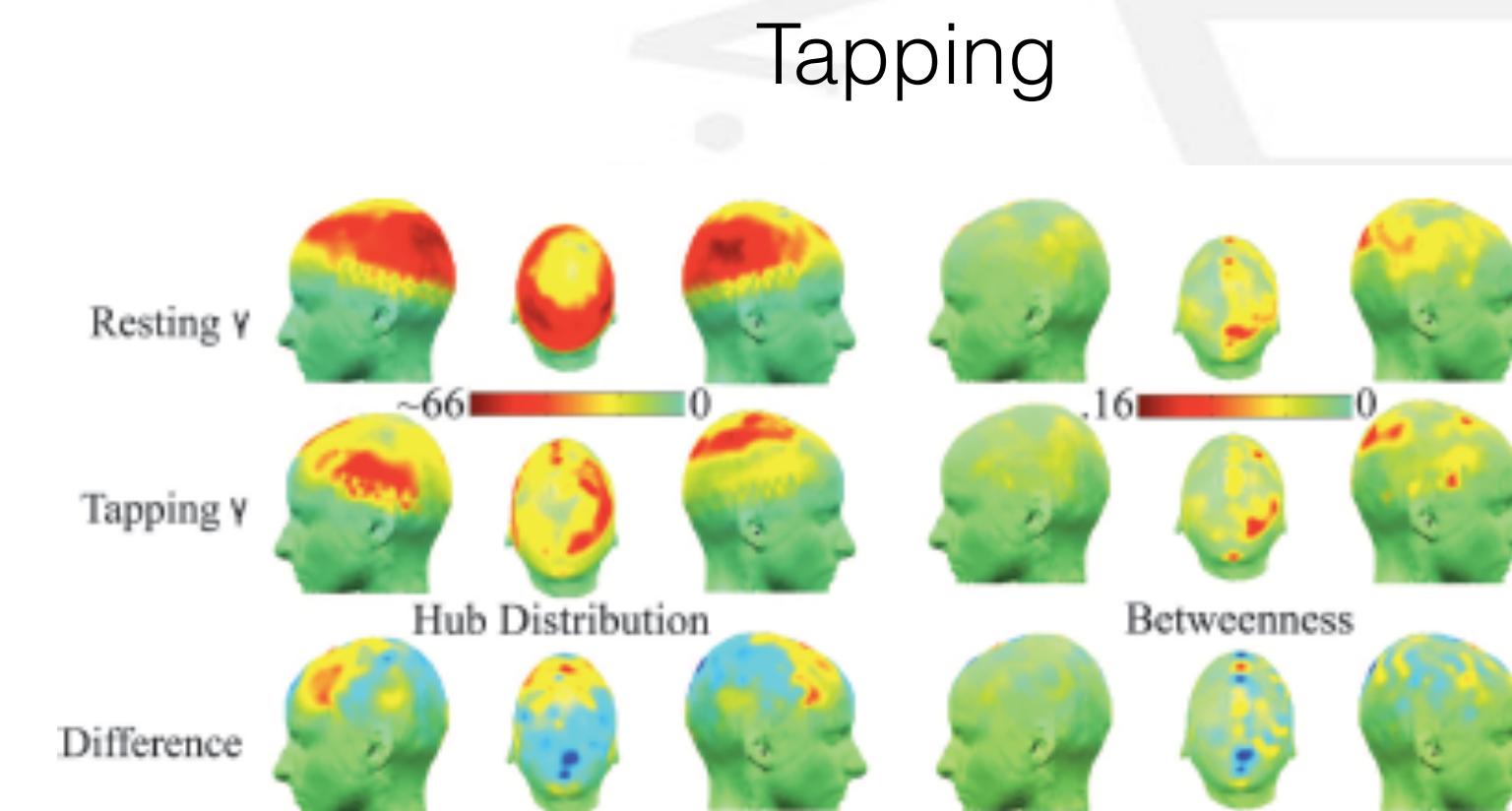


Cognitive abilities

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.

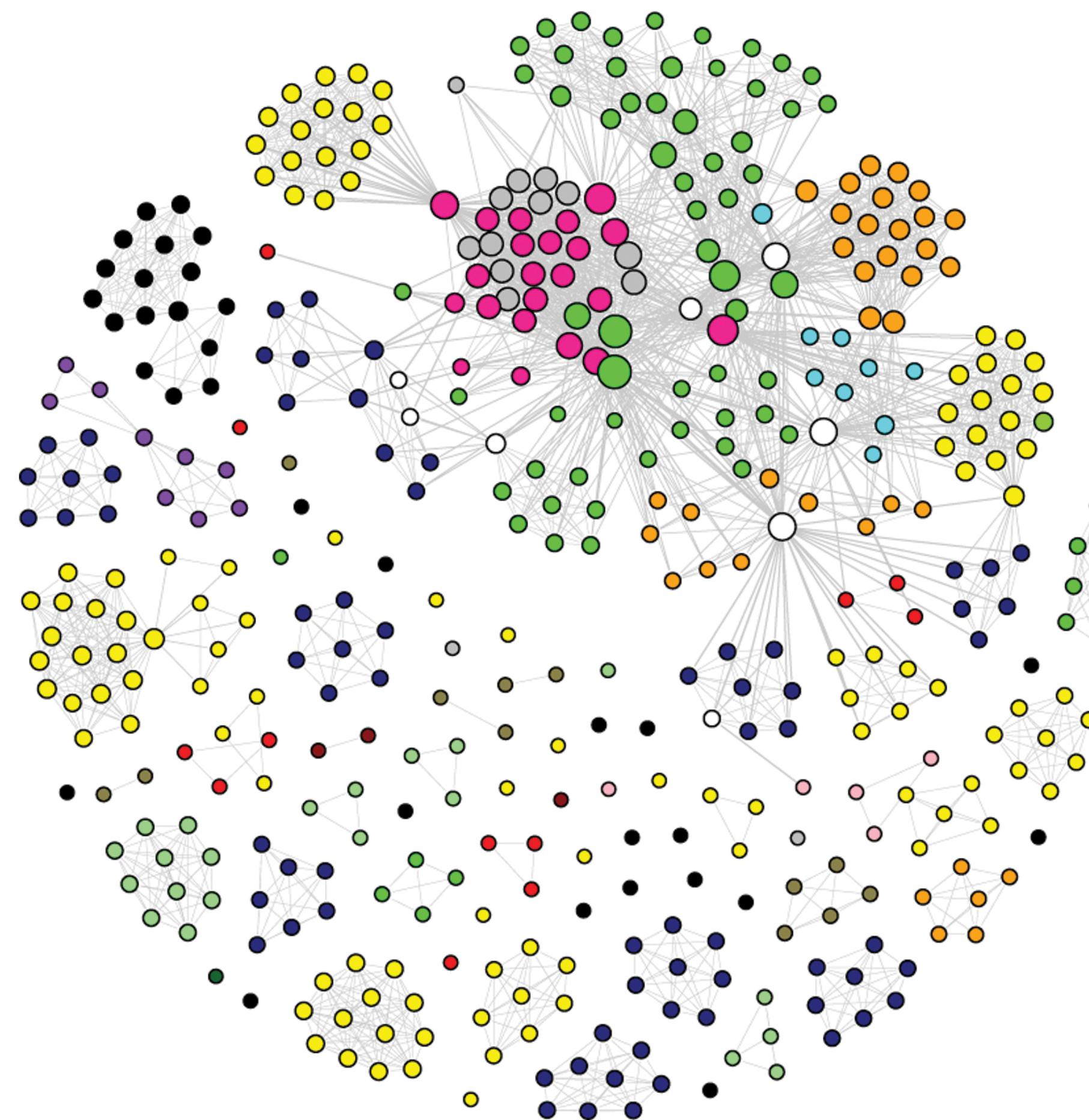
Bassett, D. S., Wymbs, N. F., Porter, M. a, Mucha, P. J., Carlson, J. M., & Grafton, S. T. (2011). Dynamic reconfiguration of human brain networks during learning. *Proceedings of the National Academy of Sciences*. doi: 10.1073/pnas.1018985108.

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.

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Symptoom netwerken Small-world of DSM-IV

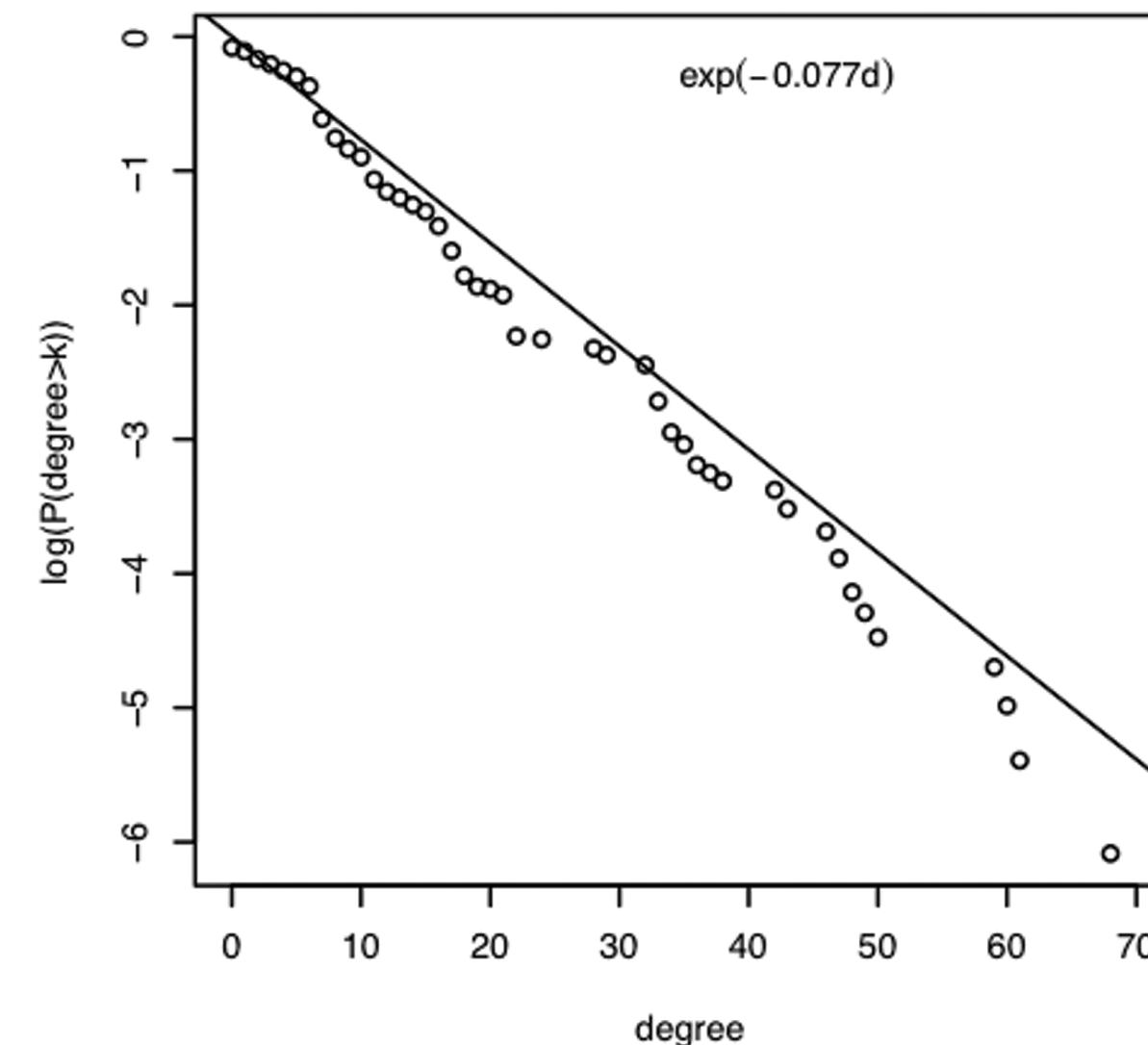
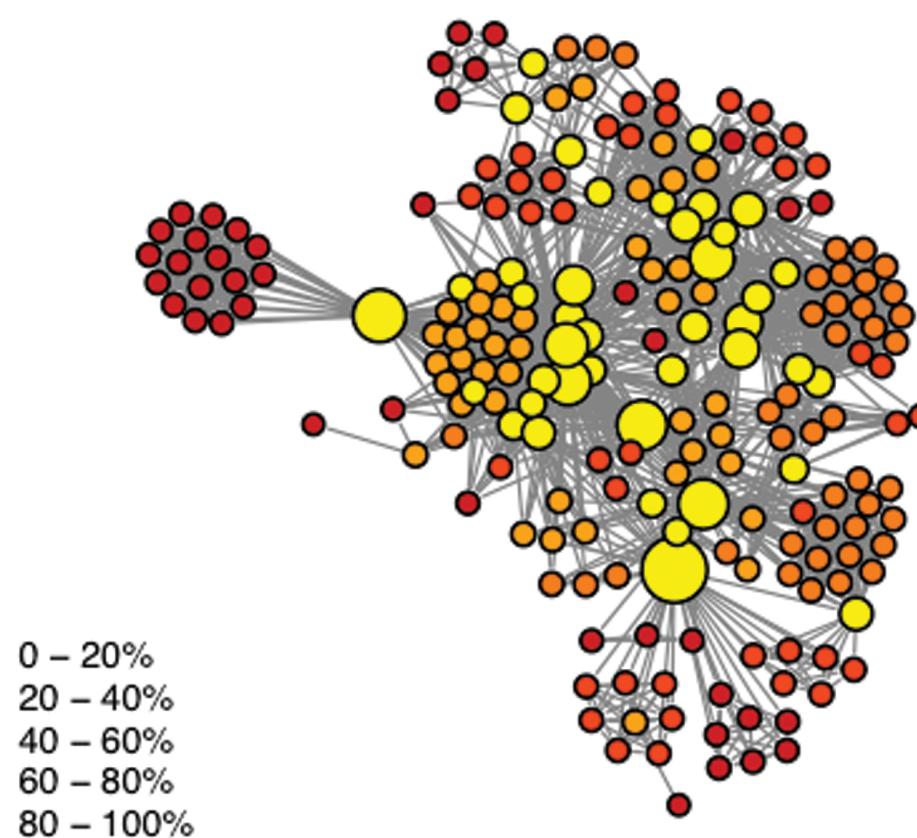


Problemen met het medisch model by psychopathologie:

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

- Disorders usually first diagnosed in infancy, childhood or adolescence
- Delirium, dementia, and amnesia and other cognitive disorders
- Mental disorders due to a general medical condition
- Substance-related disorders
- Schizophrenia and other psychotic disorders
- Mood disorders
- Anxiety disorders
- Somatoform disorders
- Factitious disorders
- Dissociative disorders
- Sexual and gender identity disorders
- Eating disorders
- Sleep disorders
- Impulse control disorders not elsewhere classified
- Adjustment disorders
- Personality disorders
- Symptom is featured equally in multiple chapters

Symptom netwerken

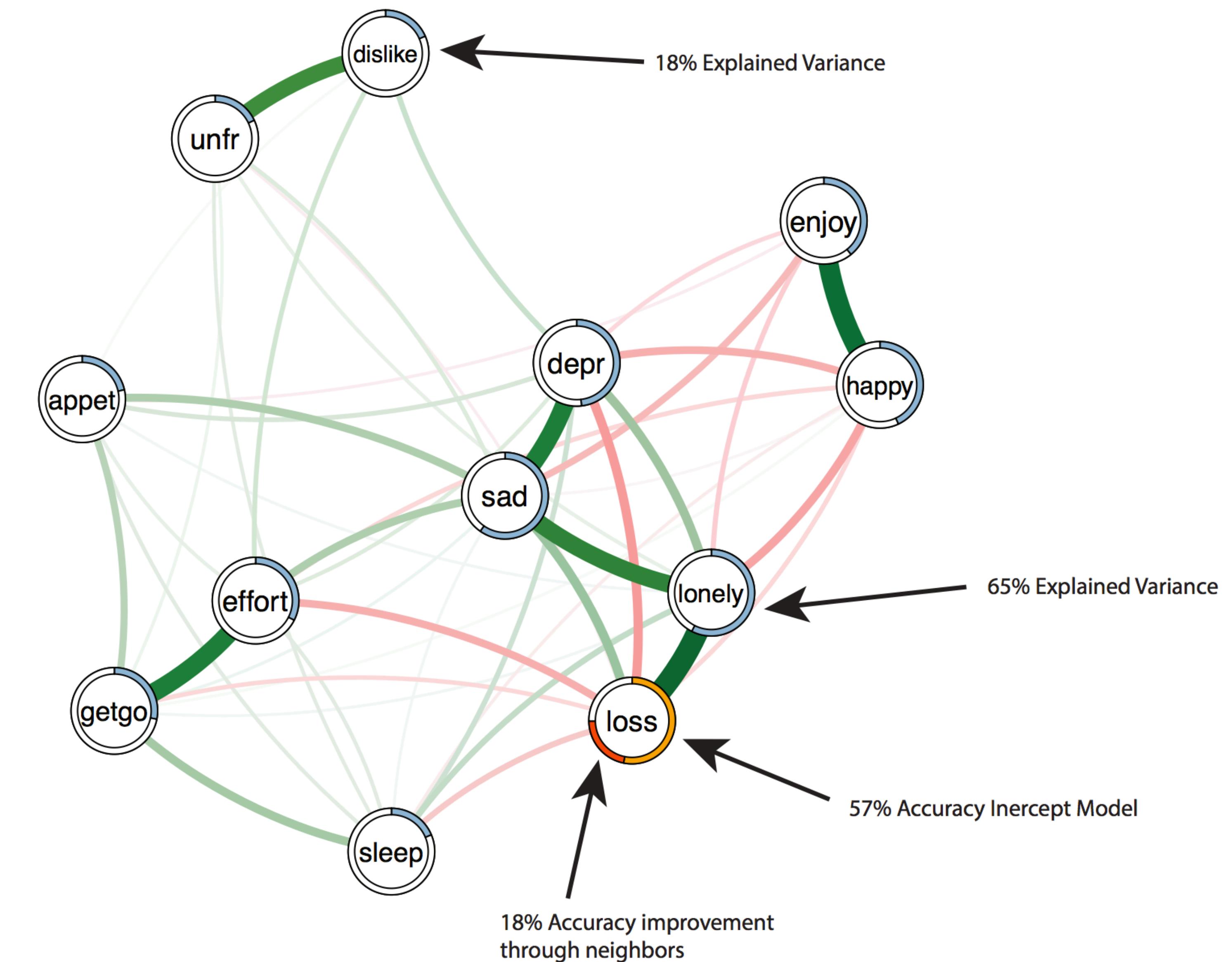


We show that

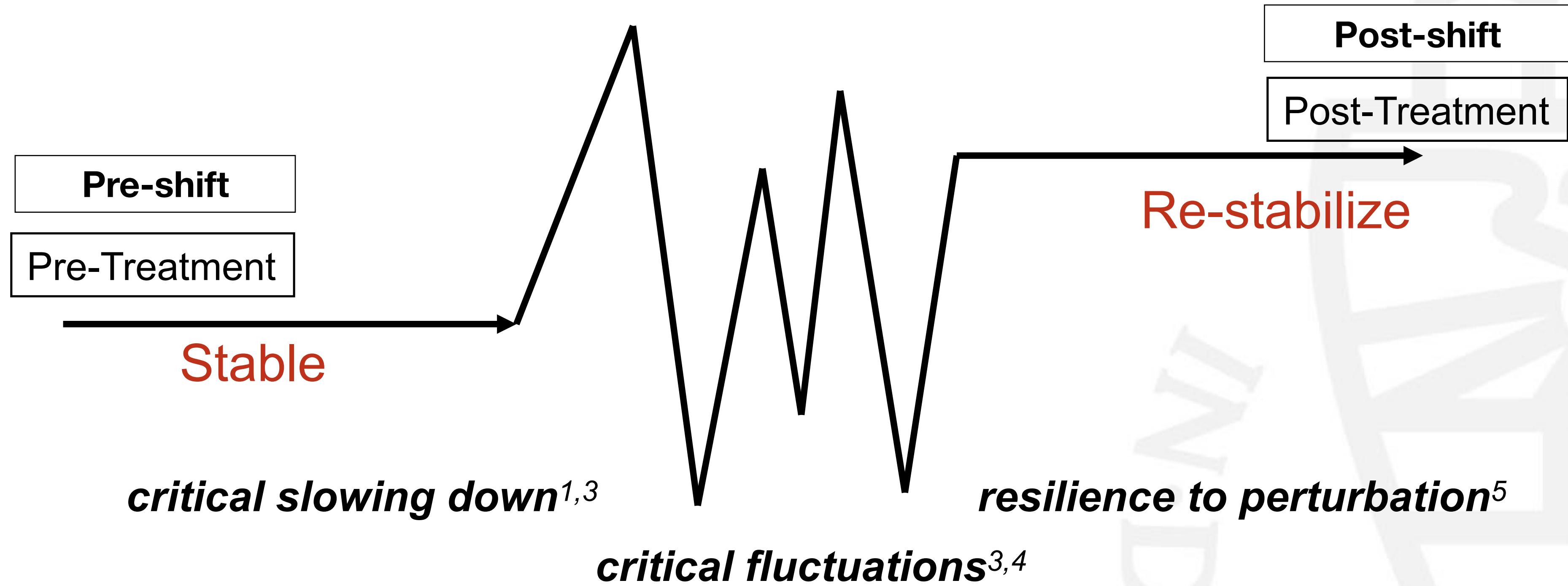
- half of the symptoms in the DSM-IV network are connected,
- the architecture of these connections conforms to a **small world structure**, featuring a **high degree of clustering** but a **short average path length**, and
- distances between disorders in this **structure predict empirical comorbidity rates**. Network simulations of Major Depressive Episode and Generalized Anxiety Disorder show that the model faithfully reproduces empirical population statistics for these disorders.

Symptom netwerken

psychosystems.org



Period of Destabilization



- 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

¹Scholz 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.

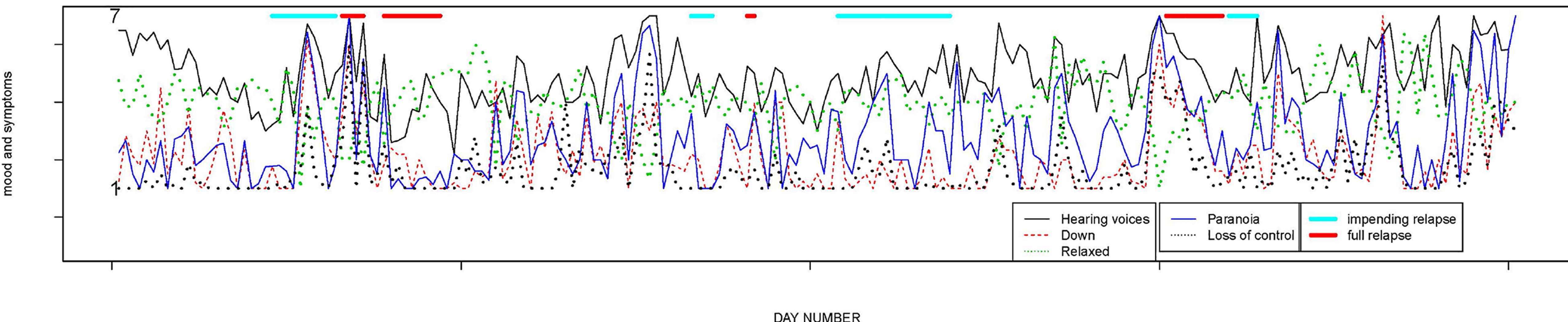
²Scheffer M, Bascompte J, Brock W A, Brovkin V, Carpenter SR, Dakos V, Held H, van Nes EH, Rietkerk M, Sugihara G. (2009). Early-warning signals for critical transitions. *Nature* 461, 53–9.

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

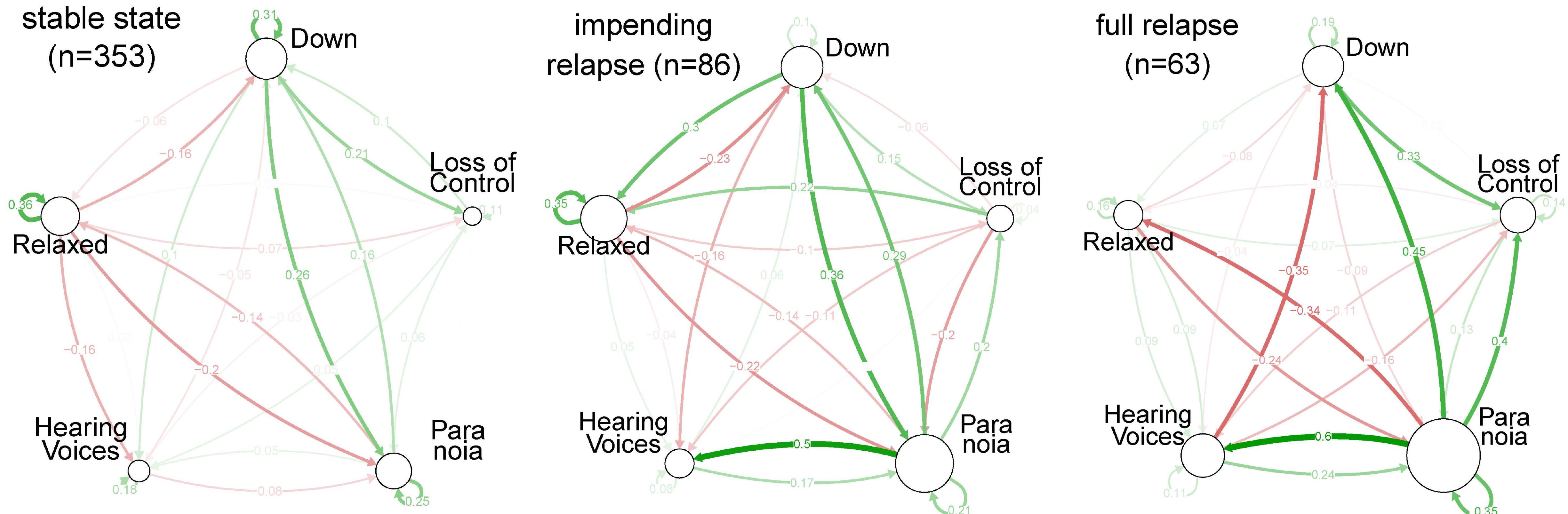
⁴Schiepek G, Strunk G. (2010). The identification of critical fluctuations and phase transitions in short term and coarse-grained time series ... *Biological cybernetics* 102, 197–207.

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

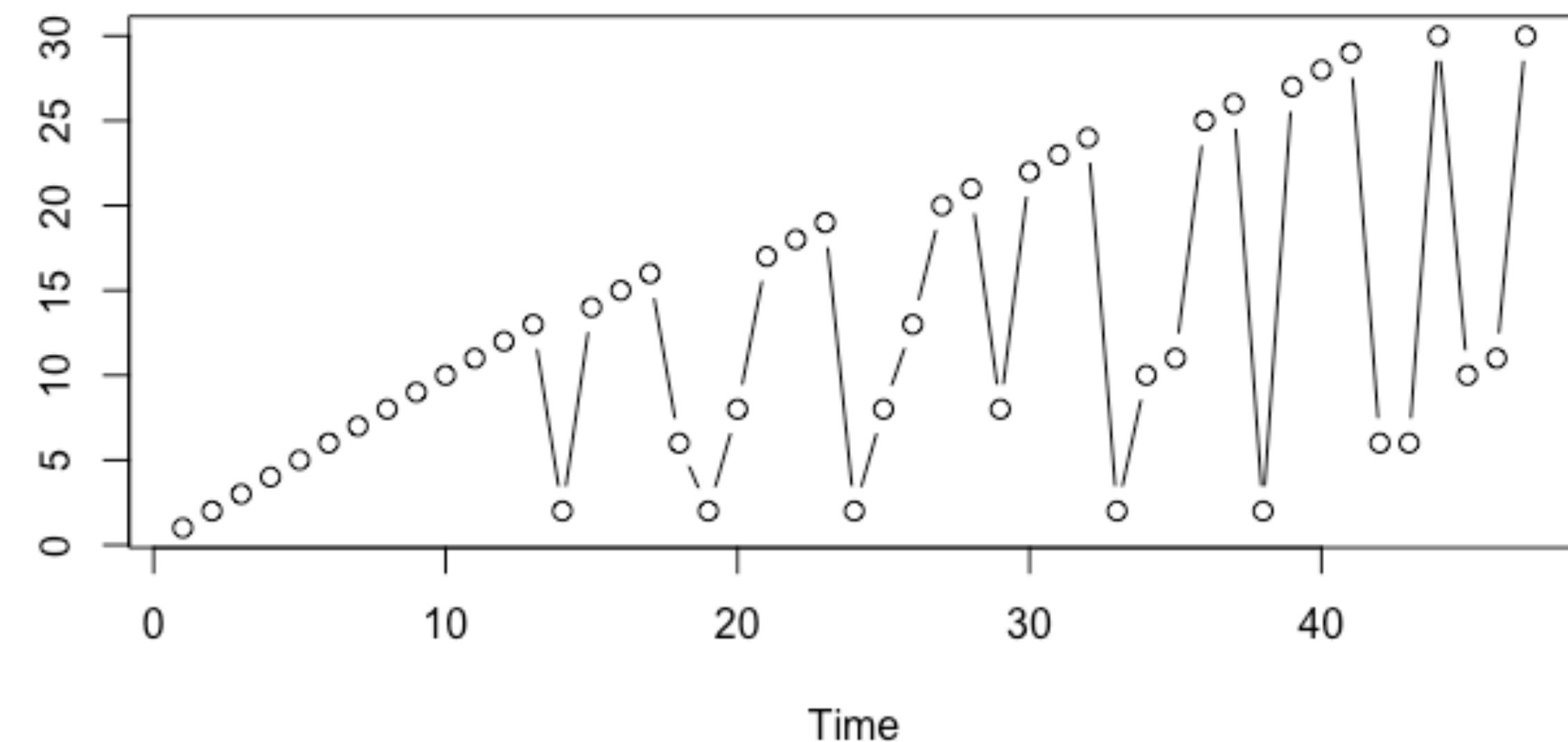
The Spearman correlations as suggested by reviewer #1

doi:10.1371/journal.pone.0162811.t002

Recurrence Quantification Analysis: Nominale Tijdseries

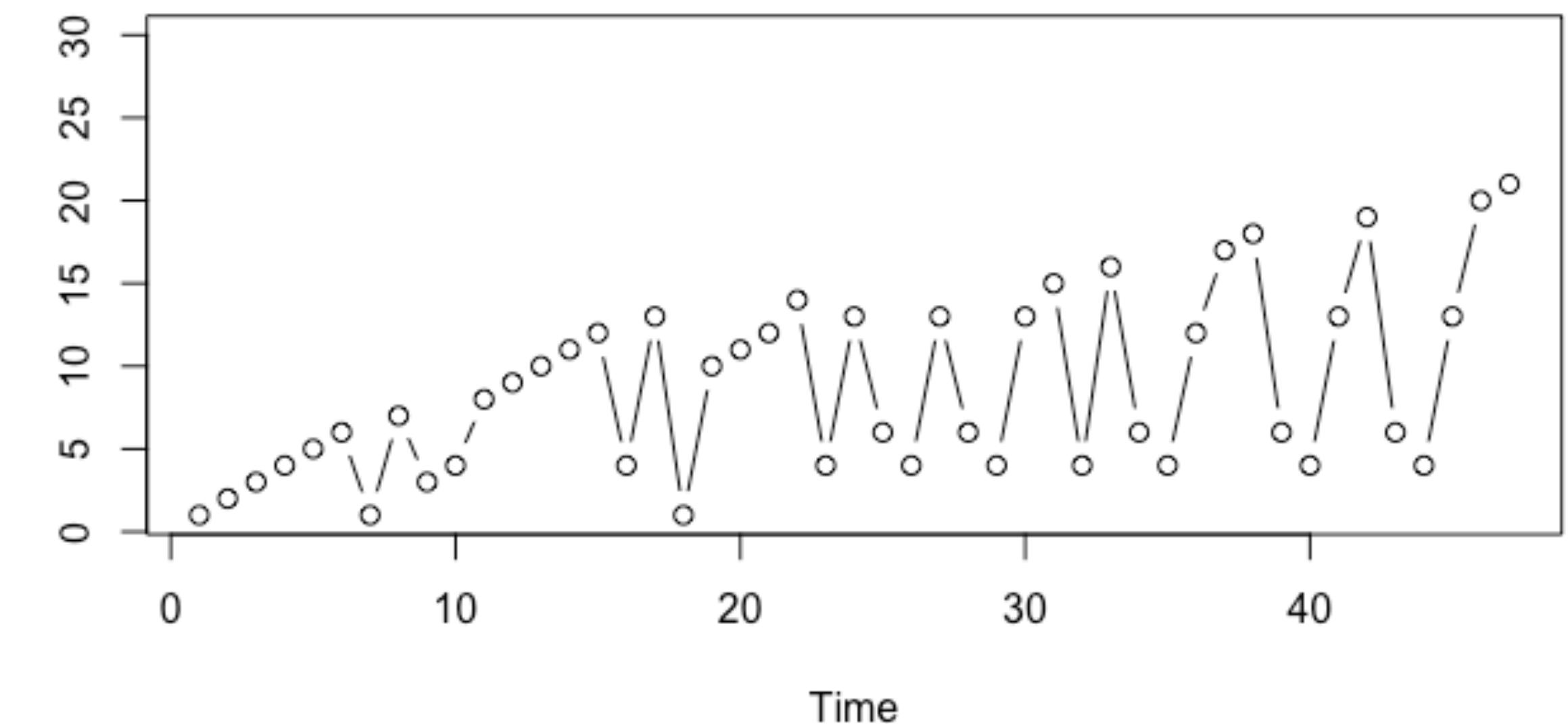
VERHAAL 1

“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”

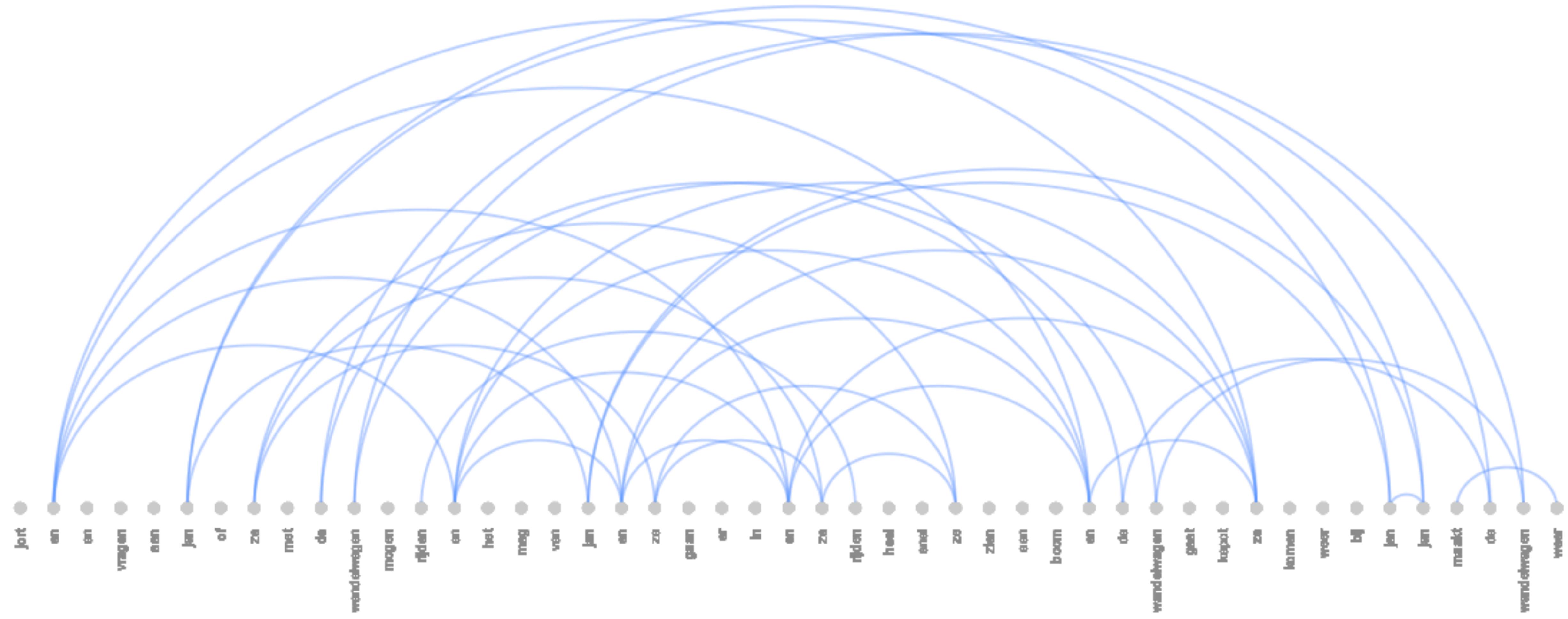


VERHAAL 2

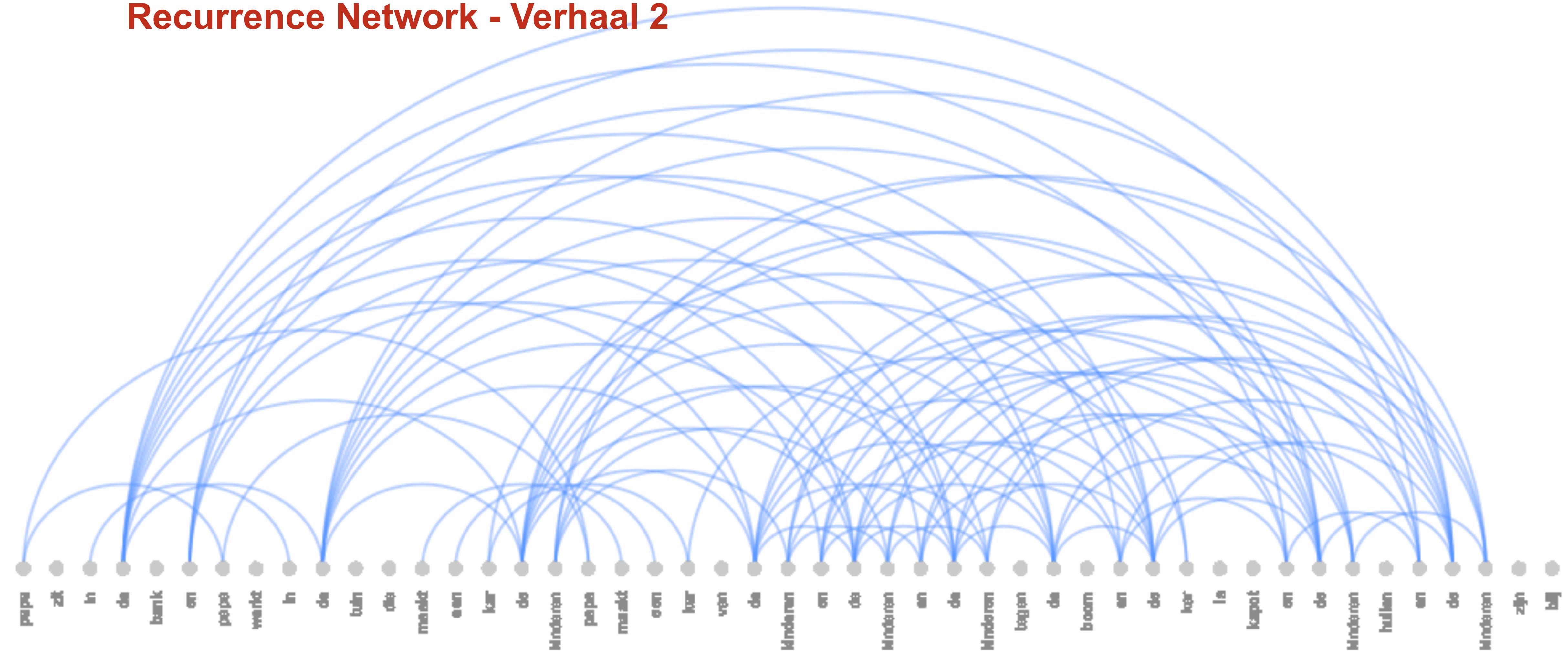
“1 2 3 4 5 6 1 7 3 4 8 9 10 11
12 4 13 1 10 11 12 14 4 13 6 4
13 6 4 13 15 4 16 6 4 12 17 18 6
4 13 19 6 4 13 20 21”



Recurrence Network - Verhaal 1



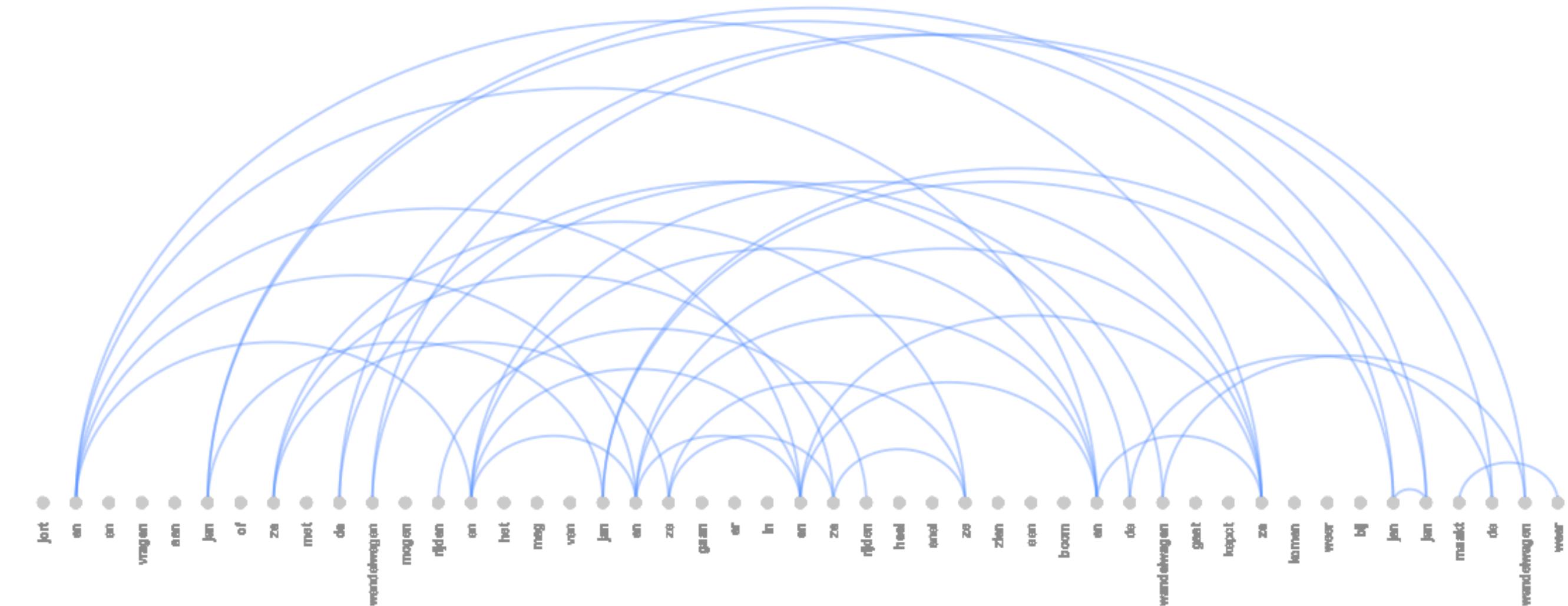
Recurrence Network - Verhaal 2



Recurrence Network

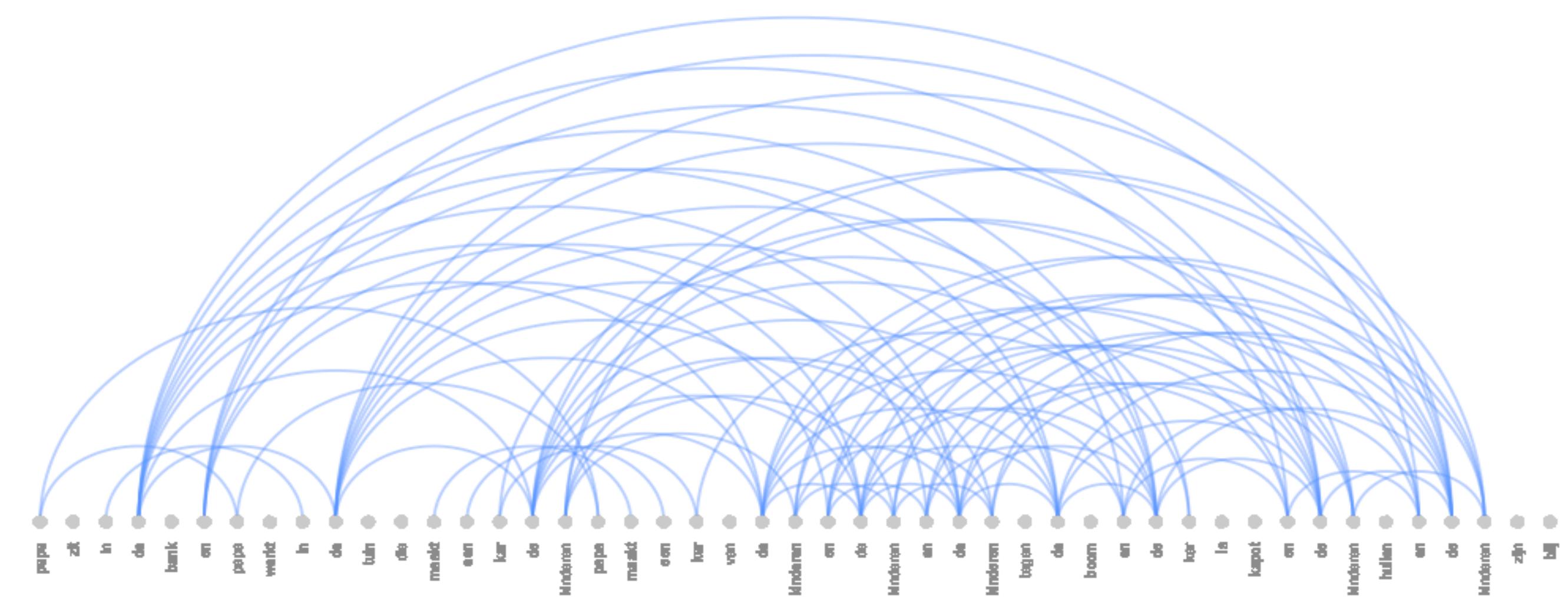
Total Degree = 70

verhaal 1



Total Degree = 168

verhaal 2



Ecological Momentary Assessment

- Measurement is considered to be like classical physical measurement:
 - ➡ It is very problematic to interpret measurement outcomes as properties of the theoretical object of measurement (interaction between instrument and object, by merely asking to rate “I feel happy today”)
 - ➡ Measurement invariance, monotonicity, etc. do not hold

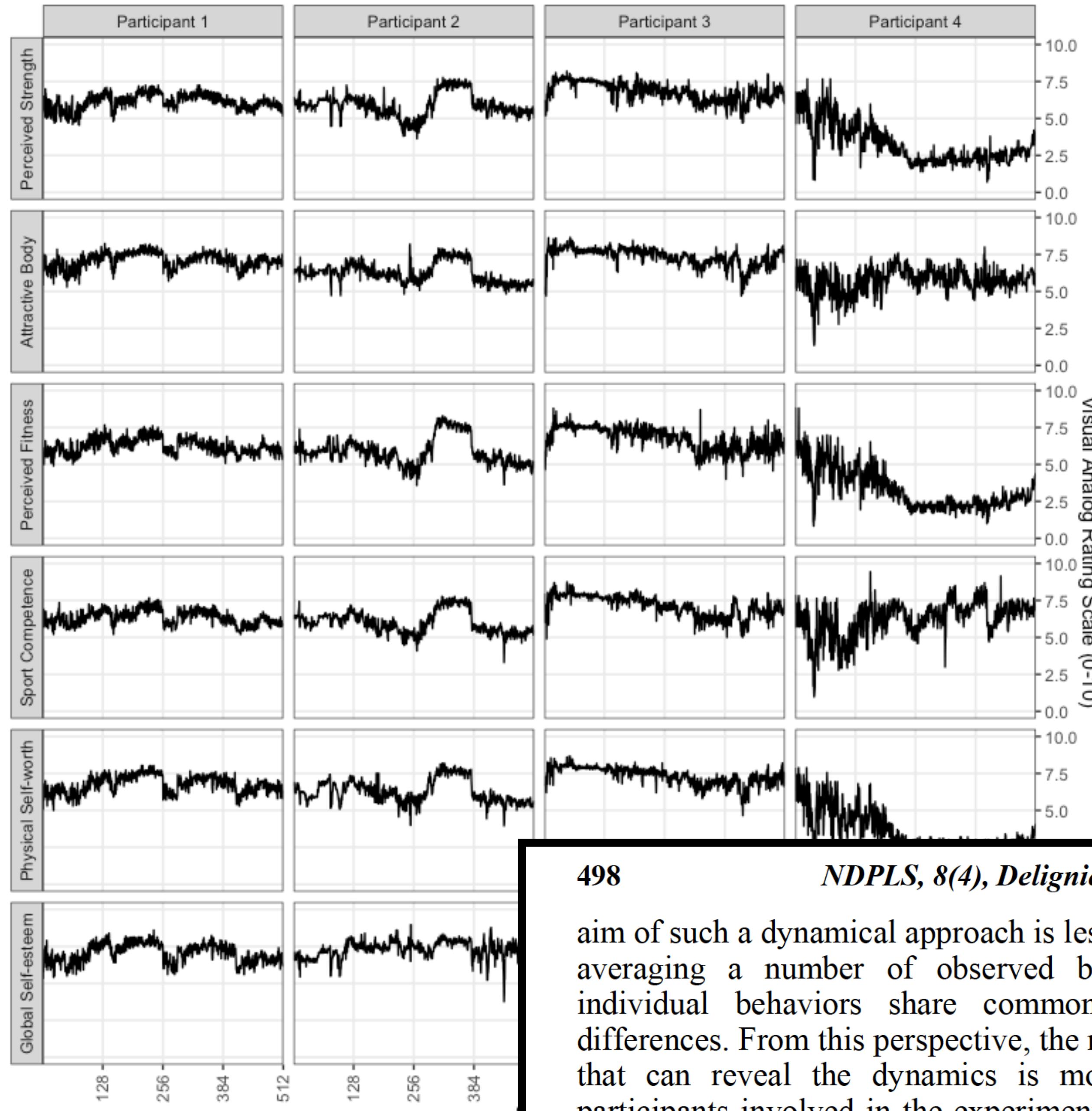
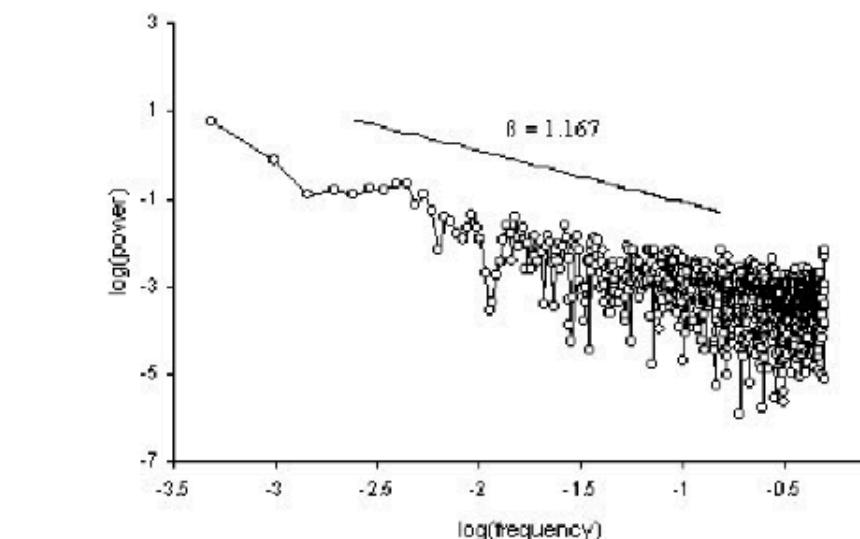


Table 2. Individual Moving Average Coefficients (α) Obtained through ARIMA Modeling.

Participant	GSE	PSW	PC	SC	APP	PS
1	0.58	0.65	0.70	0.66	0.63	0.69
2	0.35	0.46	0.48	0.50	0.45	0.46
3	0.58	0.65	0.75	0.63	0.56	0.68
4	0.66	0.56	0.60	0.59	0.64	0.53

Table 3. Individual β Exponents Obtained with Spectral Analysis.

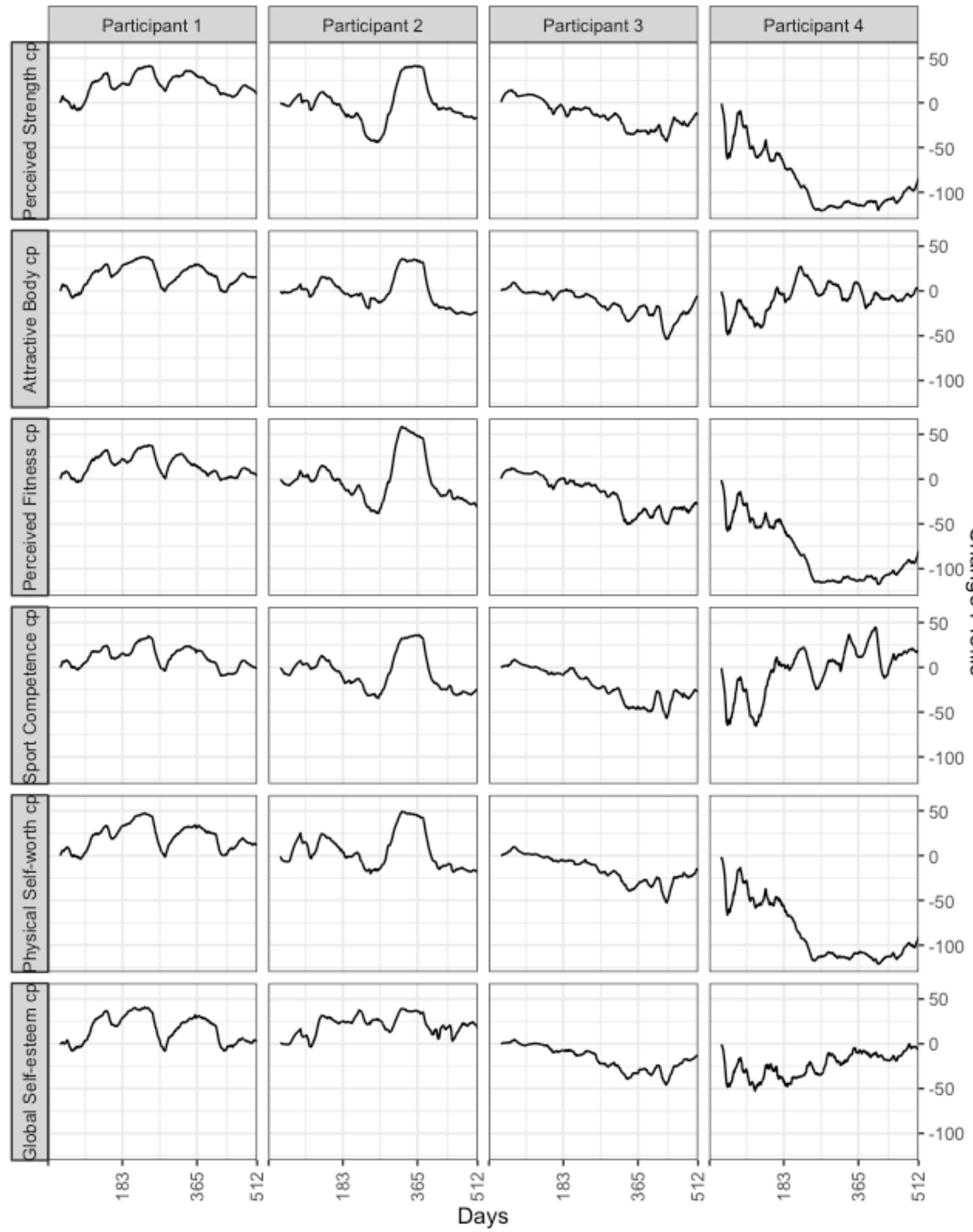
Participant	GSE	PSW	PC	SC	APP	PS
1	1.17	1.15	0.95	1.00	1.15	0.95
2	1.13	1.39	1.36	1.24	1.27	1.23
3	1.09	1.05	0.96	1.34	1.12	1.11
4	0.96	1.14	1.02	1.18	0.95	1.05



498

NDPLS, 8(4), Delignières, Fortes, & Ninot

aim of such a dynamical approach is less to derive an epistemic model by averaging a number of observed behaviors than to evidence that individual behaviors share common dynamics, despite superficial differences. From this perspective, the richness of the individual data sets that can reveal the dynamics is more crucial than the number of participants involved in the experiment. Researchers in many fields, for

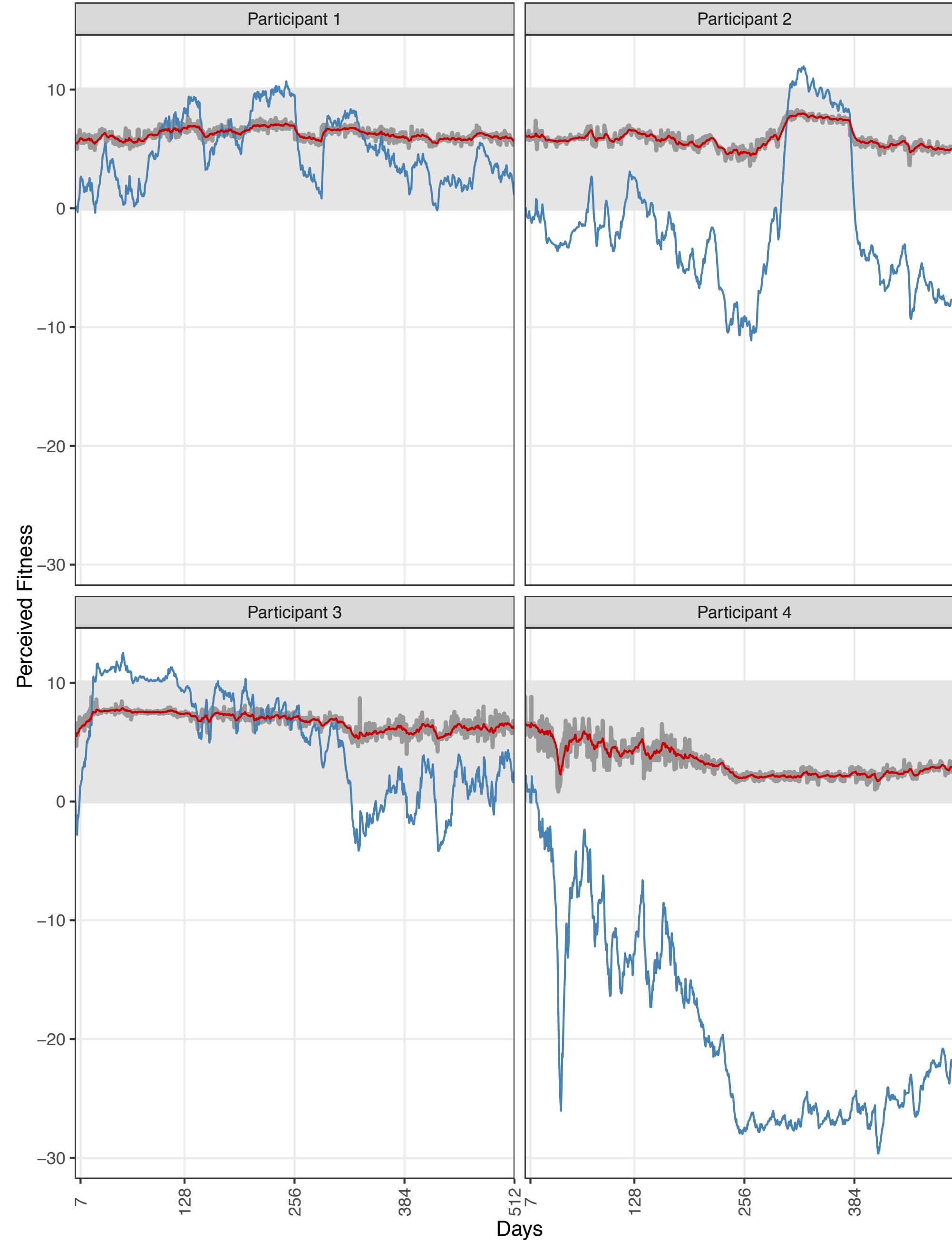


Change Profiles:

- Center on a moving average in a sliding window
- Take the cumulative sum

“Solves” some concerns:

- Scale is irrelevant/relative
- Small fluctuations are added in the cum. sum but, don't impact the shape of the overall profile
- If present, persistent levels & fluctuation patterns can be “exaggerated” (see y-scale)



Change Profiles:

- Center on a moving average in a sliding window
- Take the cumulative sum

Time series

- Original
- Change Profile
- Moving Average

“Solves” some concerns:

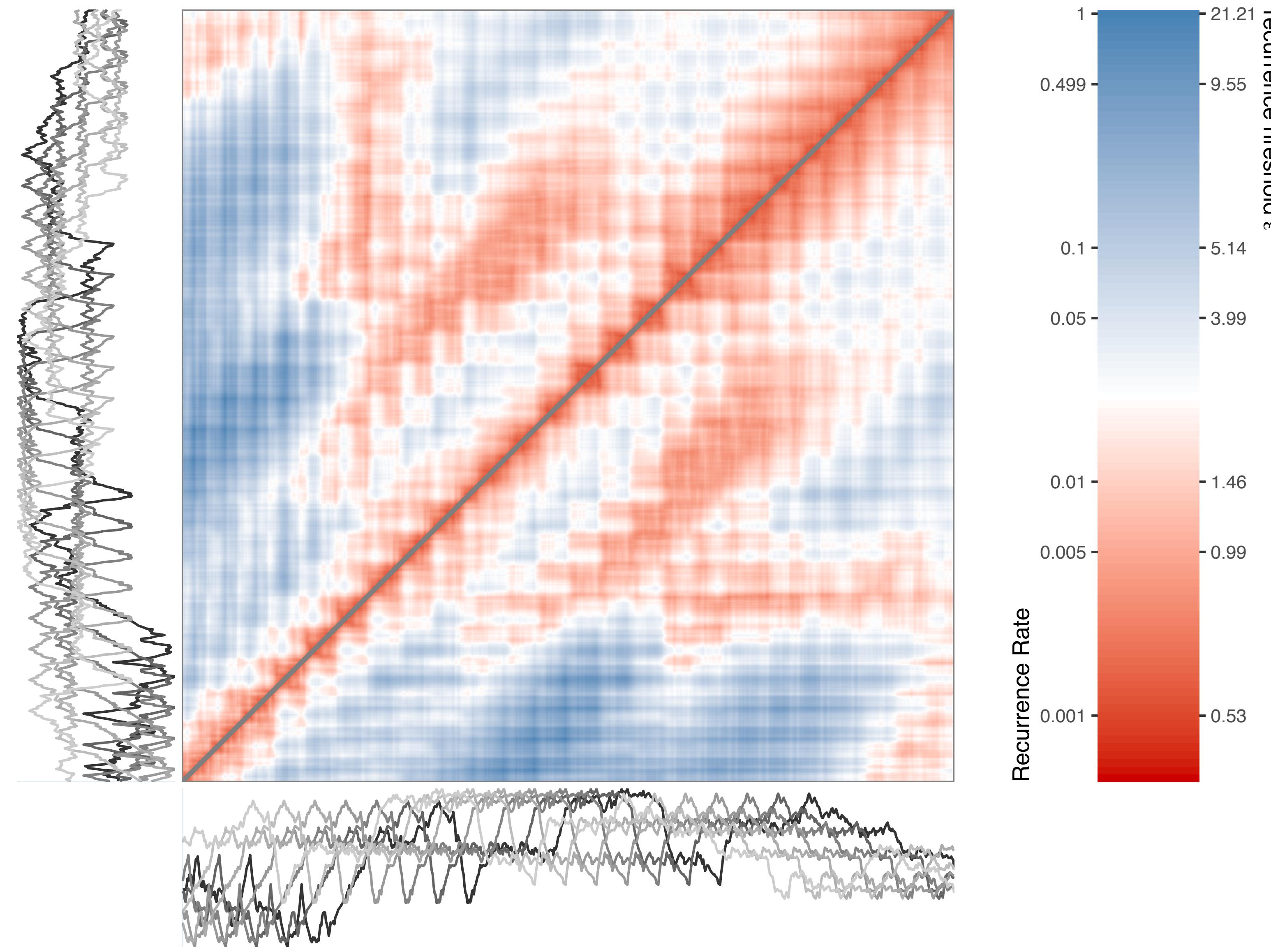
- Scale is irrelevant/relative
- Small fluctuations are added in the cum. sum but, don't impact the shape of the overall profile
- If present, persistent levels & fluctuation patterns can be “exaggerated” (see y-scale)

Recurrence Based Approach

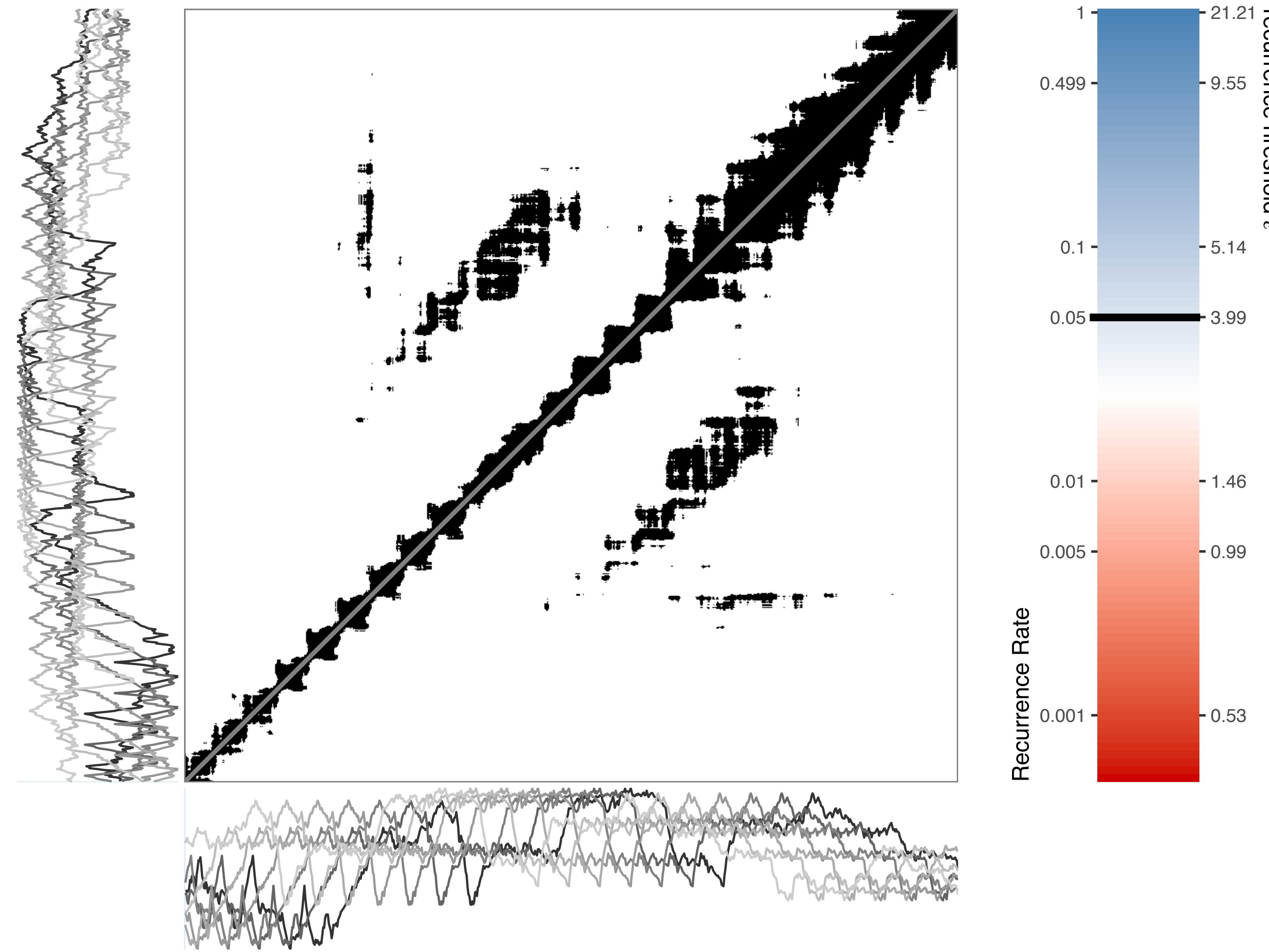
Quantifying State Dynamics

- Essentially “model free”
- Few data assumptions
- Can detect and quantify nonstationarity, etc
- Recurrence Networks can deal with multivariate time series data

Distance Matrix >> Recurrence Matrix

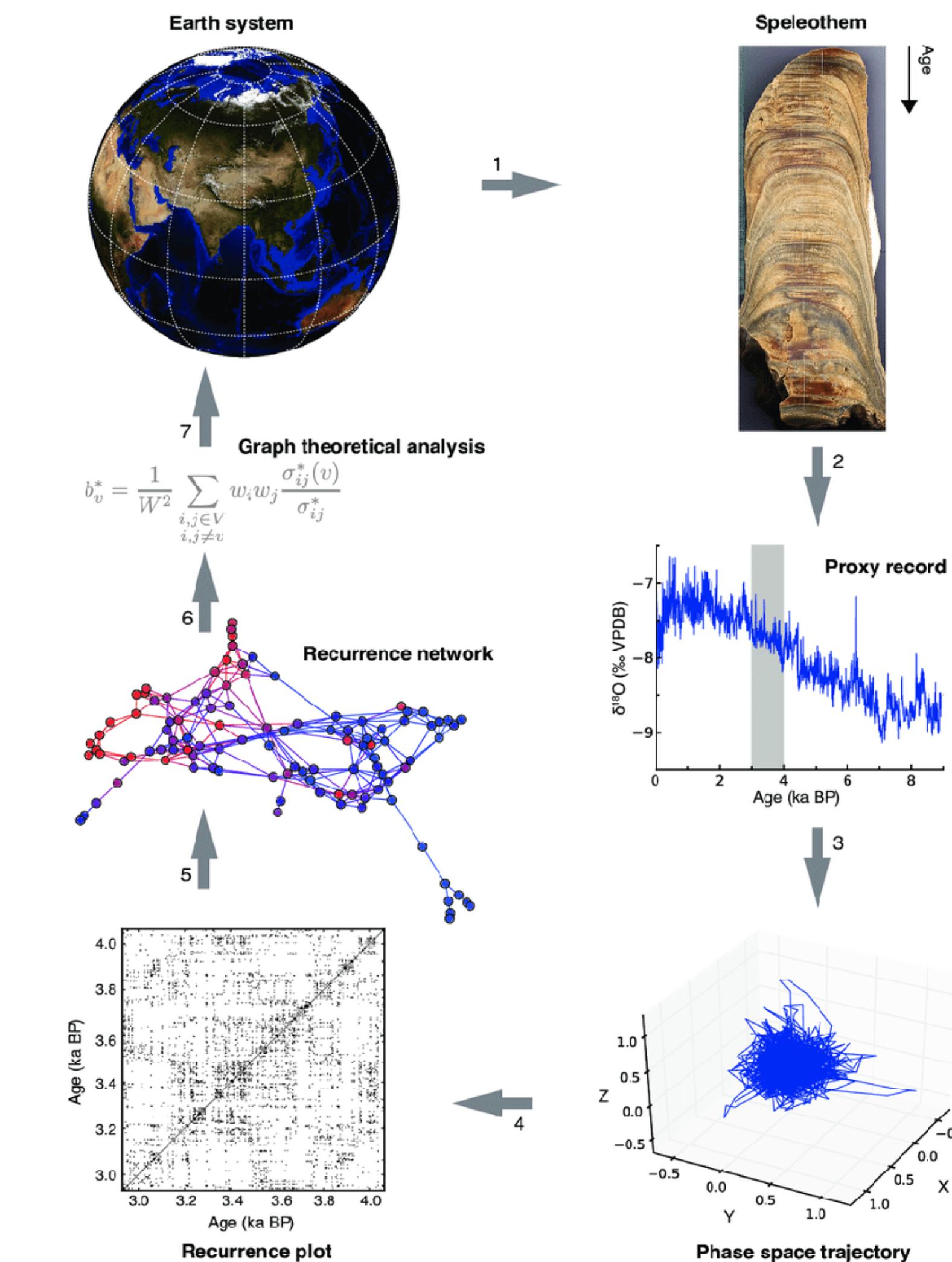


Recurrence/Incidence/Adjacency Matrix



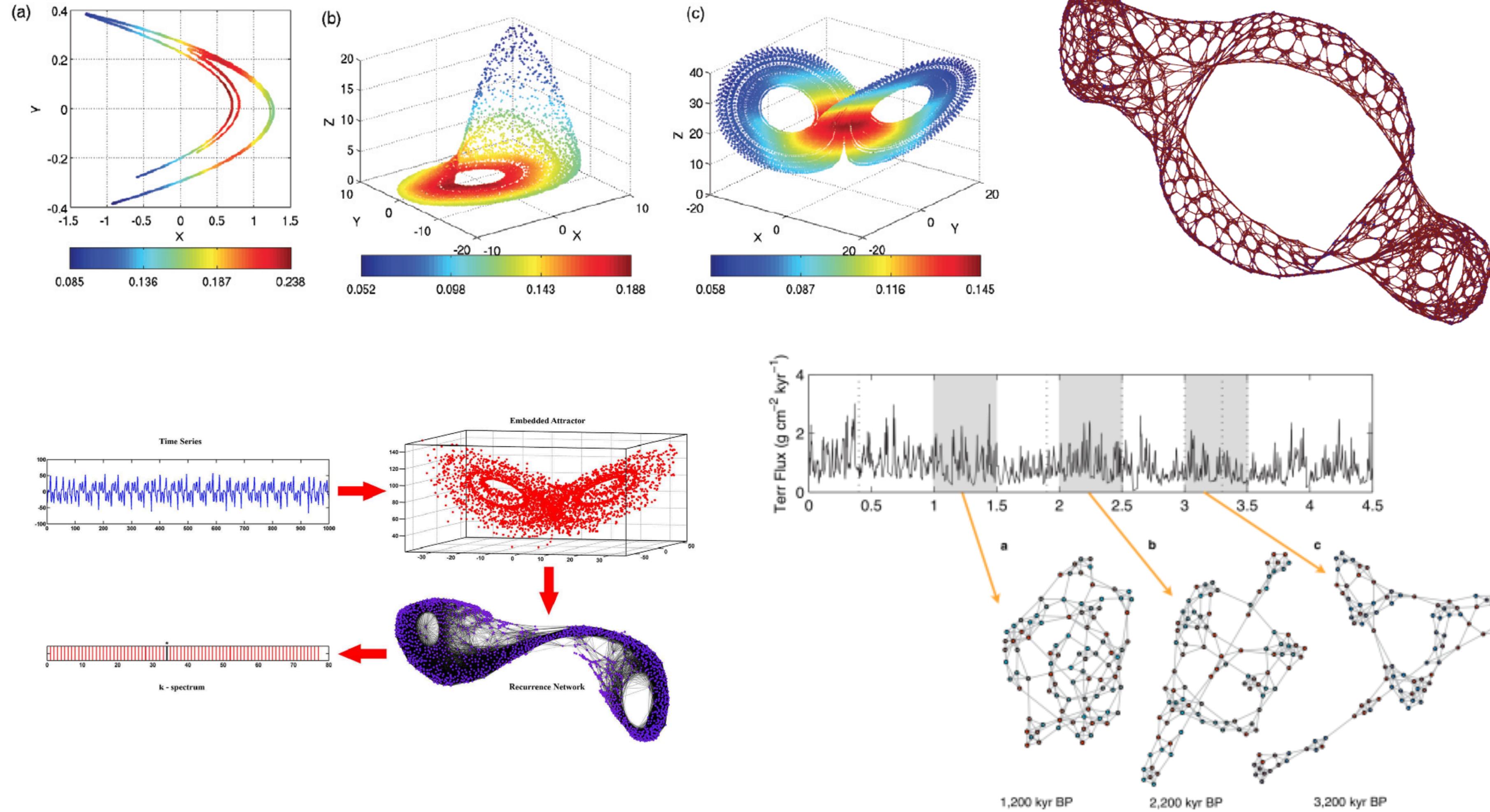
Recurrence/Incidence/Adjacency Matrix

- Time points are nodes (vertices)
- Nodes are connected by lines (edges) if they recur at some later point in time
- Network measures can be interpreted as quantifying aspects of the temporal dynamics, some are equivalent to RQA measures... some are different (e.g. weighted and/or directed network measures)



Donges, J. F., Donner, R., Marwan, N., Breitenbach, S. F., Rehfeld, K., & Kurths, J. (2015). Non-linear regime shifts in Holocene Asian monsoon variability: potential impacts on cultural change and migratory patterns. *Climate of the Past*, 11(5), 709-741.

Recurrence/Incidence/Adjacency Matrix

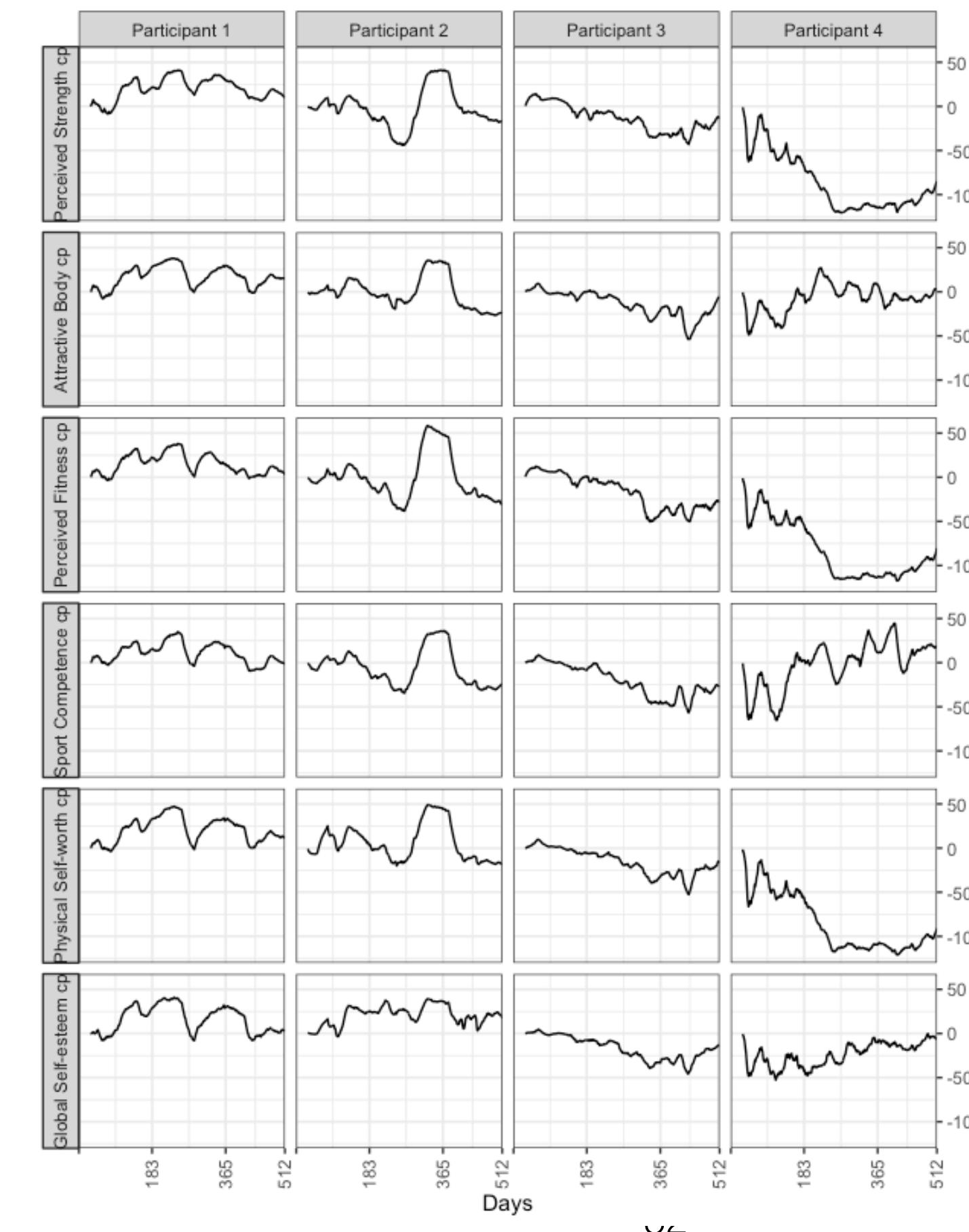


Small, M., Zhang, J., & Xu, X. (2009). Transforming time series into complex networks. *Complex Sciences*, 2078–2089.

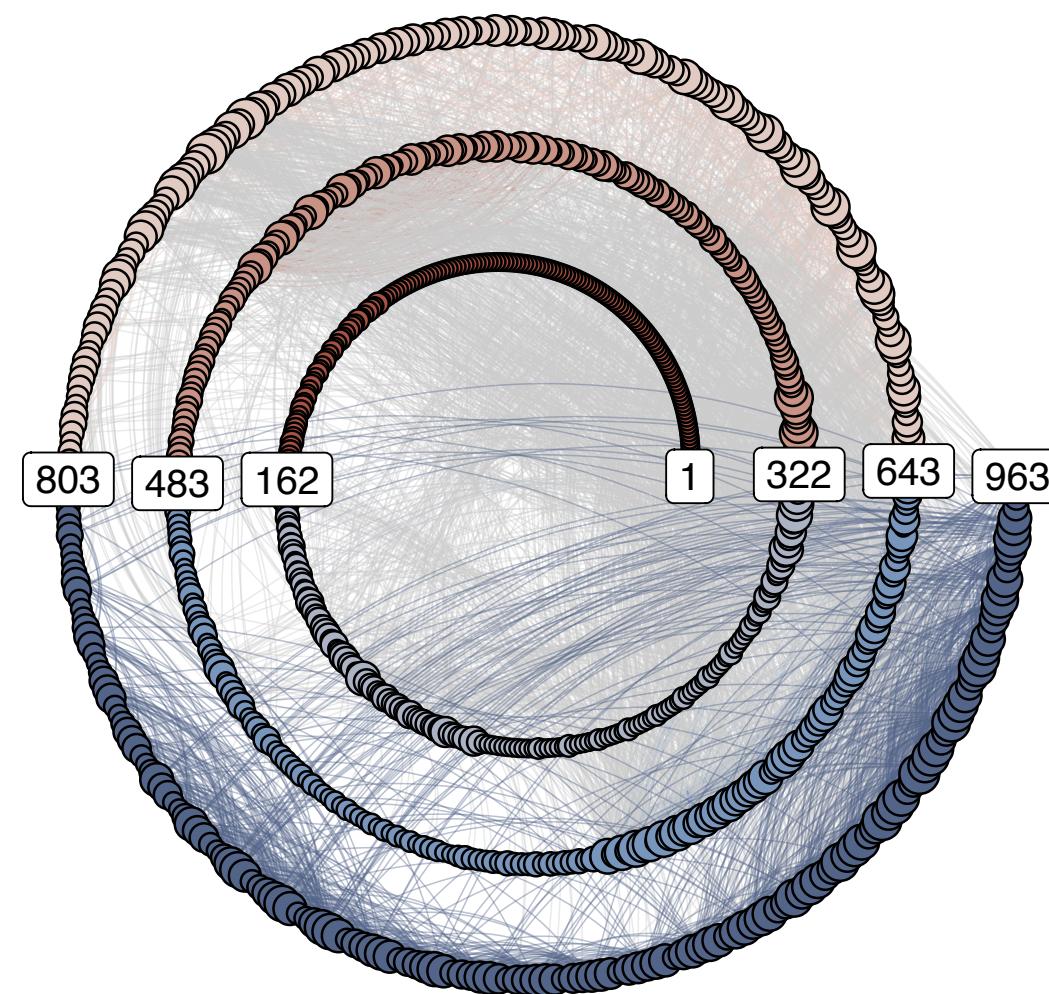
Jacob, R., Harikrishnan, K. P., Misra, R., & Ambika, G. (2015). How does noise affect the structure of a chaotic attractor: A recurrence network perspective. *arXiv preprint arXiv:1508.02724*.

Recurrence/Incidence/Adjacency Matrix

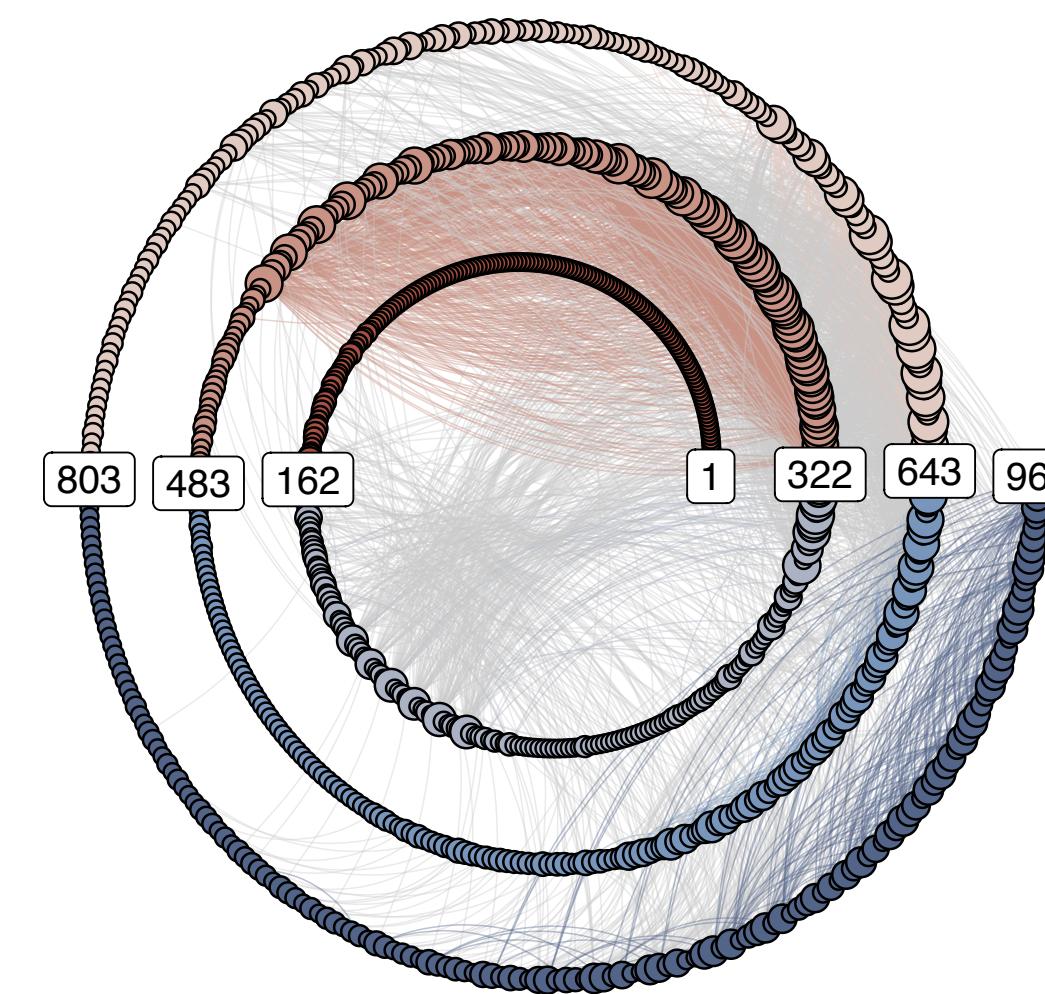
- Find a graph layout that makes a bit more sense



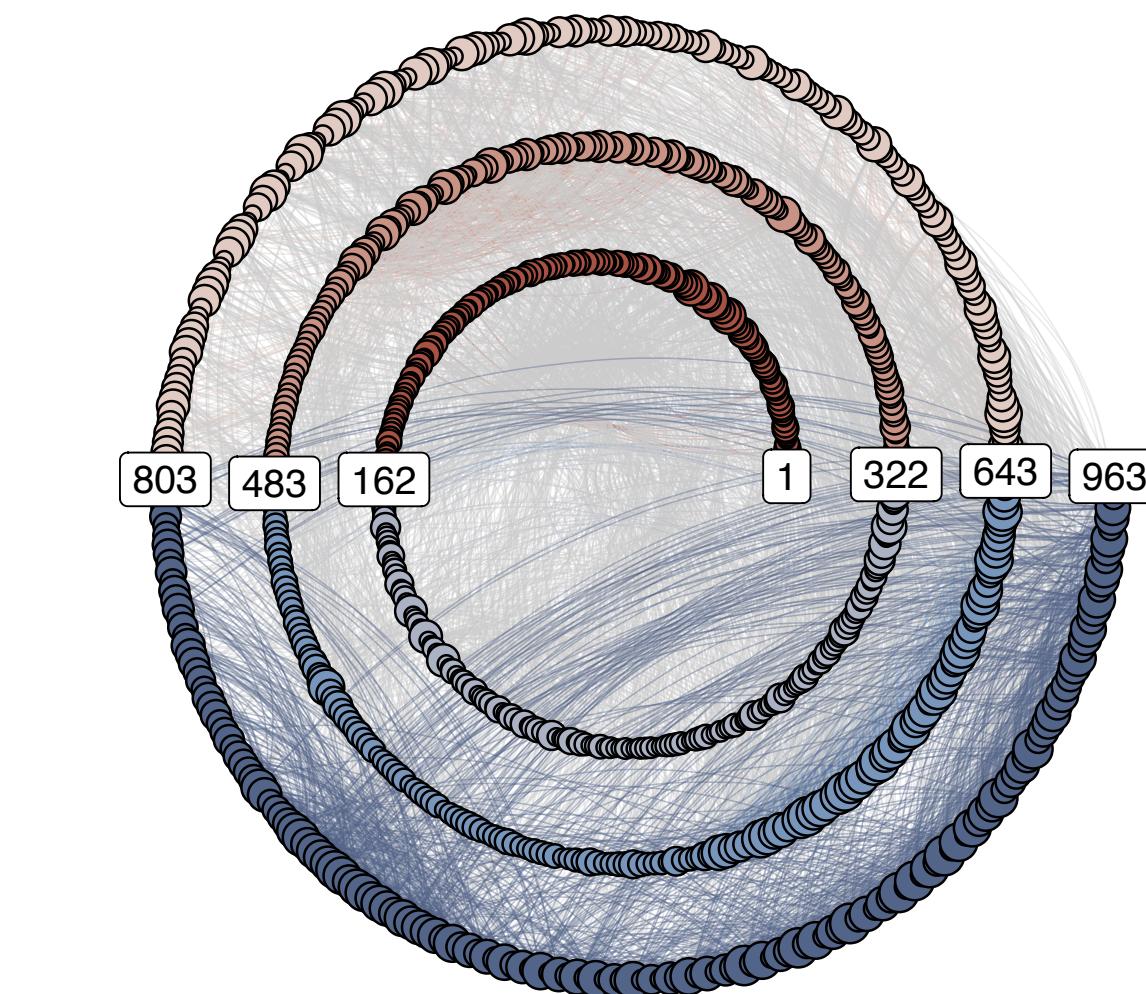
(a) Perceived Strength



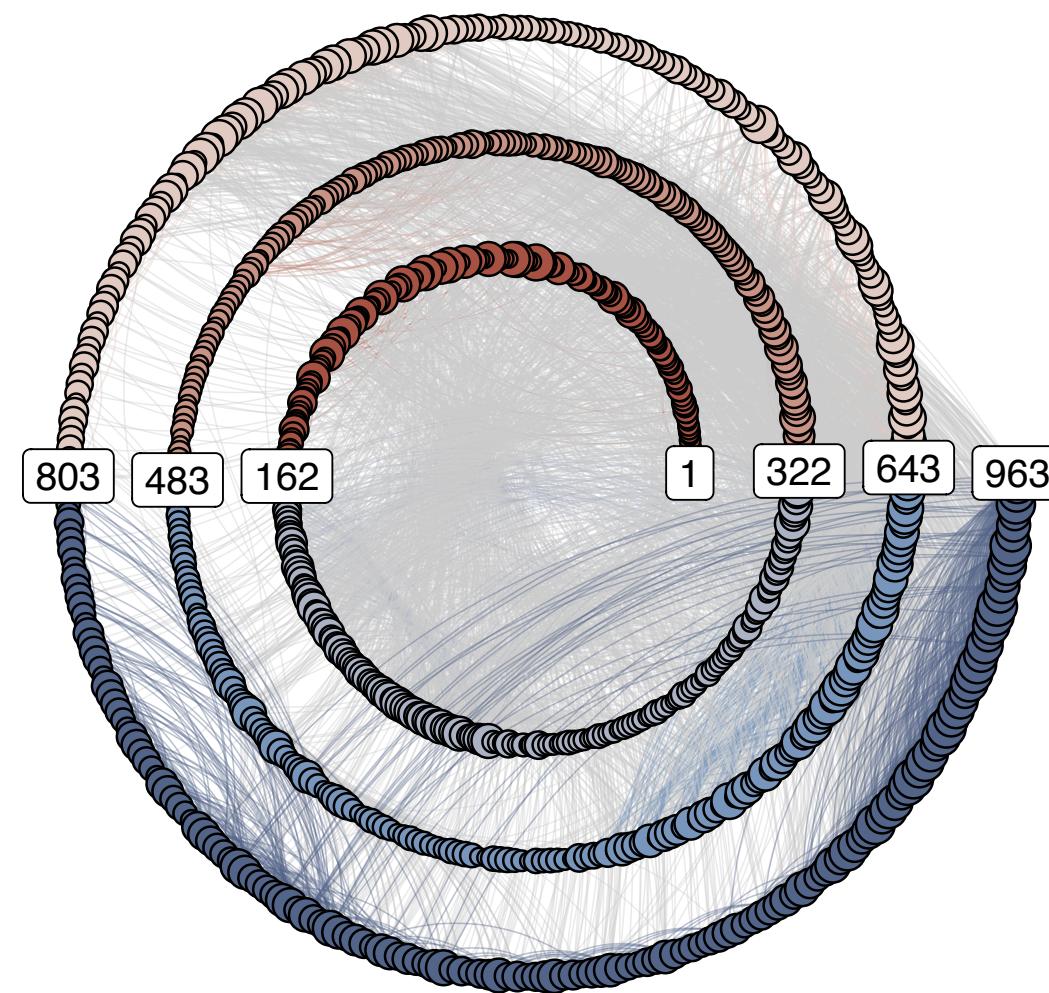
(b) Attractive Body



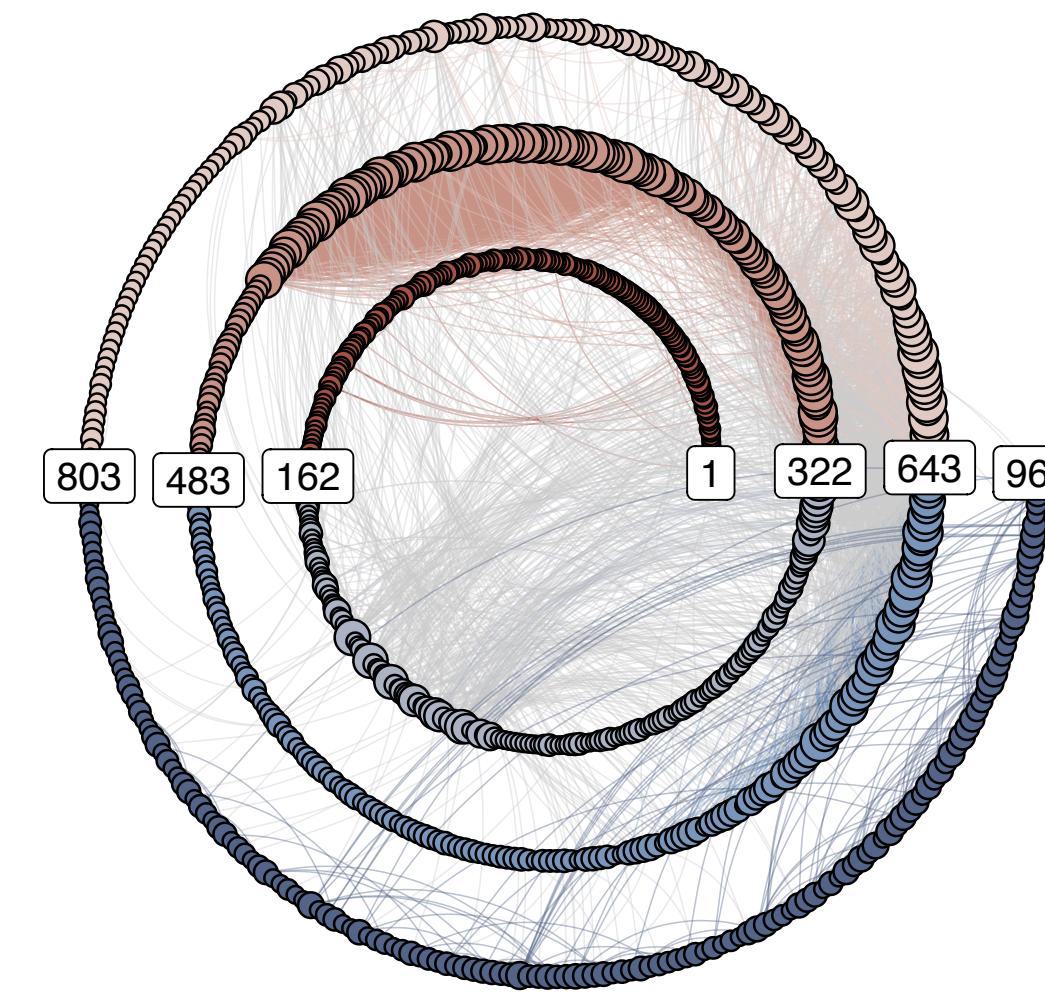
(c) Perceived Fitness



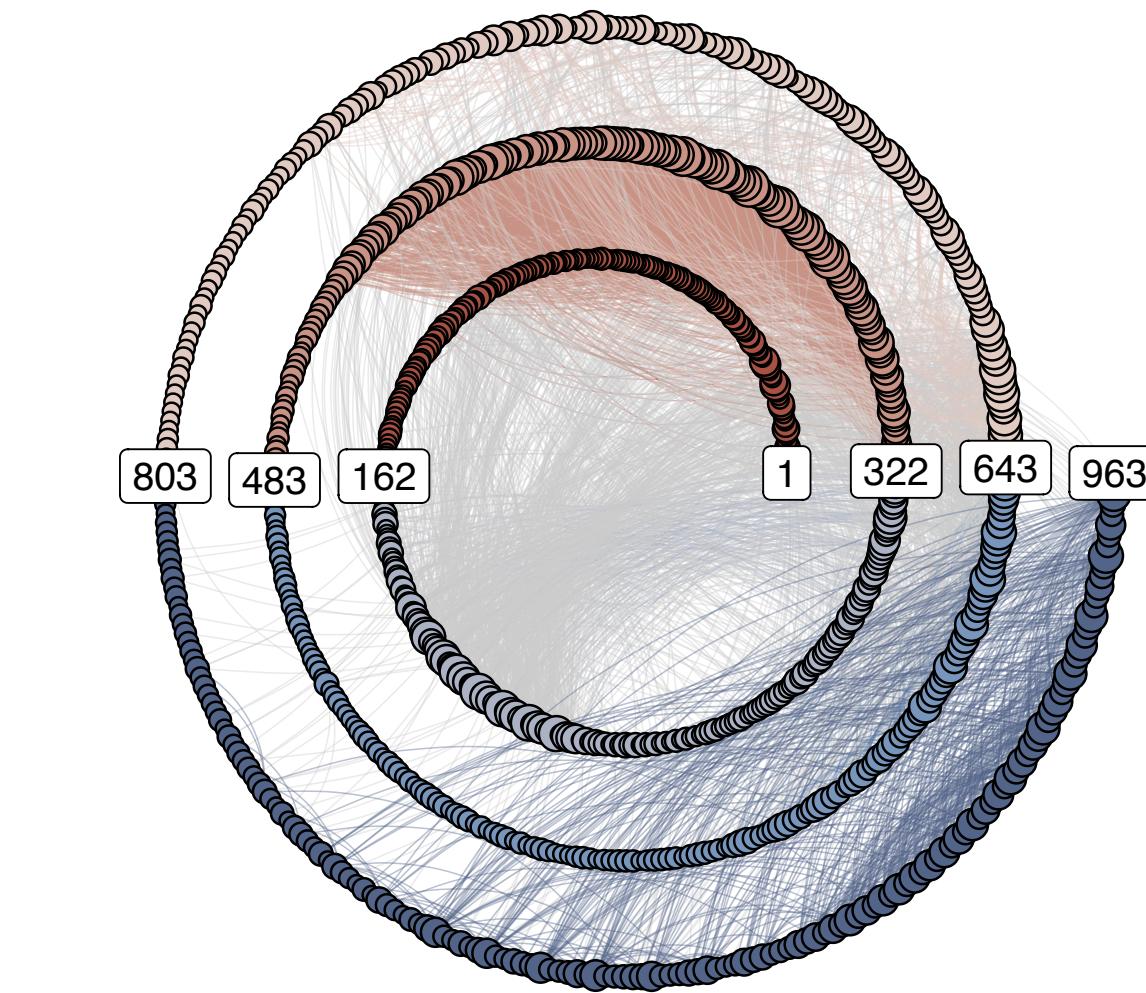
(d) Sport Competence



(e) Physical Self-worth

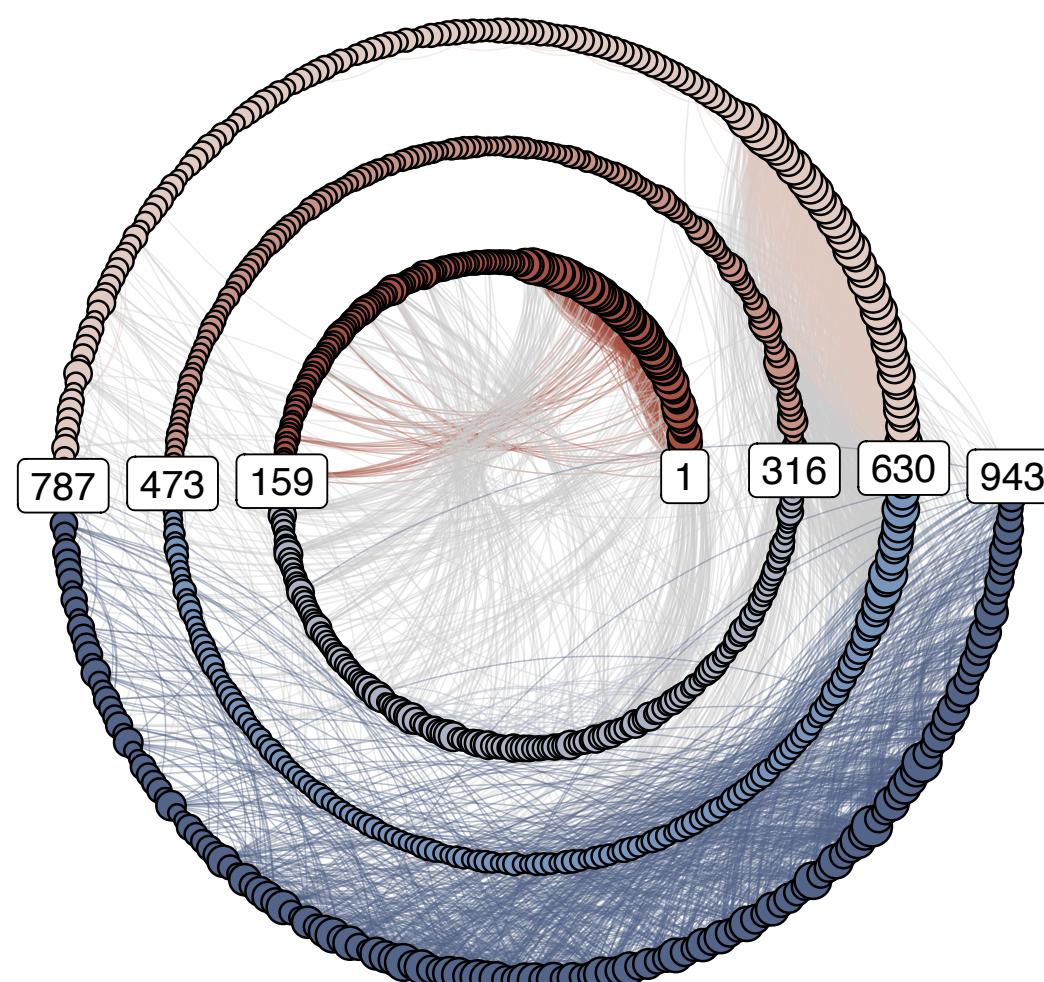


(f) Global Self-esteem

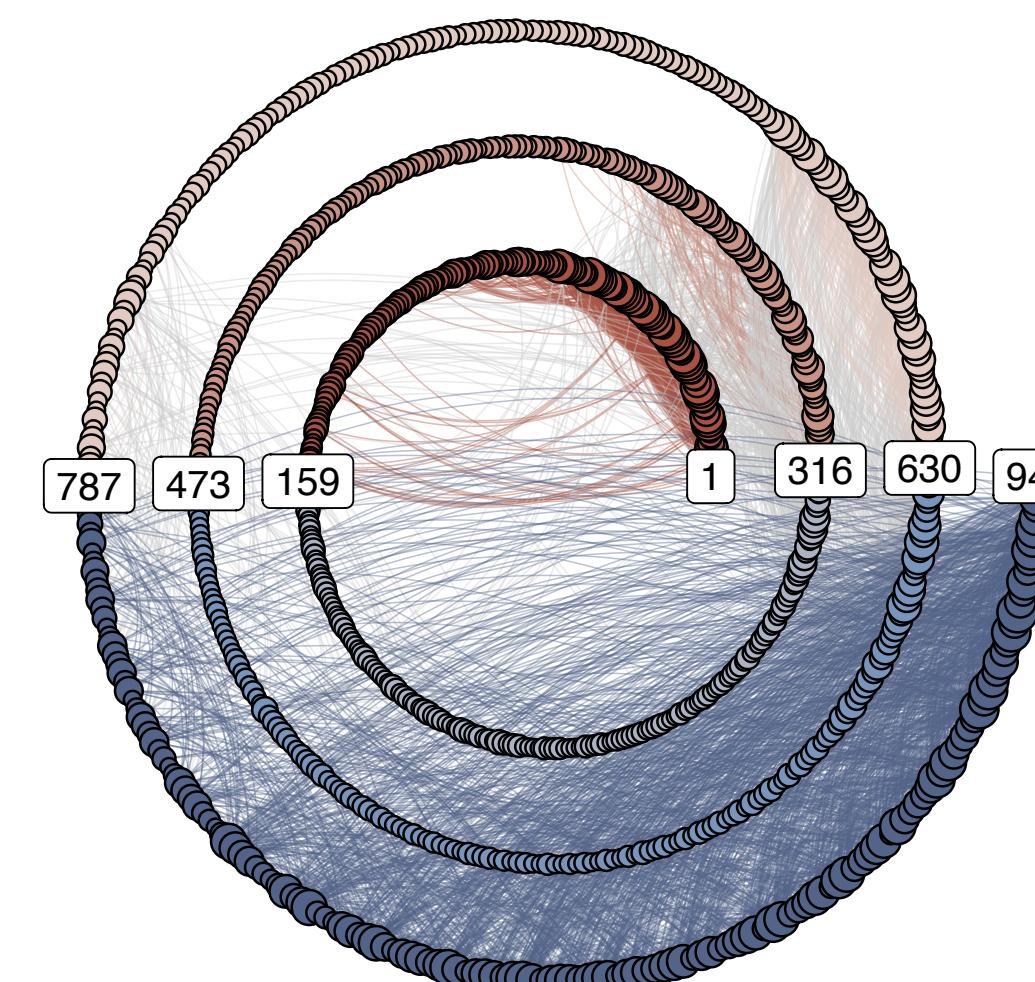


Participant 1

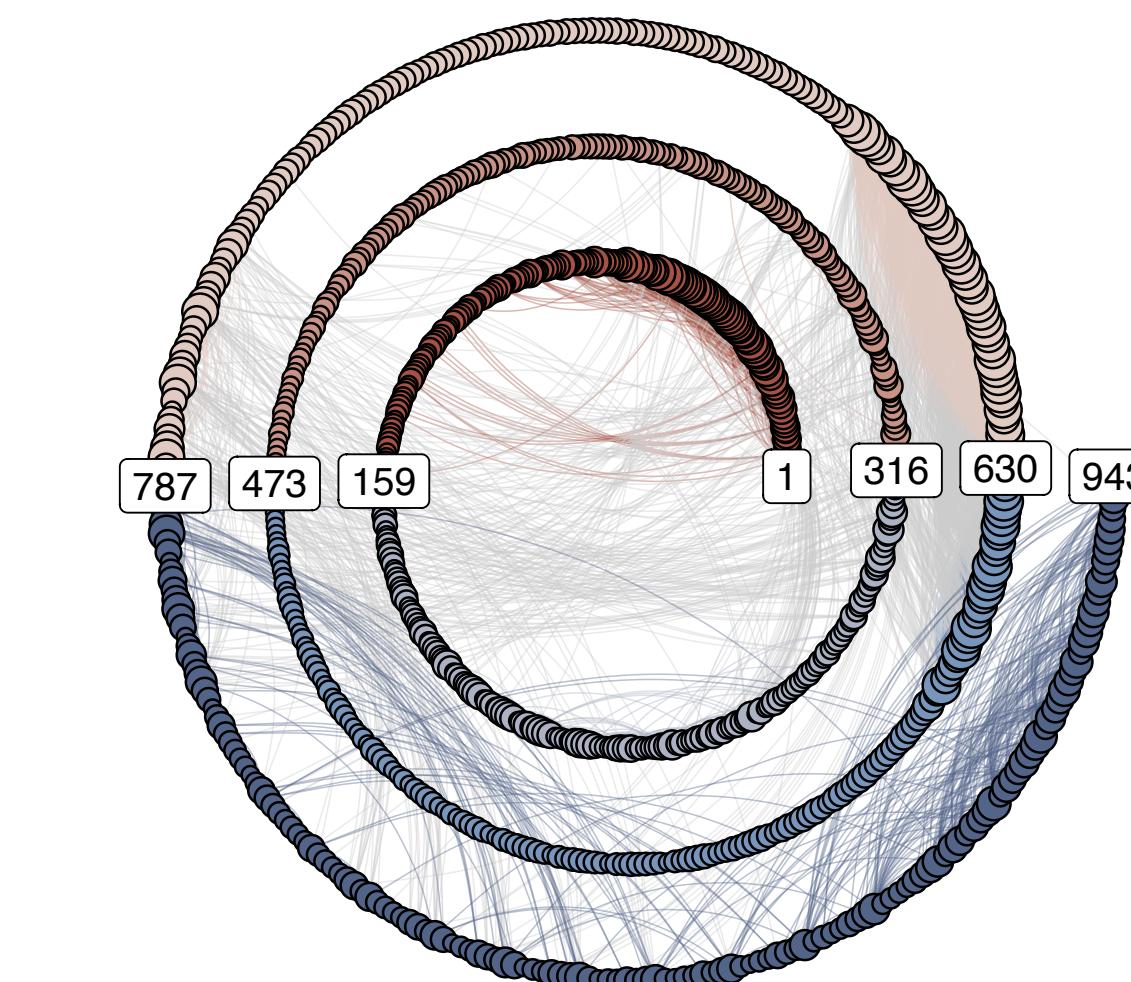
(a) Perceived Strength



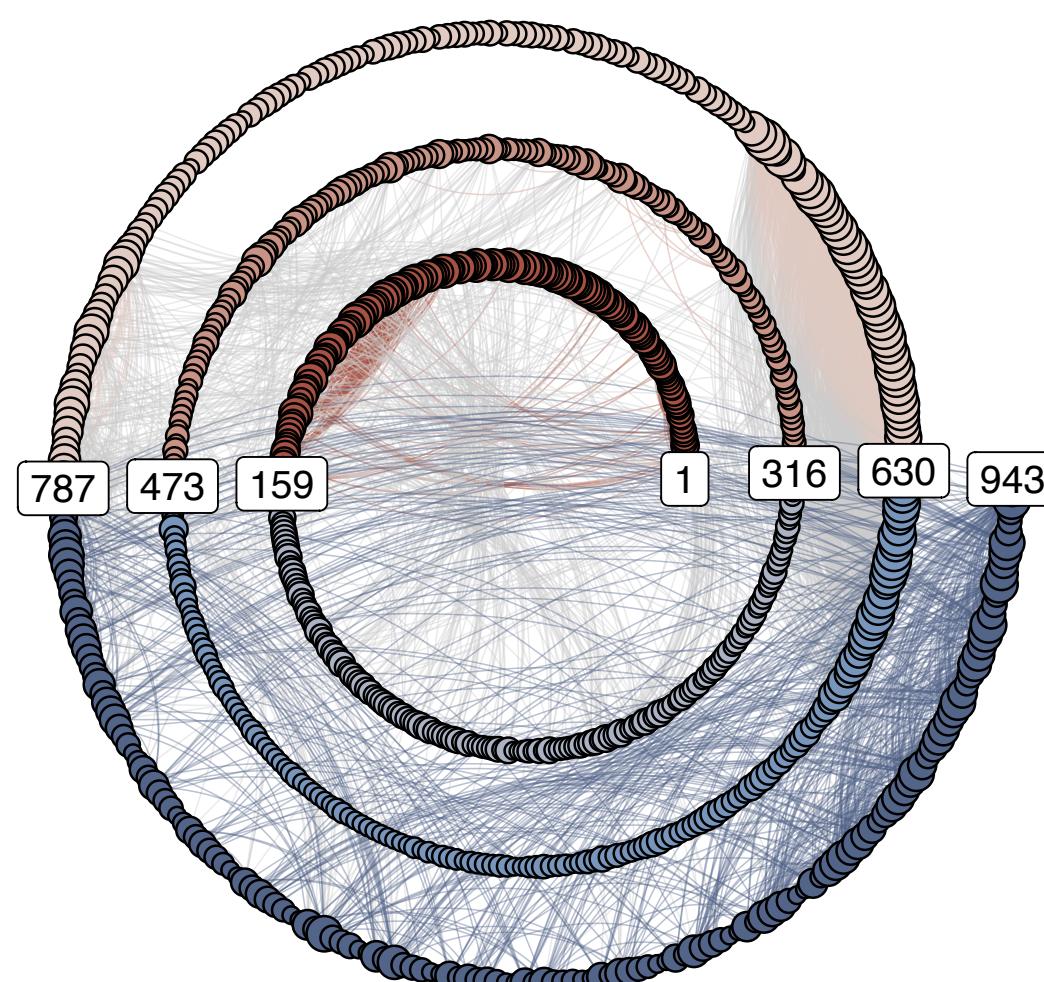
(b) Attractive Body



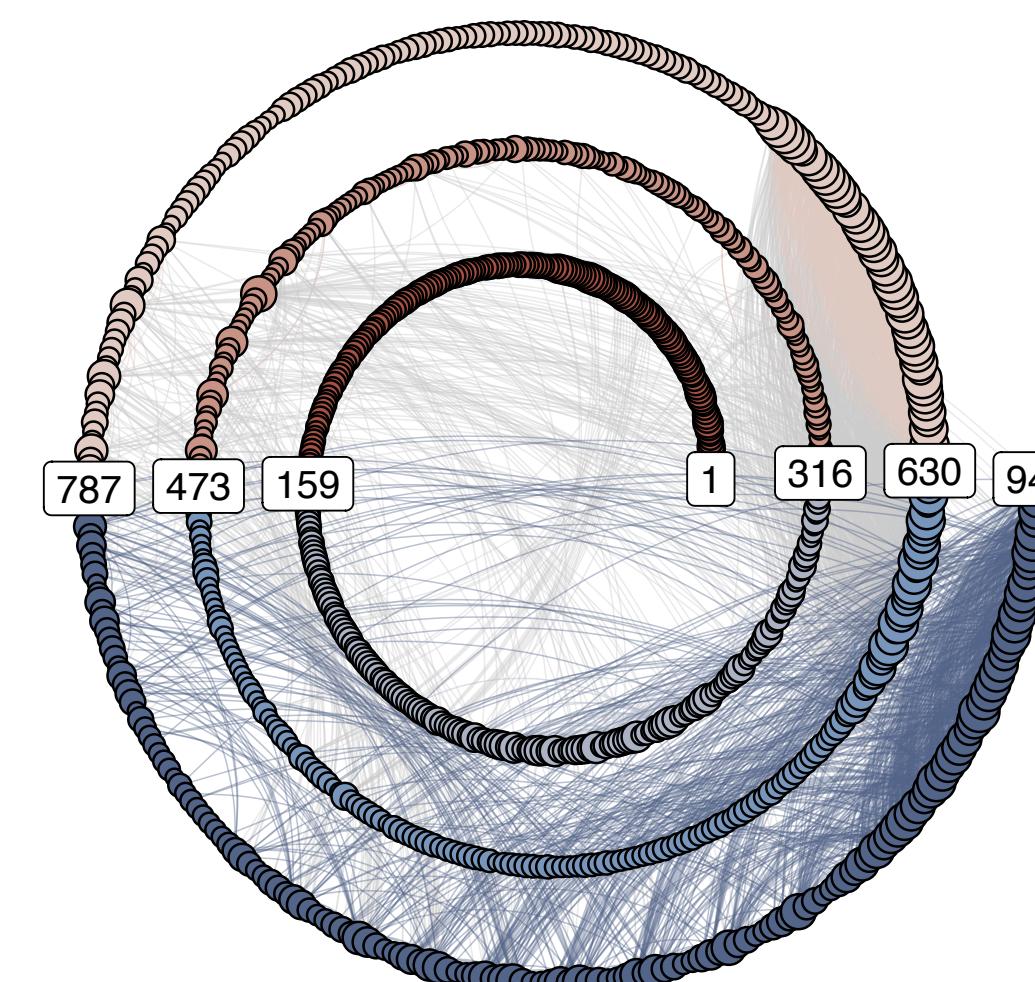
(c) Perceived Fitness



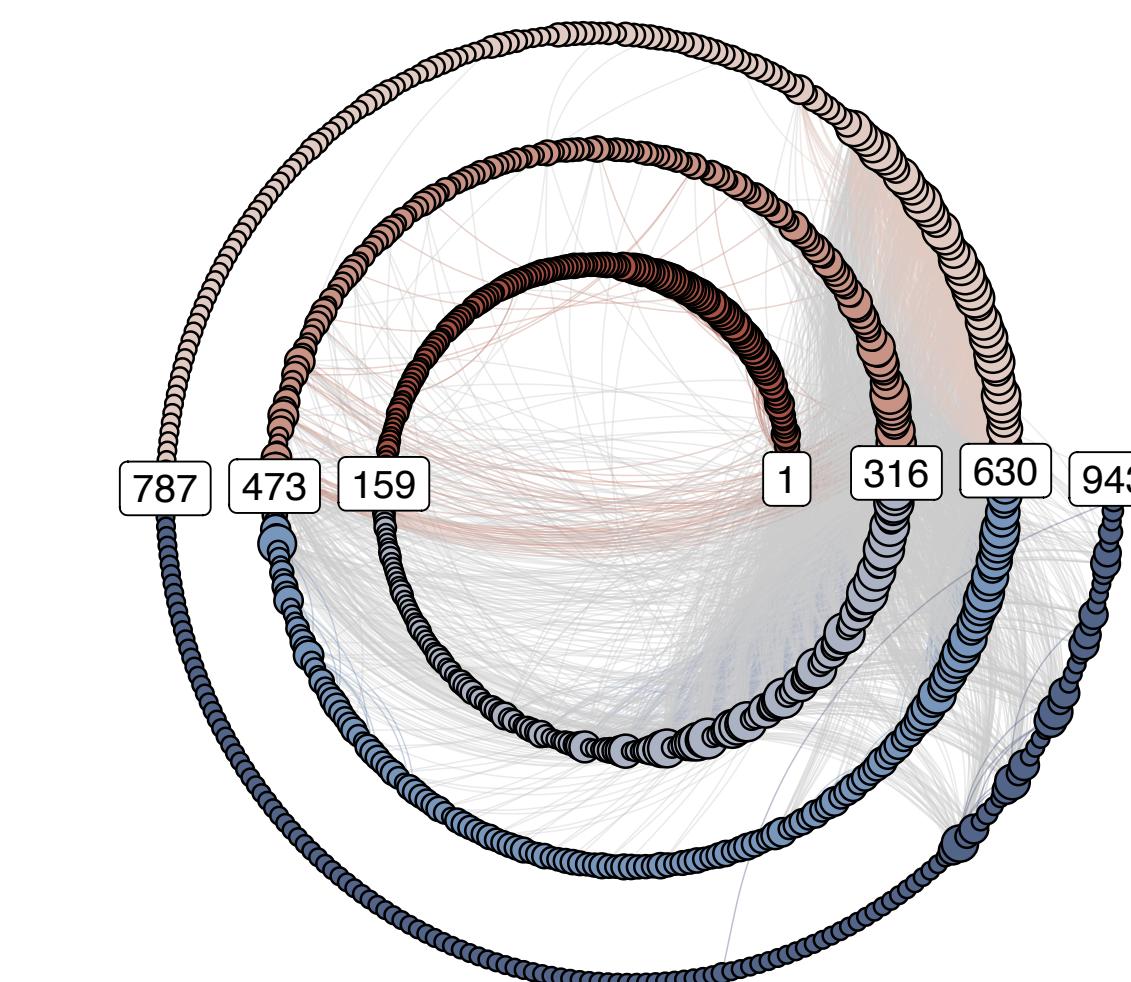
(d) Sport Competence



(e) Physical Self-worth

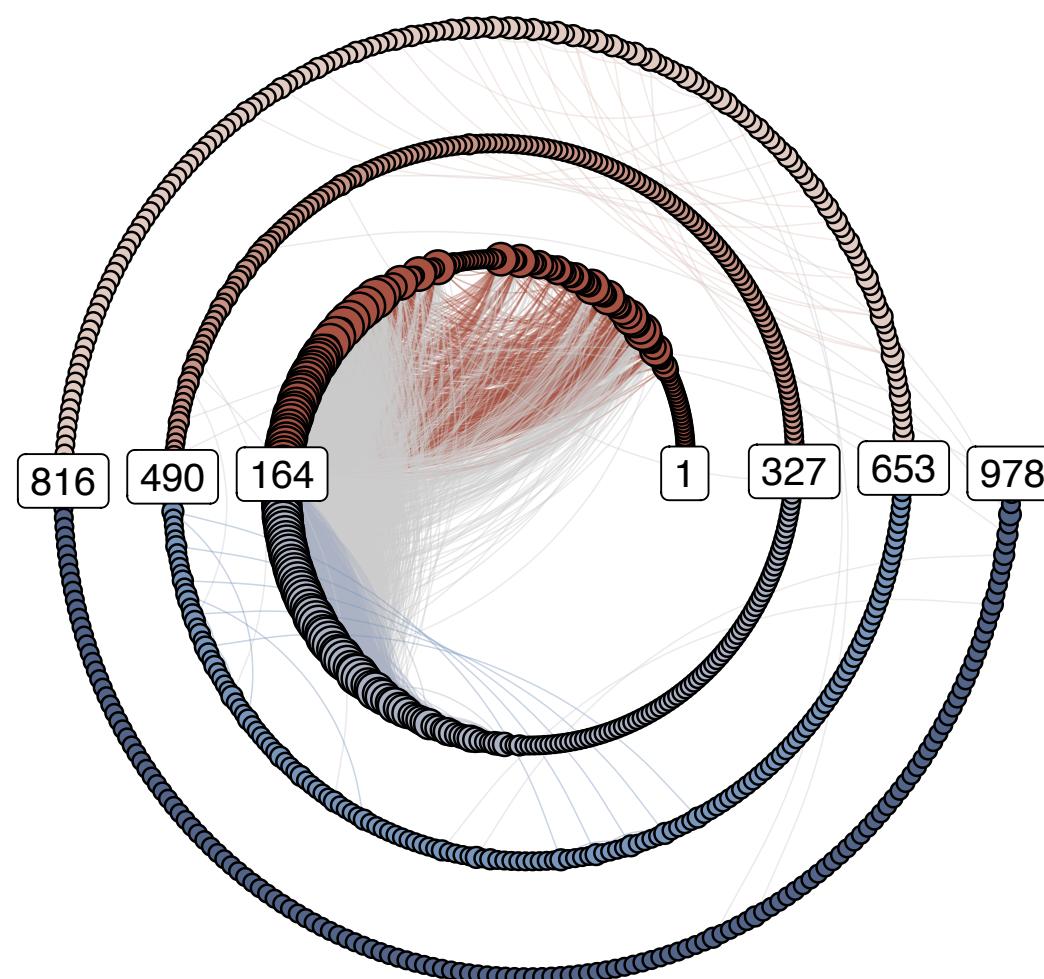


(f) Global Self-esteem

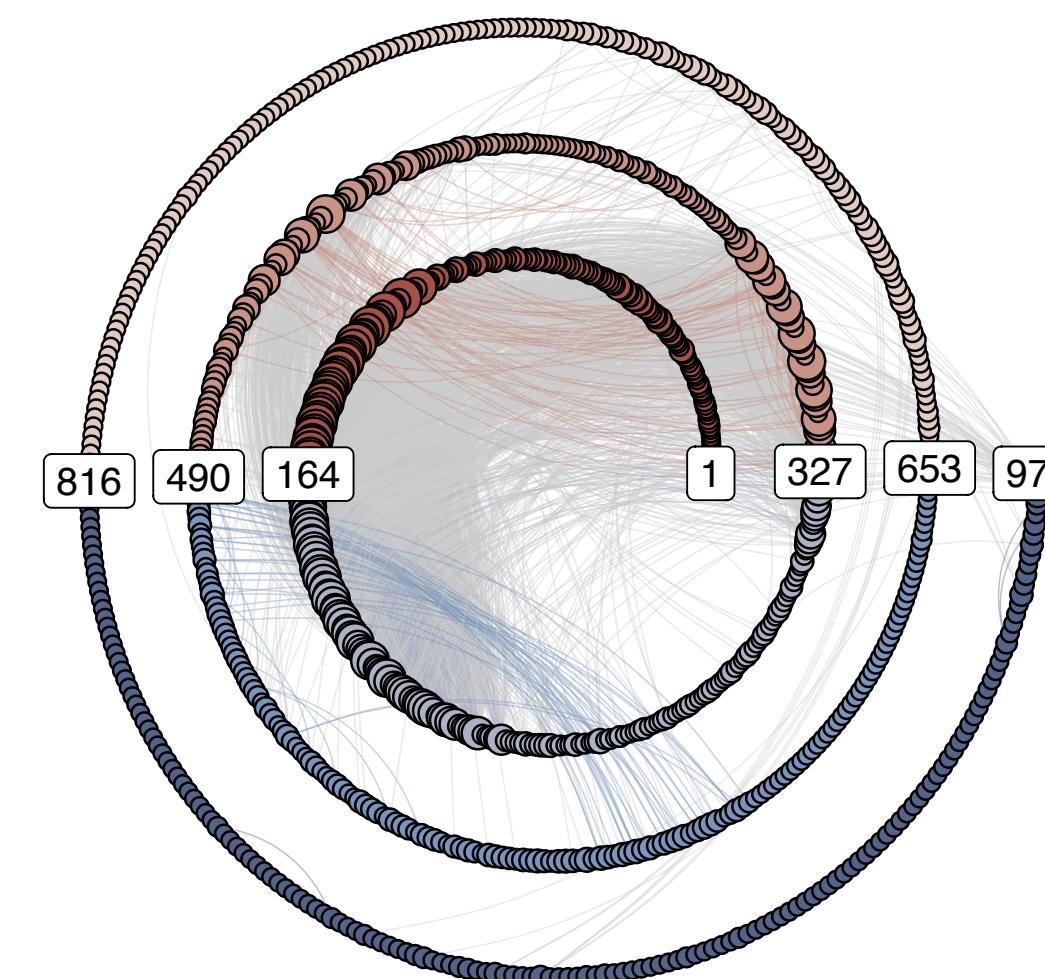


Participant 2

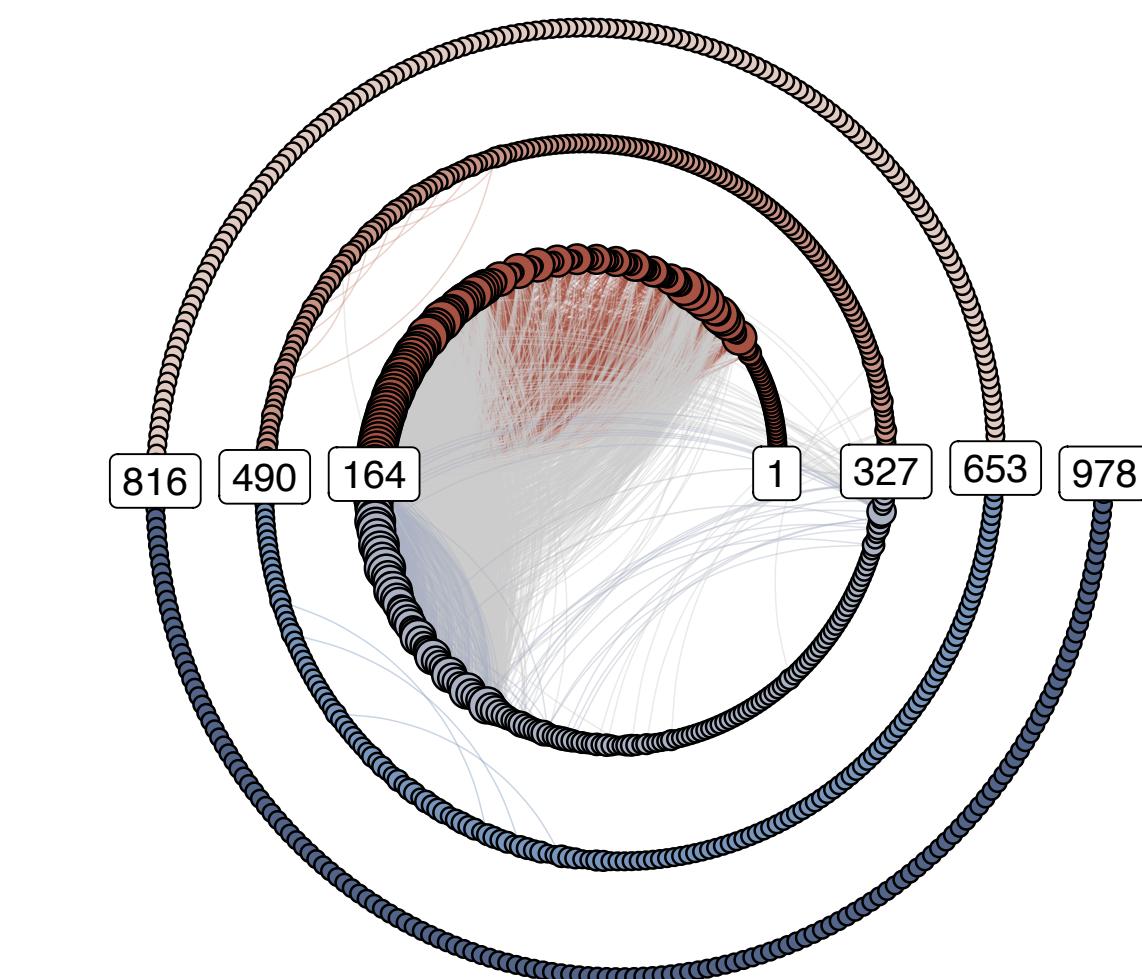
(a) Perceived Strength



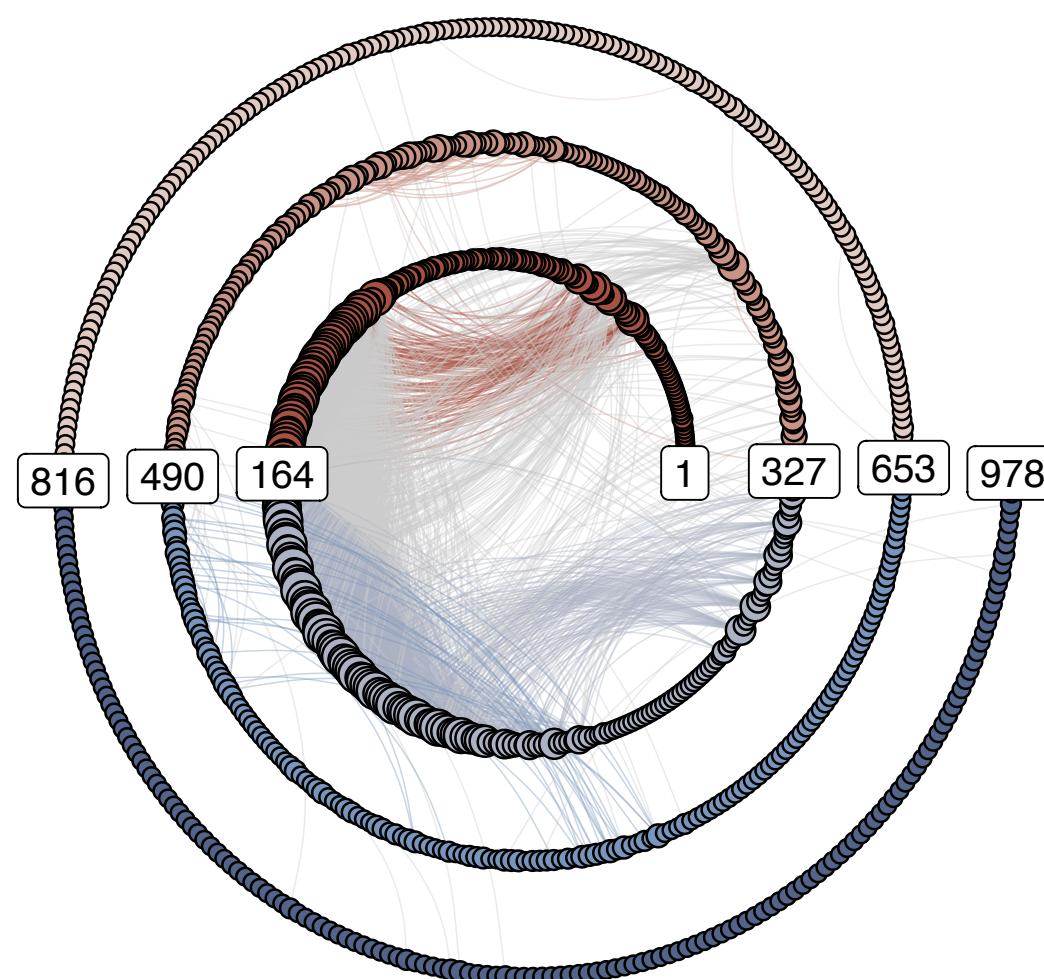
(b) Attractive Body



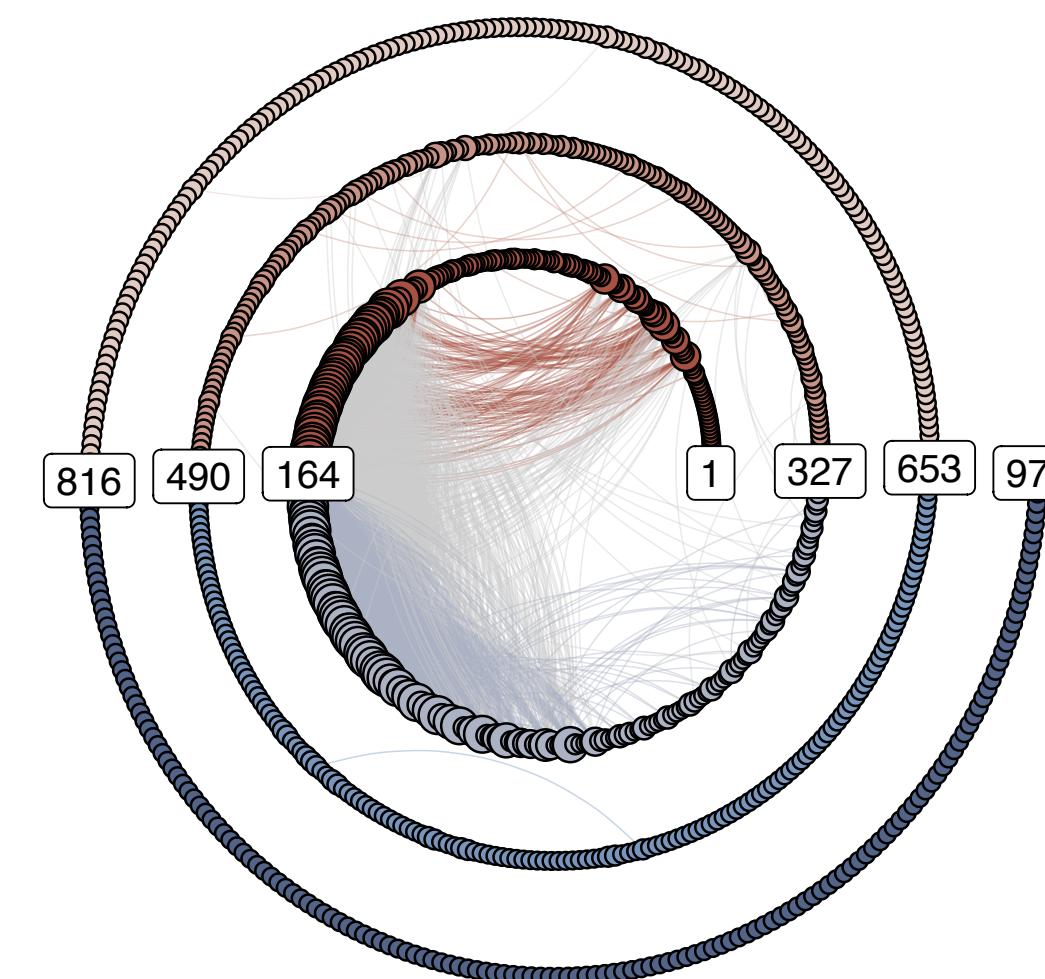
(c) Perceived Fitness



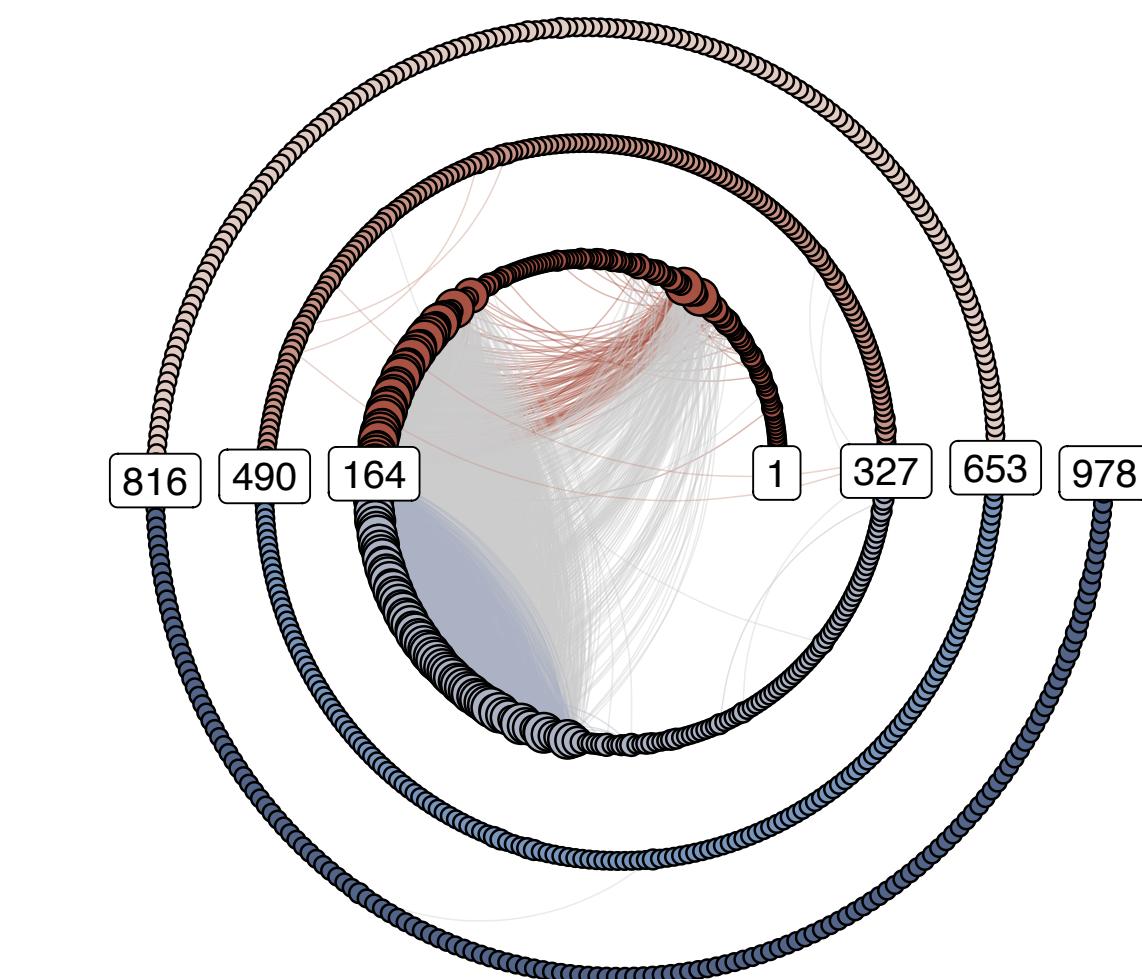
(d) Sport Competence



(e) Physical Self-worth

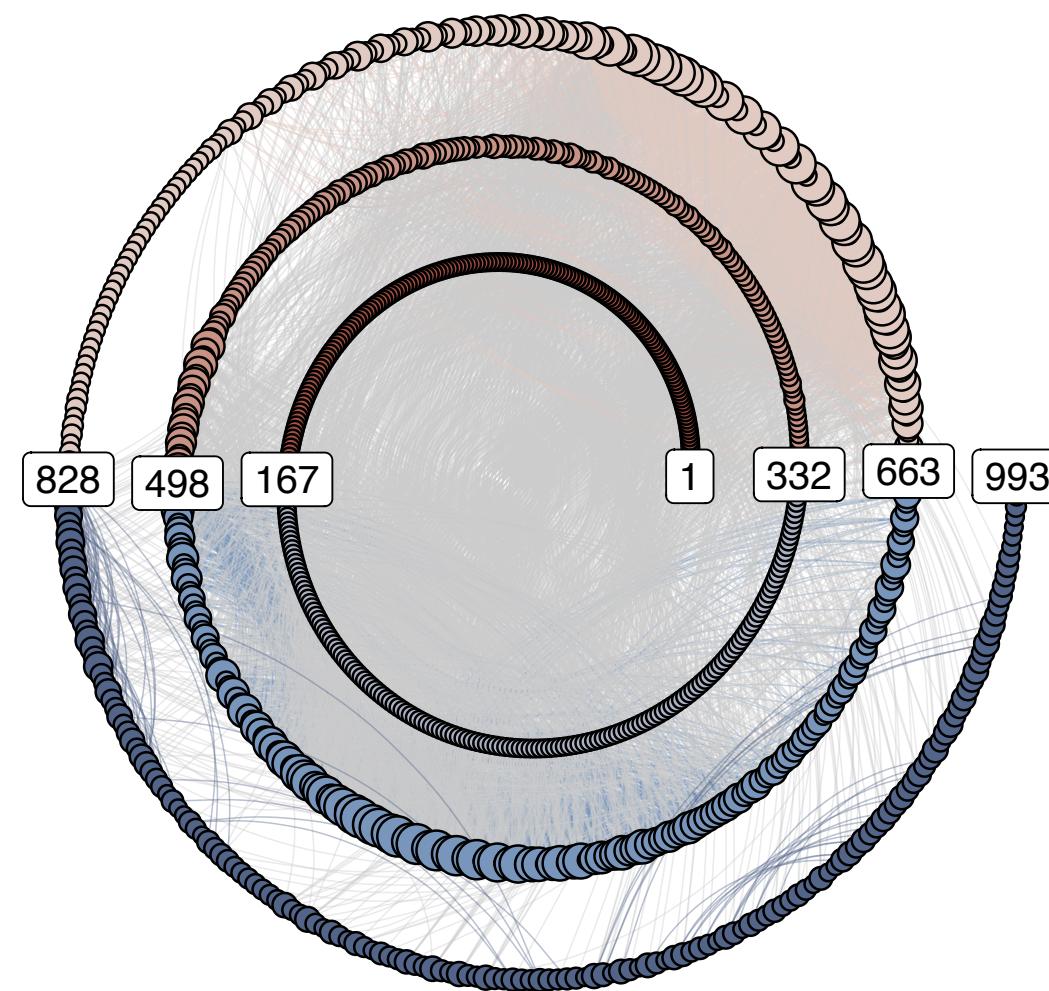


(f) Global Self-esteem

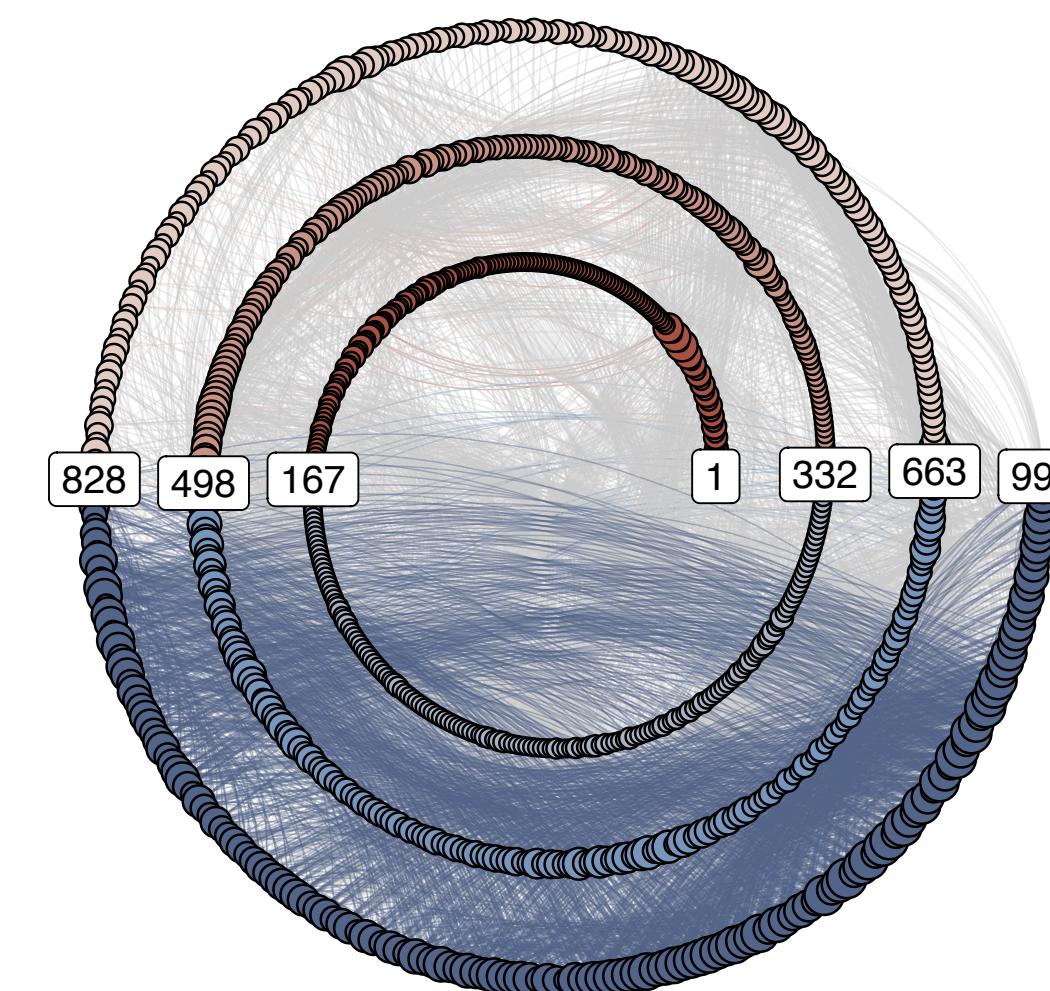


Participant 3

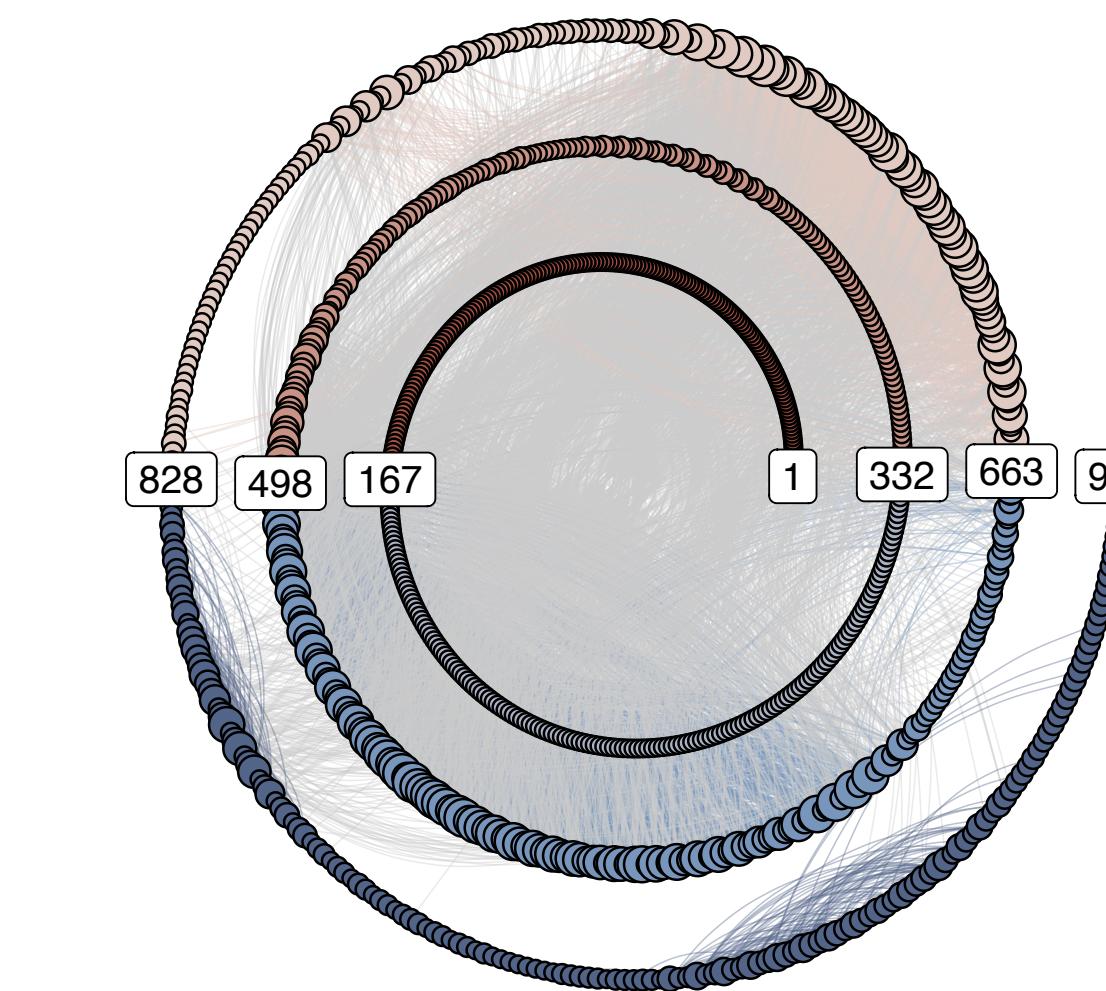
(a) Perceived Strength



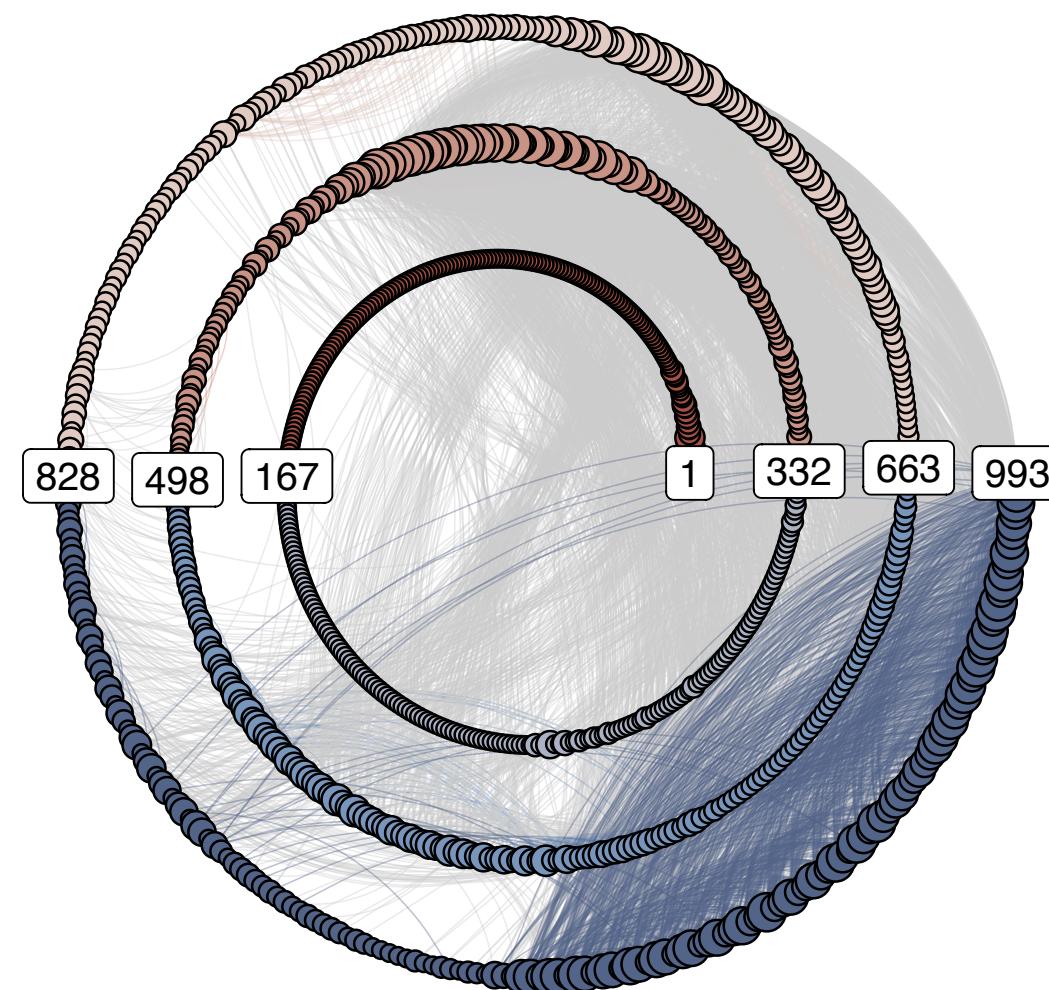
(b) Attractive Body



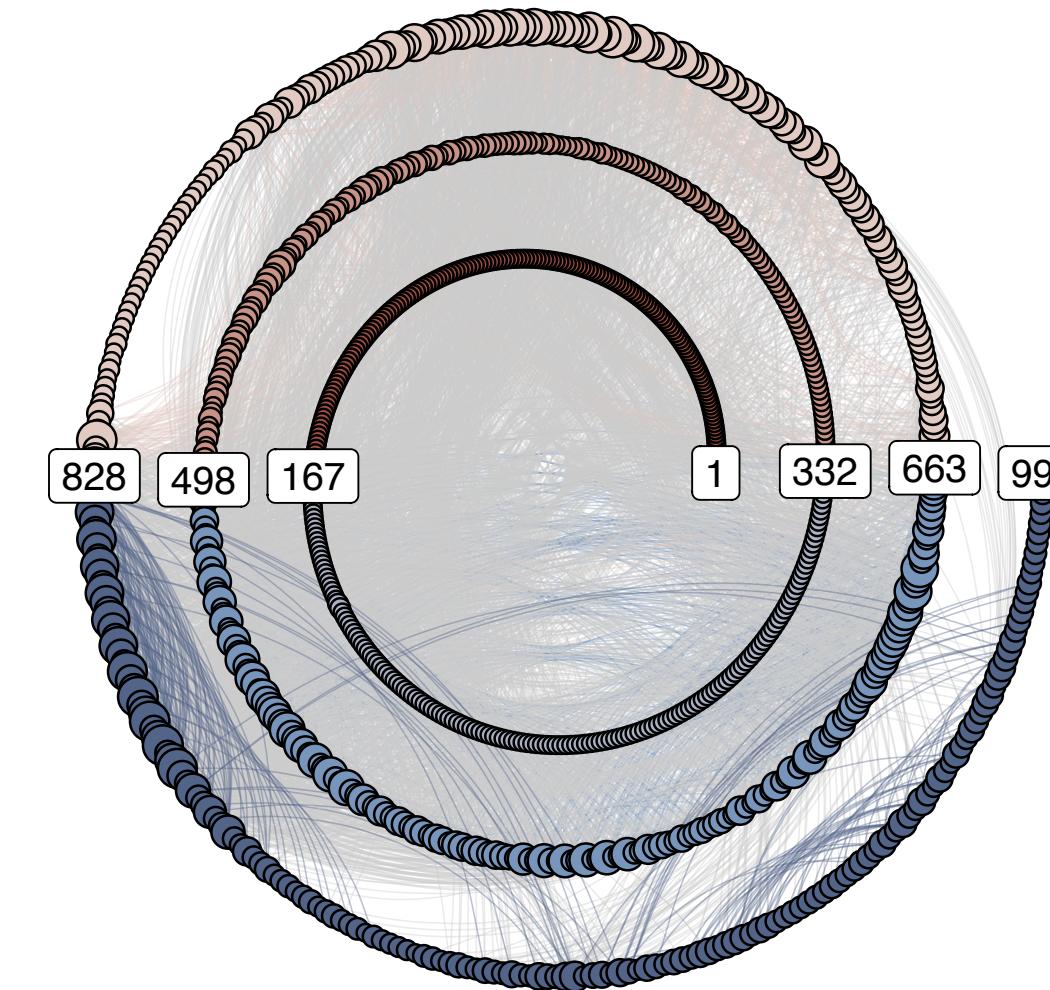
(c) Perceived Fitness



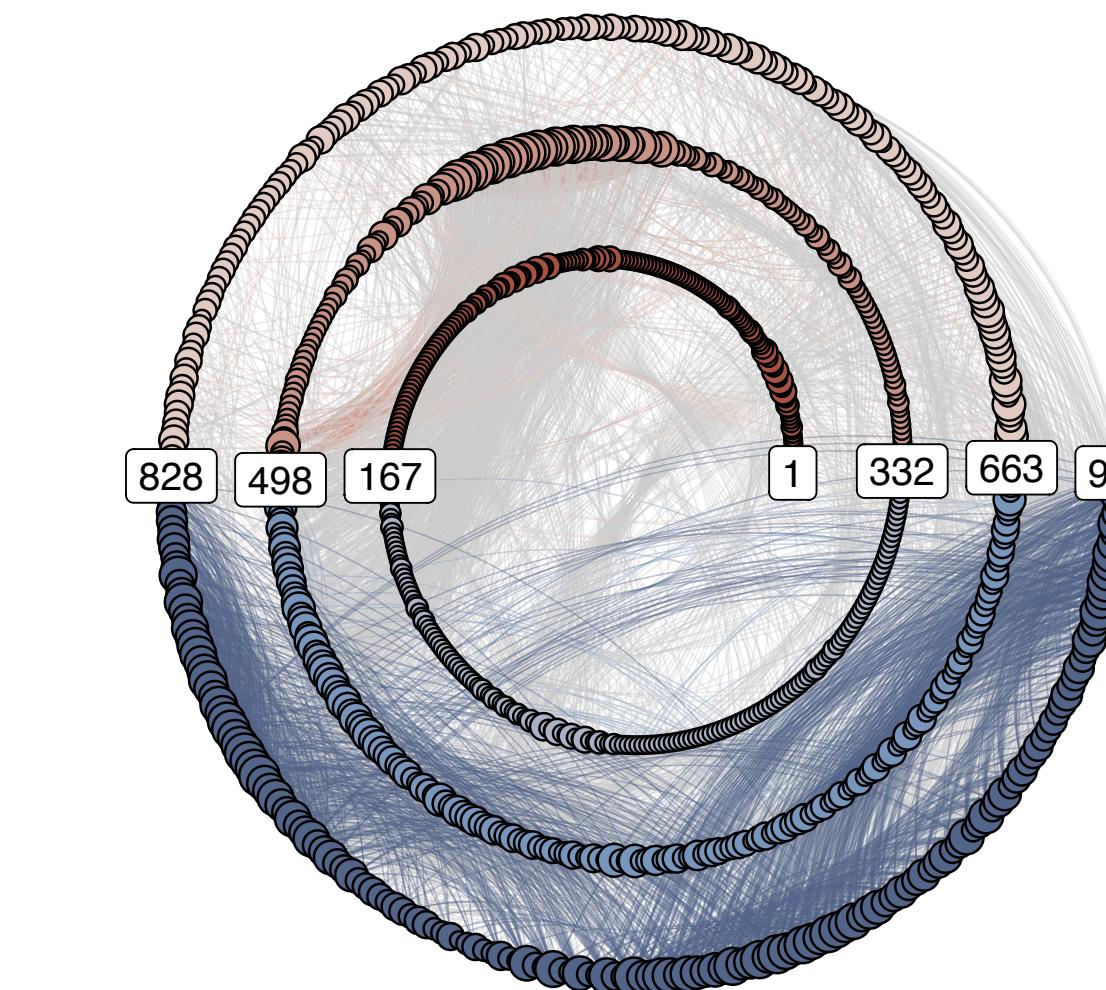
(d) Sport Competence



(e) Physical Self-worth

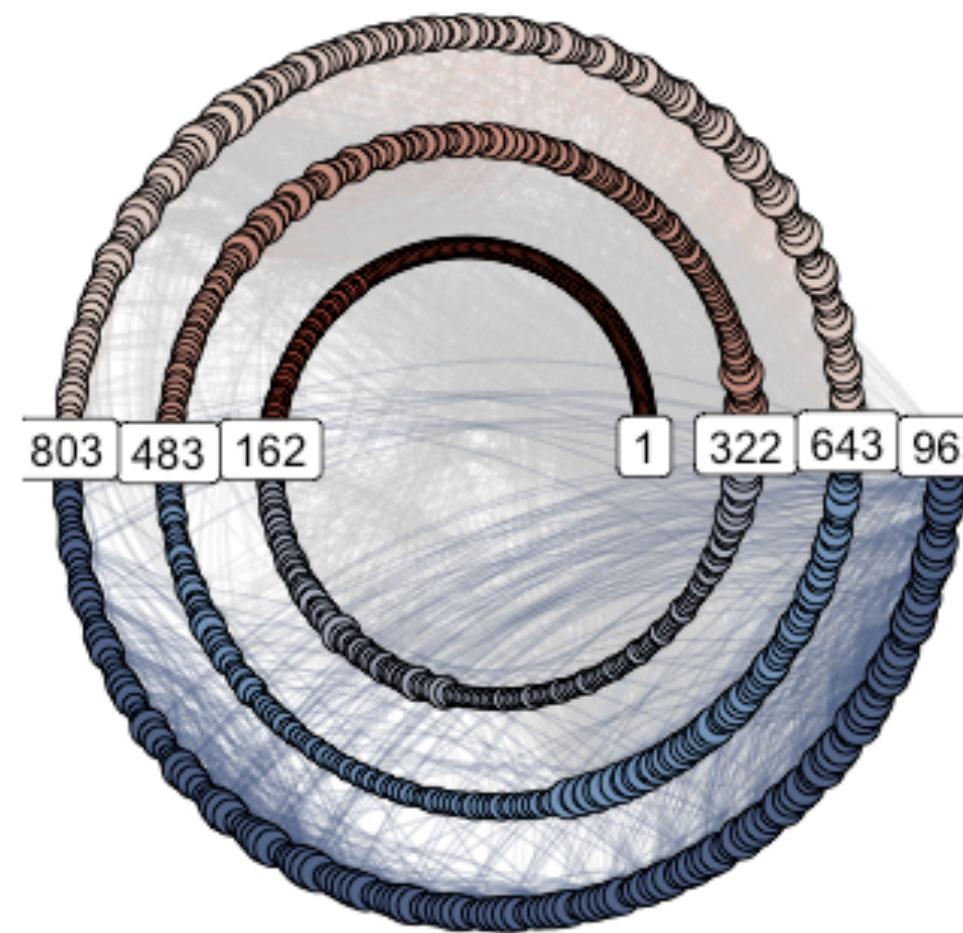


(f) Global Self-esteem

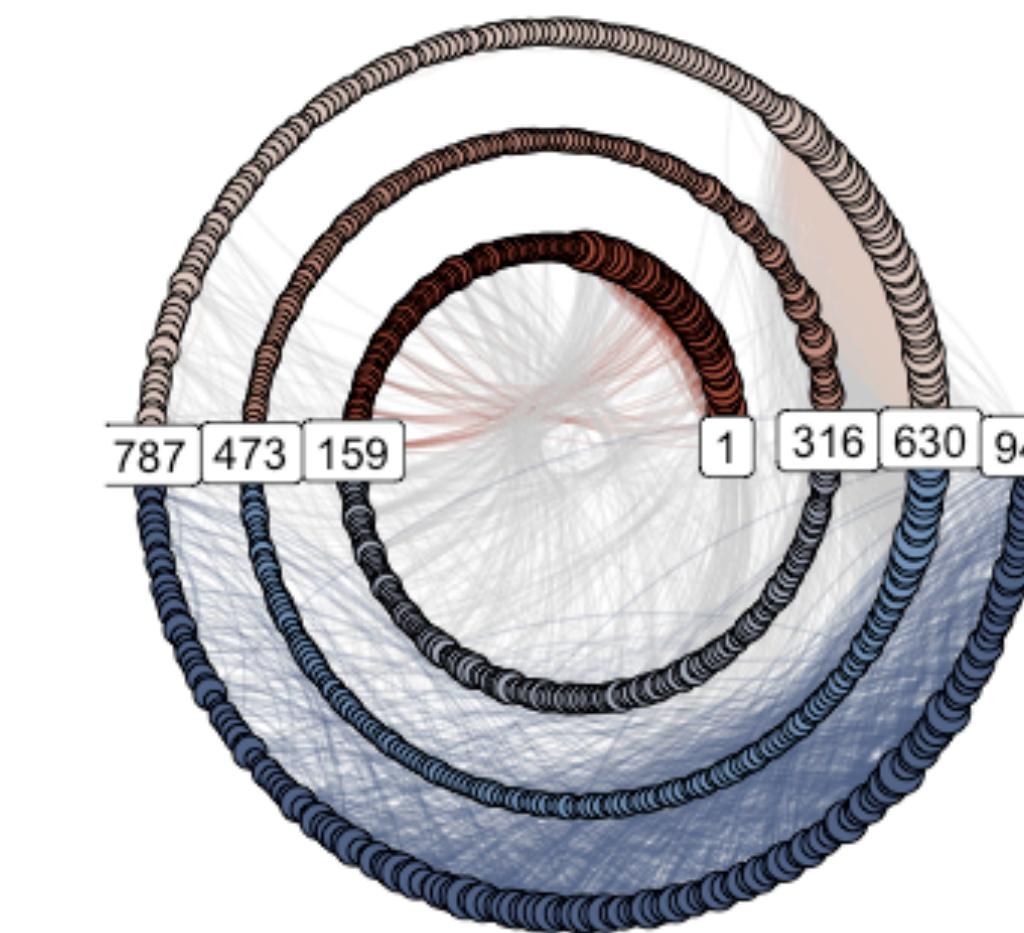


Participant 4

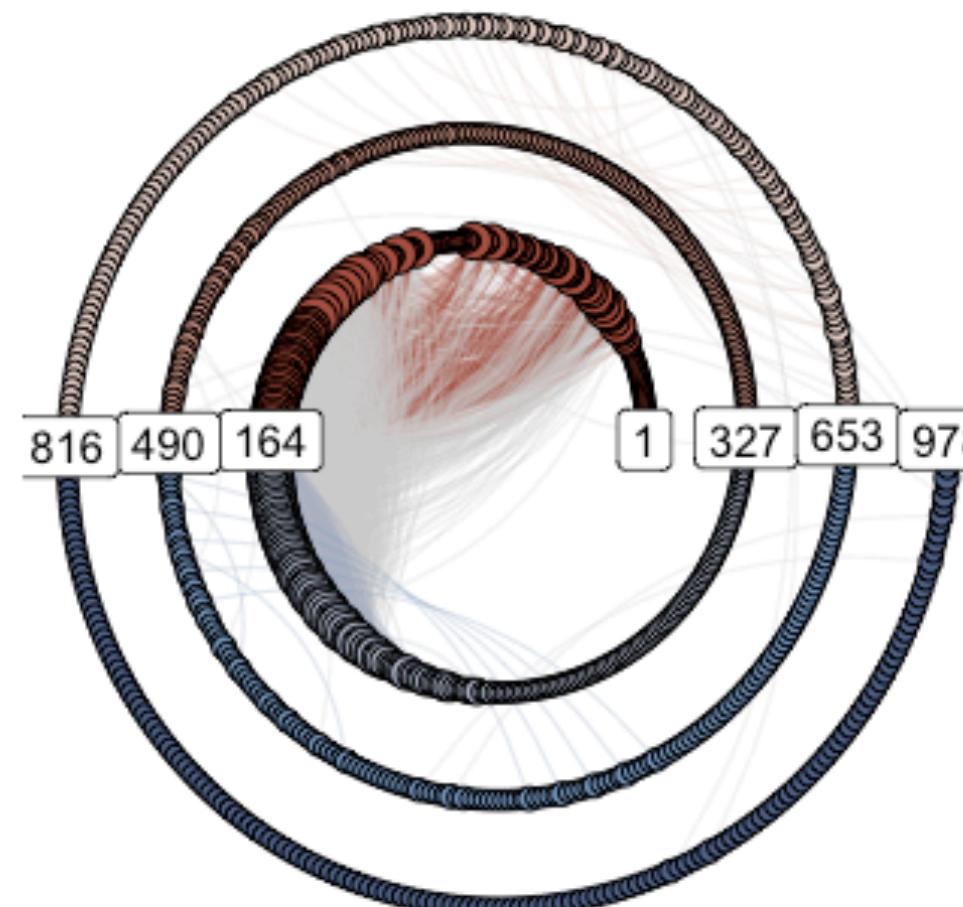
Participant 1 - FD = 1.21



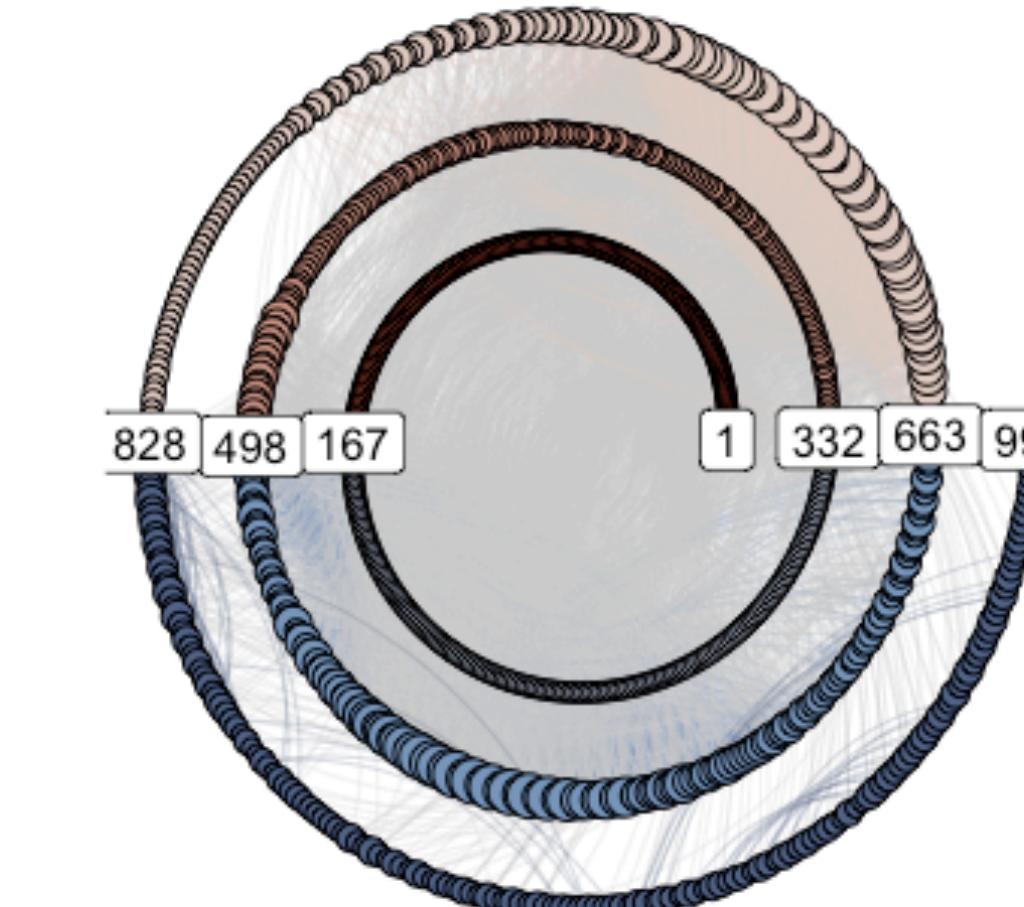
Participant 2 - FD = 1.16



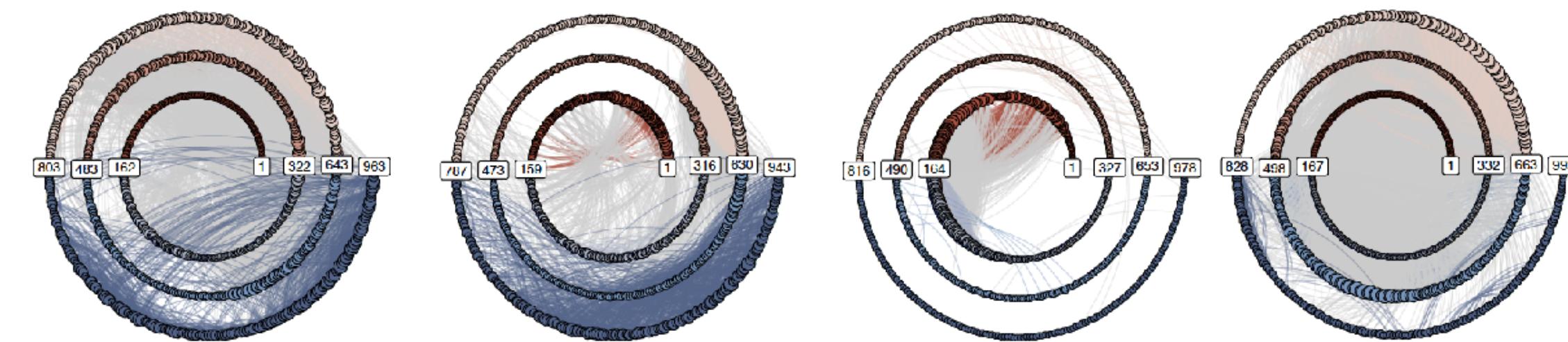
Participant 3 - FD = 1.18



Participant 4 - FD = 1.19



Perceived Strength



Perceived Strength	P1	P2	P3	P4
Centralization Degree	0.056	0.068	0.093	0.091
Centralization Betweenness	0.036	0.028	0.002	0.076
Centralization Closeness	0.002	0.001	0	0.001
Transitivity	0.387	0.528	0.783	0.51
Assortativity Degree	0.332	0.436	0.479	0.361
average Path Length	4.98	4.69	2.41	6.82
SWI	28.50	36.48	112.61	27.87
Diameter	12	36	9	22
Fractal Dimension	1.21	1.16	1.18	1.19

Multiplex Recurrence Networks

MULTIPLEX RECURRENCE NETWORKS

PHYSICAL REVIEW E 97, 012312 (2018)

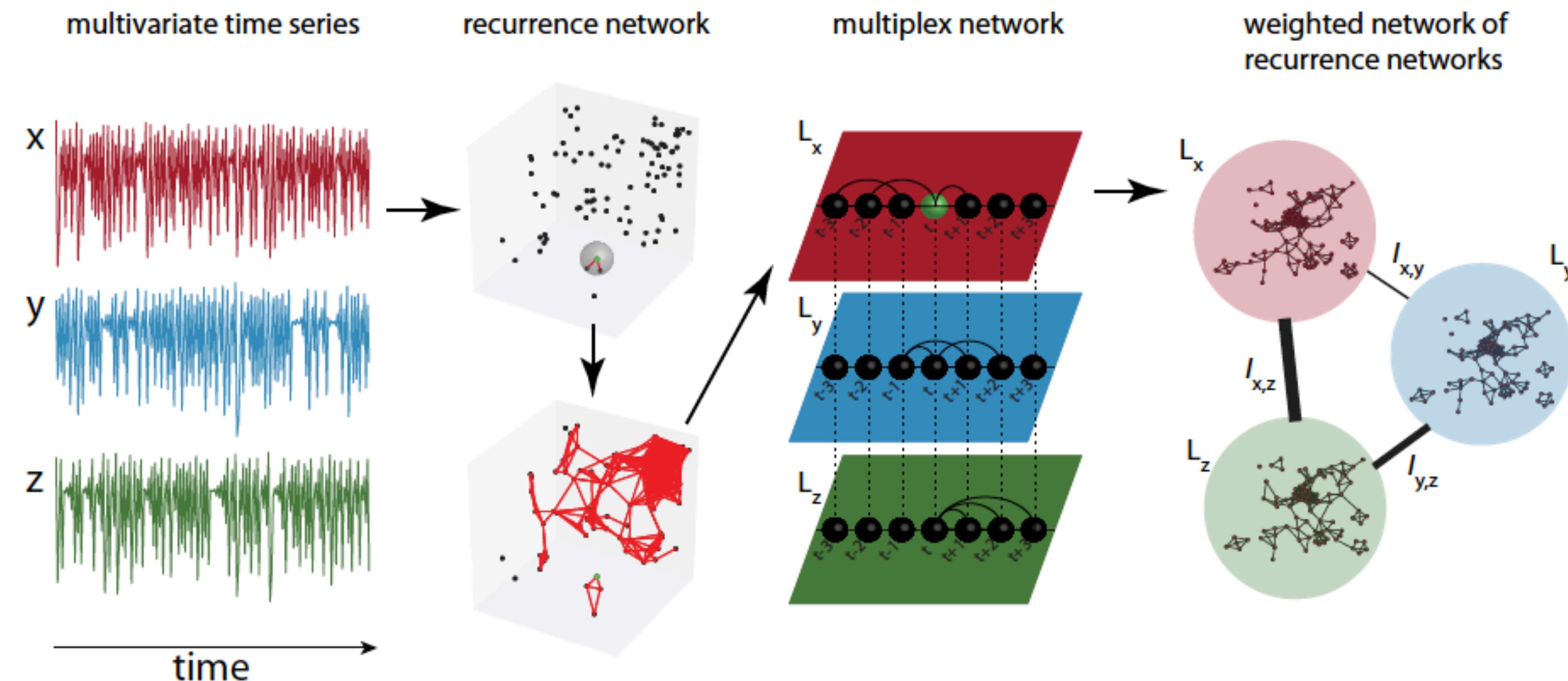


FIG. 1. Illustration of the procedure for generating network structures from a multivariate time series: multivariate time series → recurrence networks → multiplex recurrence network → weighted network of recurrence networks. Dashed lines between multiplex networks' layers connect all layers to all.

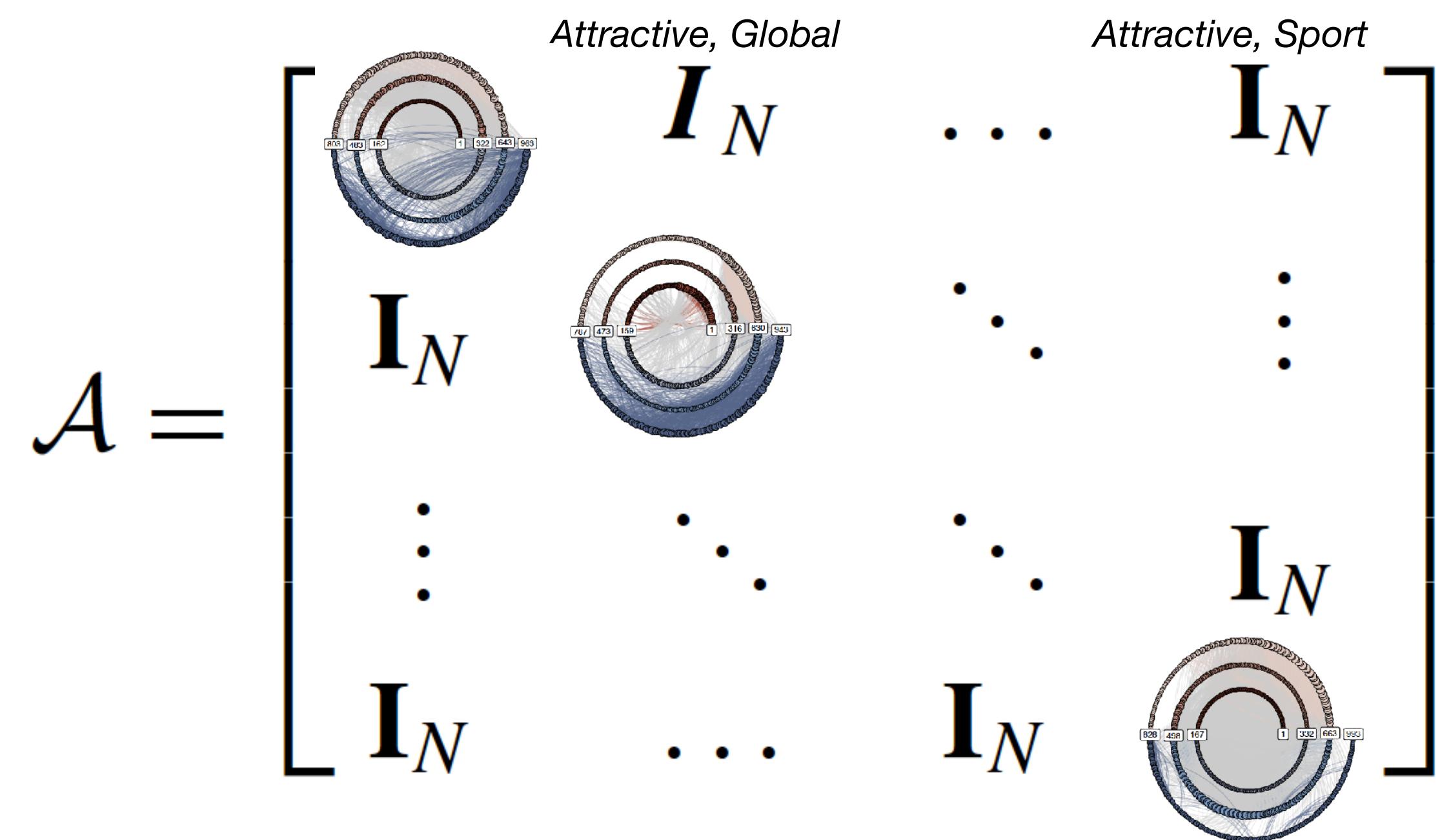
Interlayer Mutual Information

$$I_{\alpha,\beta} = \sum_{\kappa^{[\alpha]}} \sum_{\kappa^{[\beta]}} P(\kappa^{[\alpha]}, \kappa^{[\beta]}) \log \frac{P(\kappa^{[\alpha]}, \kappa^{[\beta]})}{P(\kappa^{[\alpha]}), P(\kappa^{[\beta]})}$$

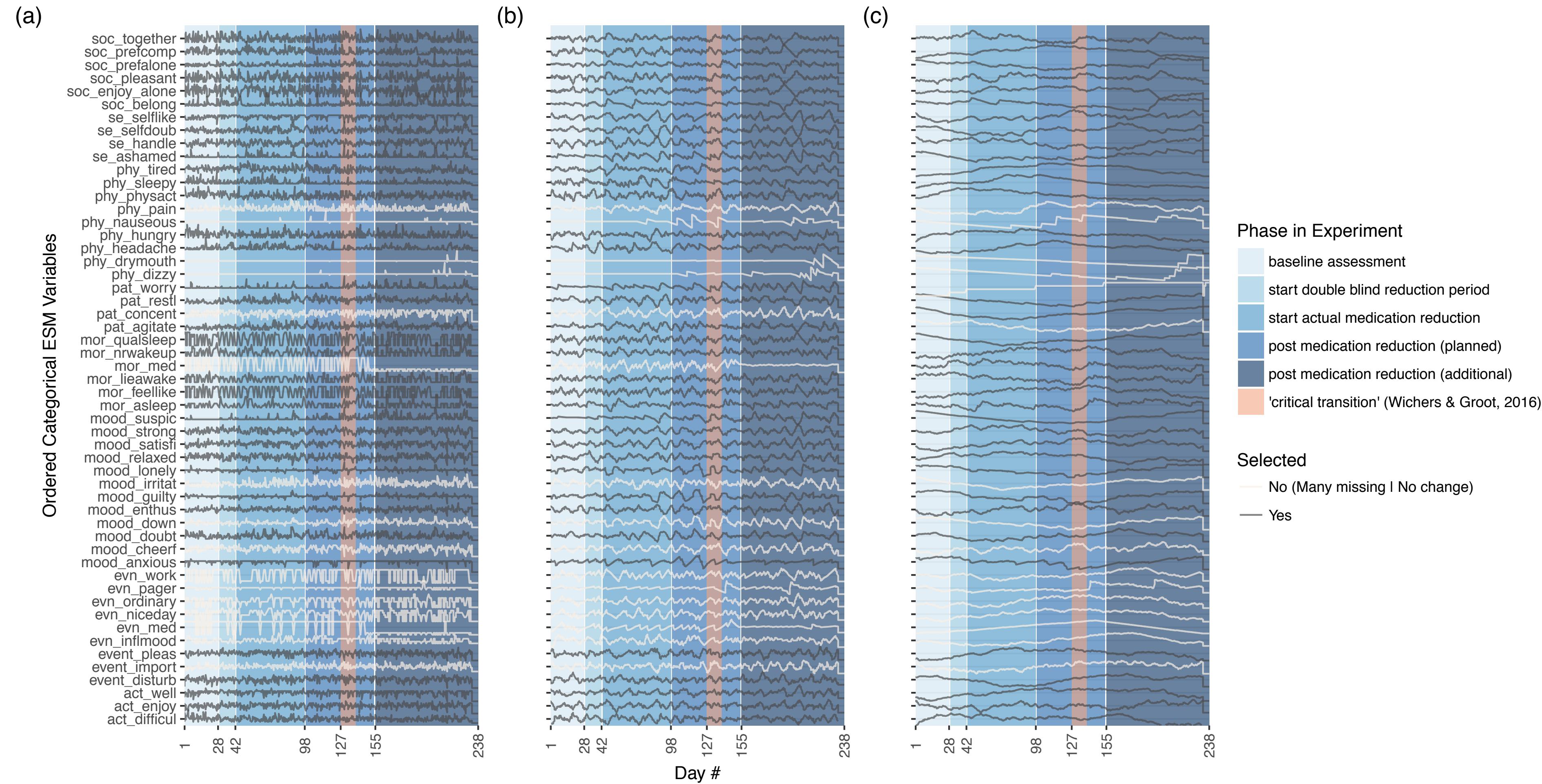
**Same number of nodes (time points)
Different degree, etc.**

Interlayer Mutual Information

$$I_{\alpha,\beta} = \sum_{\kappa^{[\alpha]}} \sum_{\kappa^{[\beta]}} P\left(\kappa^{[\alpha]}, \kappa^{[\beta]}\right) \log \frac{P\left(\kappa^{[\alpha]}, \kappa^{[\beta]}\right)}{P\left(\kappa^{[\alpha]}\right), P\left(\kappa^{[\beta]}\right)}$$



Critical Slowing Down as a Personalized Early Warning Signal for Depression



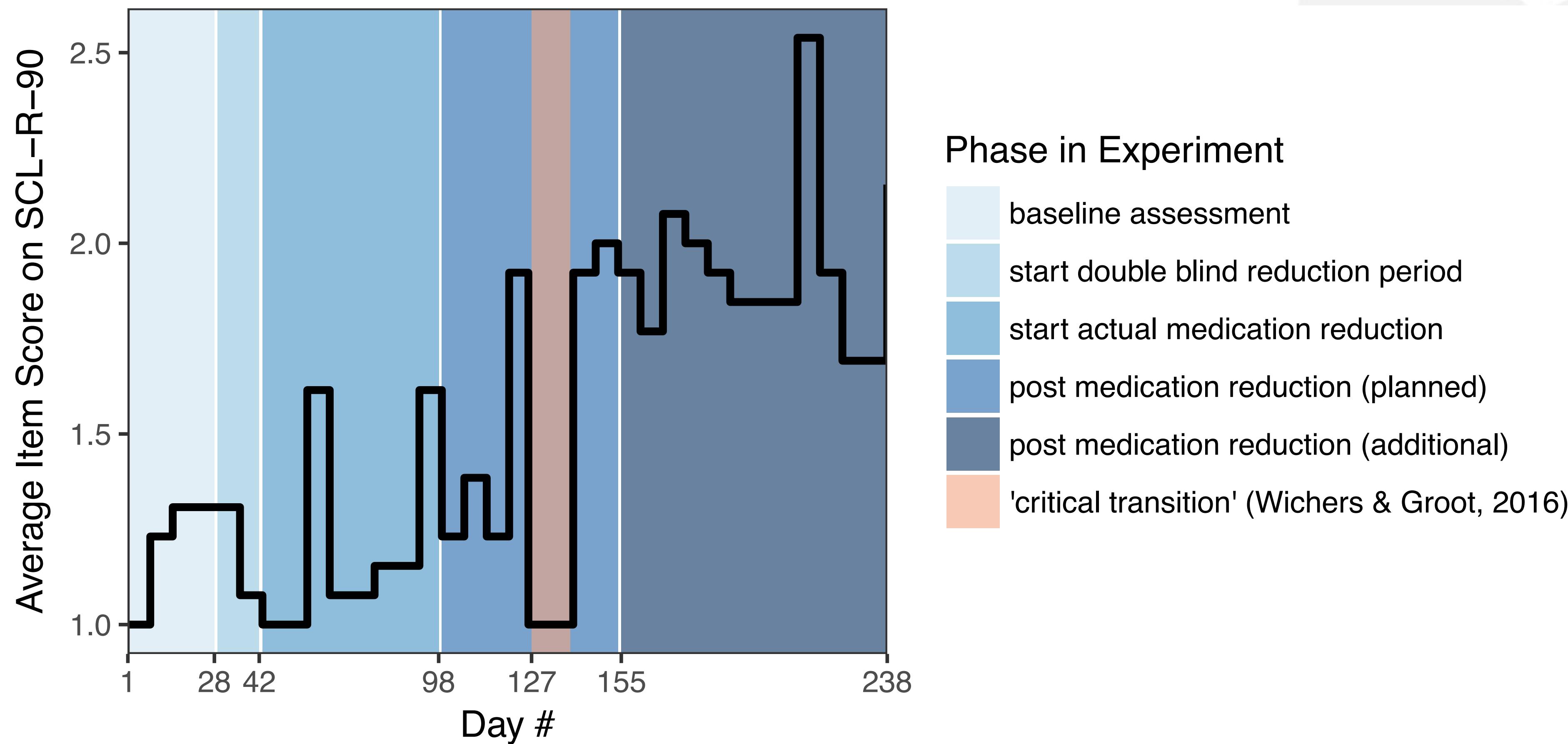
Wichers, M., Groot, P. C., Psychosystems, ESM Grp, & EWS Grp (2016). Critical Slowing Down as a Personalized Early Warning Signal for Depression. Psychotherapy and psychosomatics, 85(2), 114-116.
DOI: 10.1159/000441458

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



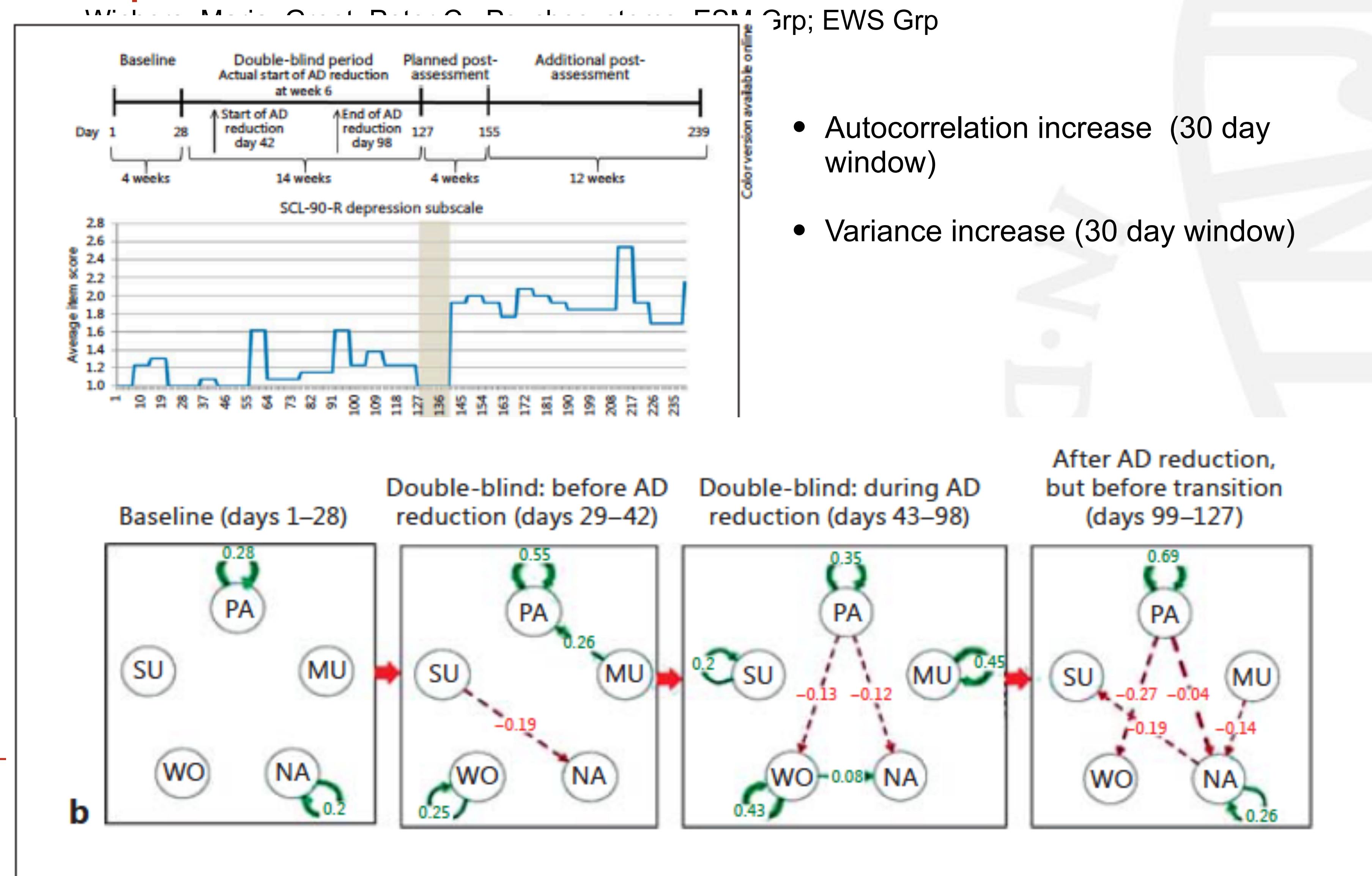
Wichers, M., Groot, P. C., Psychosystems, ESM Grp, & EWS Grp (2016). Critical Slowing Down as a Personalized Early Warning Signal for Depression. *Psychotherapy and psychosomatics*, 85(2), 114-116.
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Radboud University Nijmegen

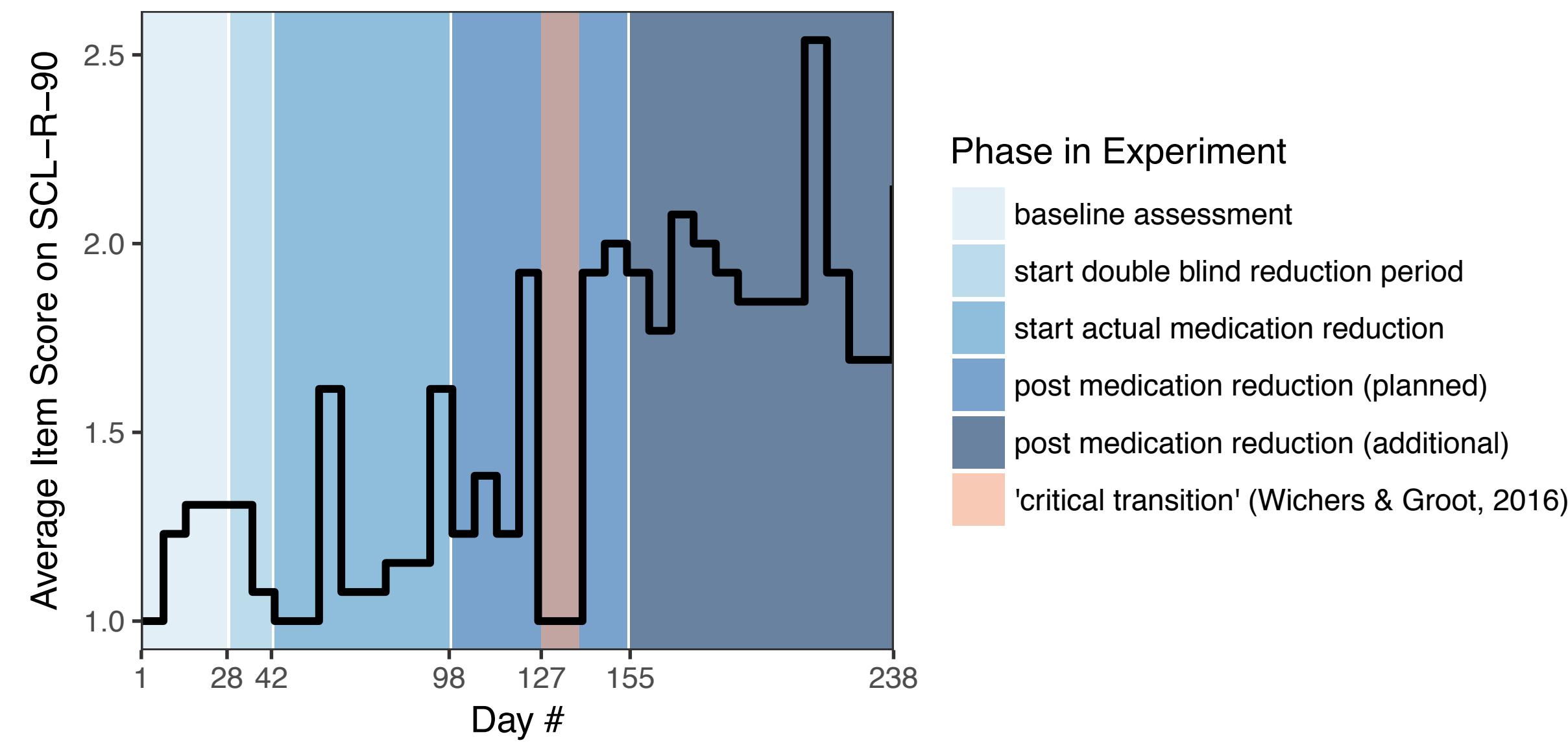
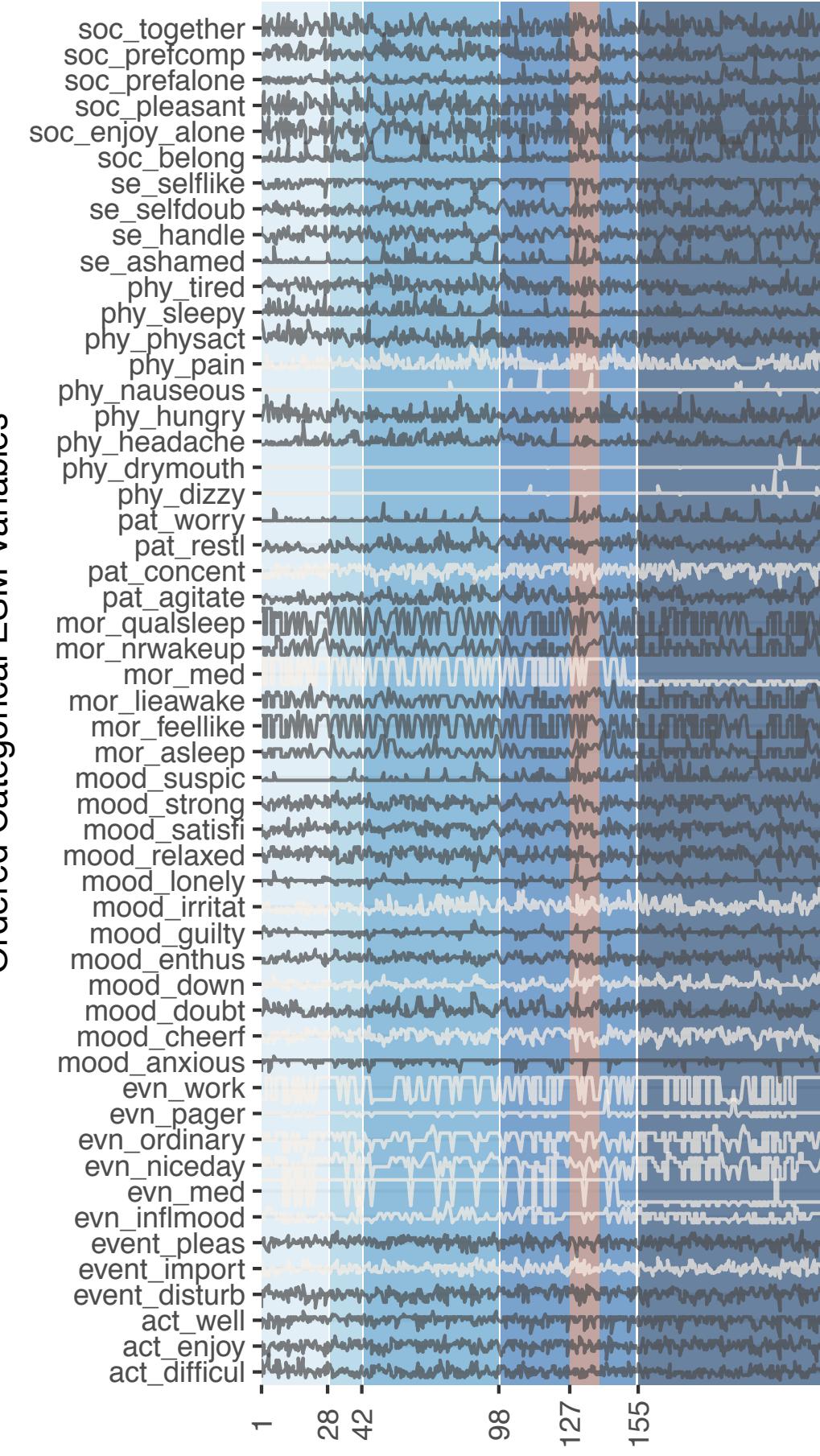


Critical Slowing Down as a Personalized Early Warning Signal for Depression



“Critical Slowing Down as a Personalized Early Warning Signal for Depression”

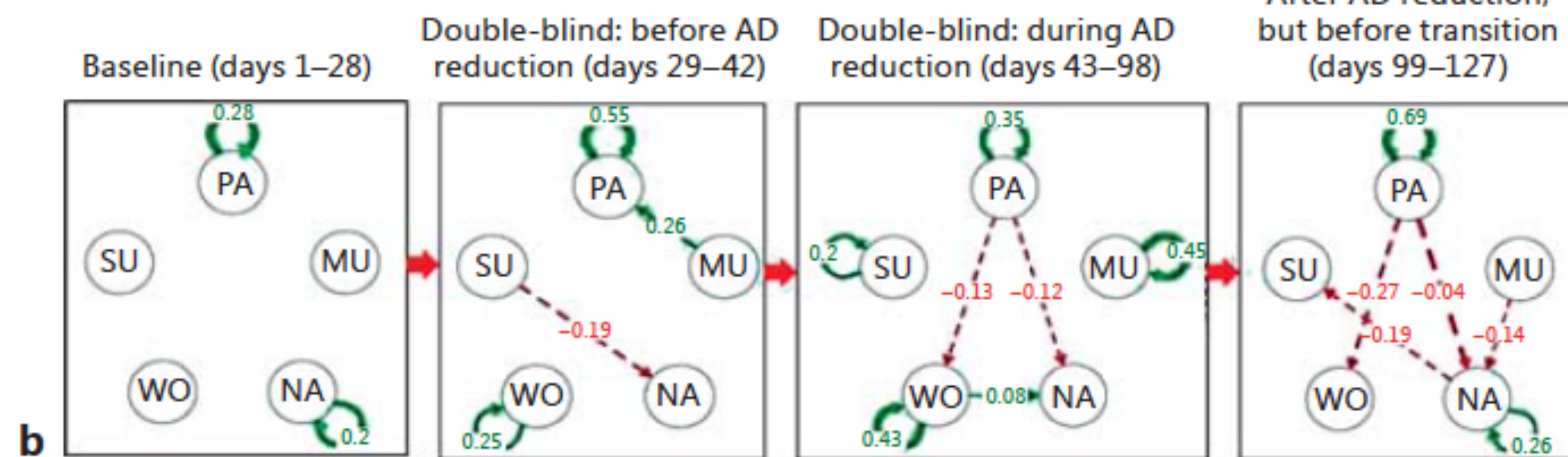
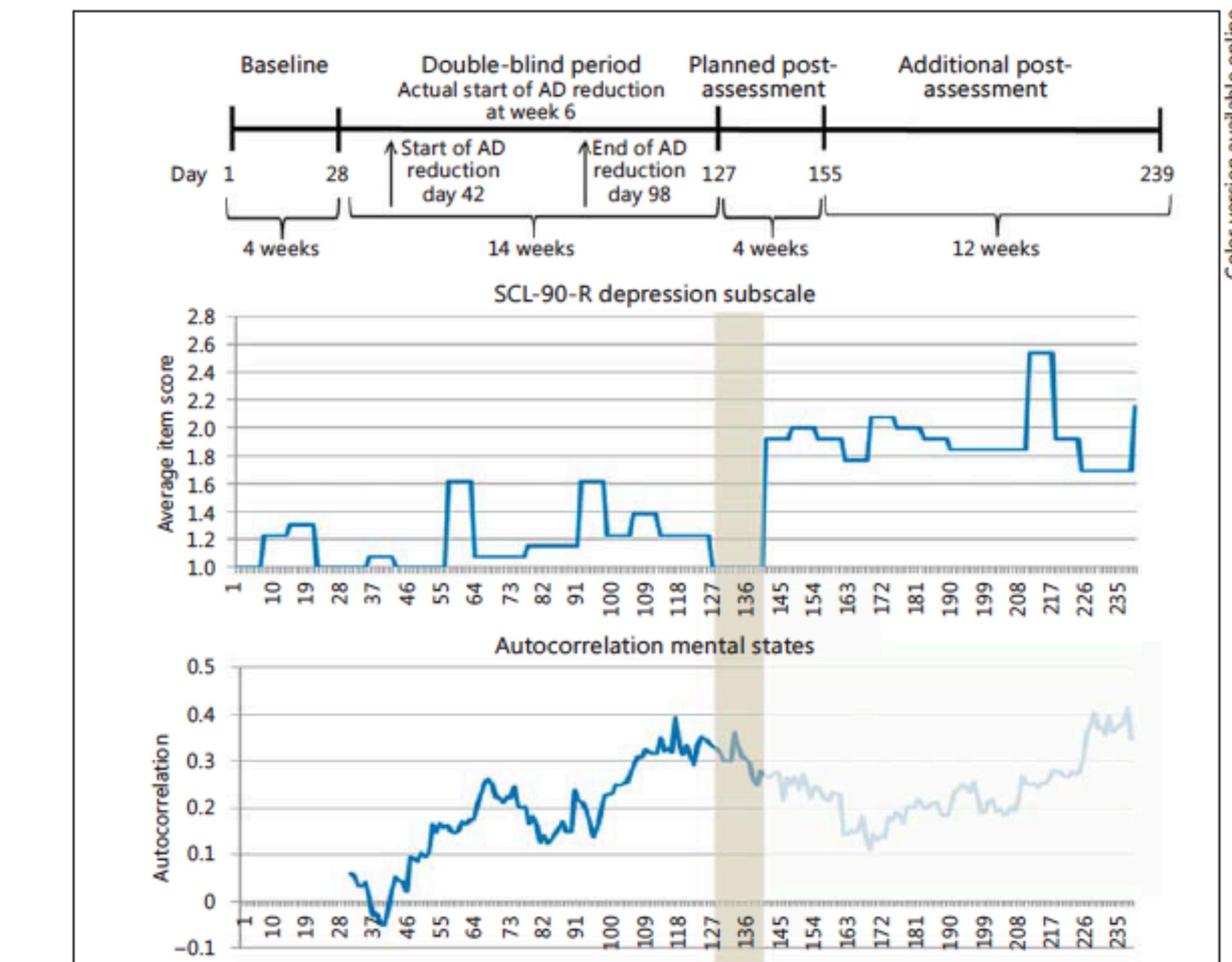
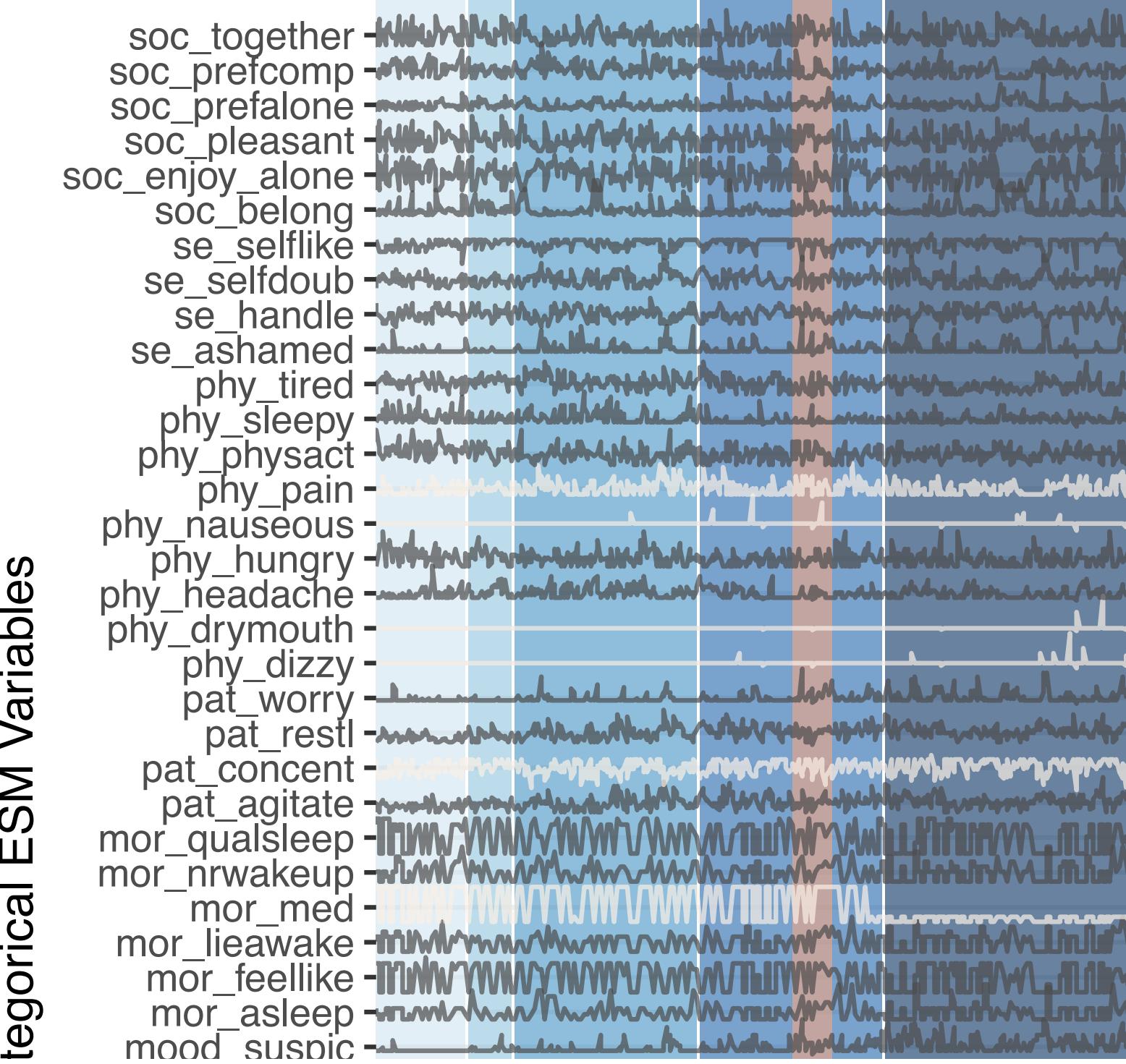
(a)



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).

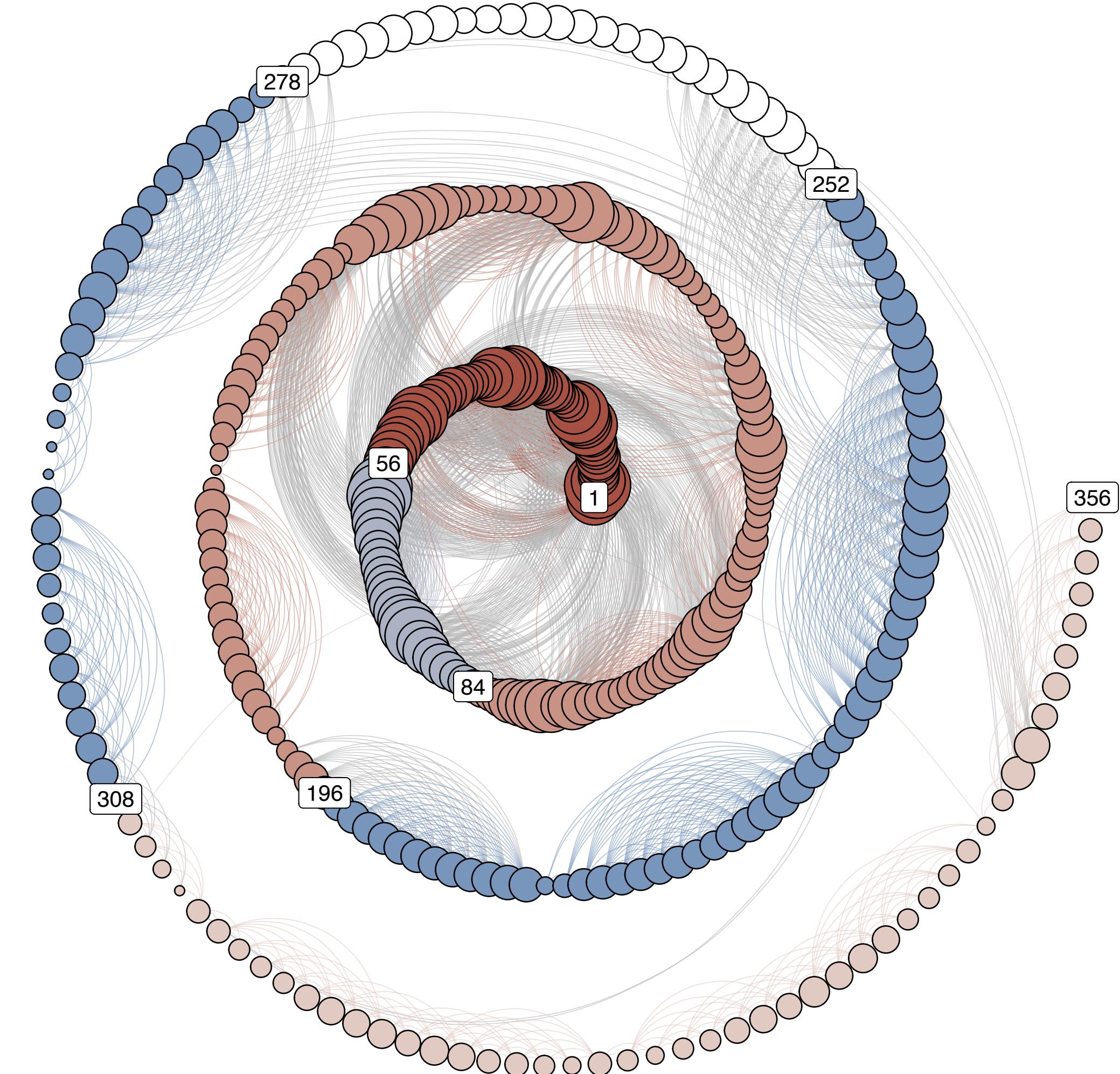
(a)



"I feel down"

Phase in Experiment

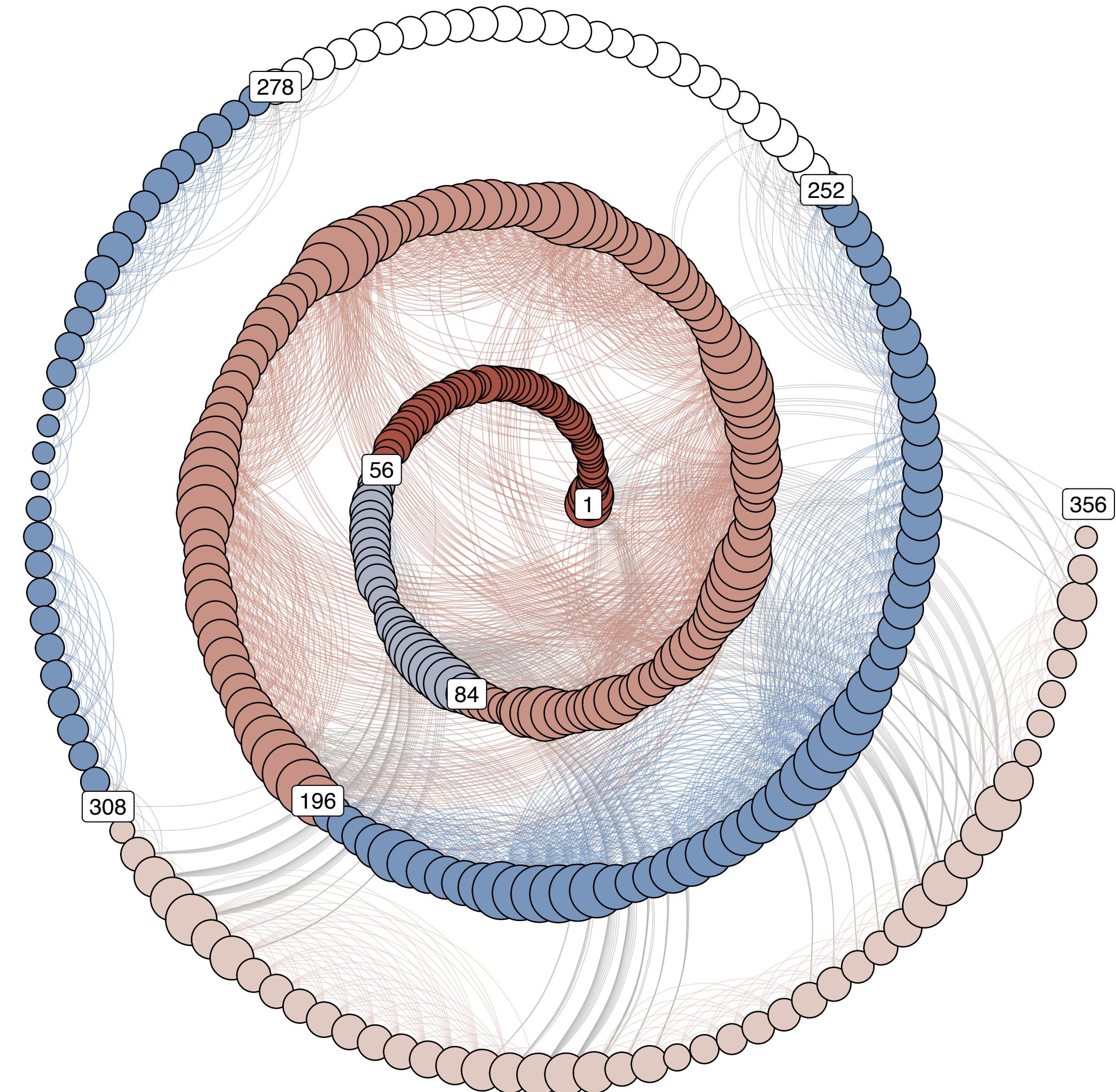
- baseline assessment
- start double blind period
- start actual reduction
- post reduction (planned)
- 'critical transition'
- post reduction (additional)



"I feel relaxed"

Phase in Experiment

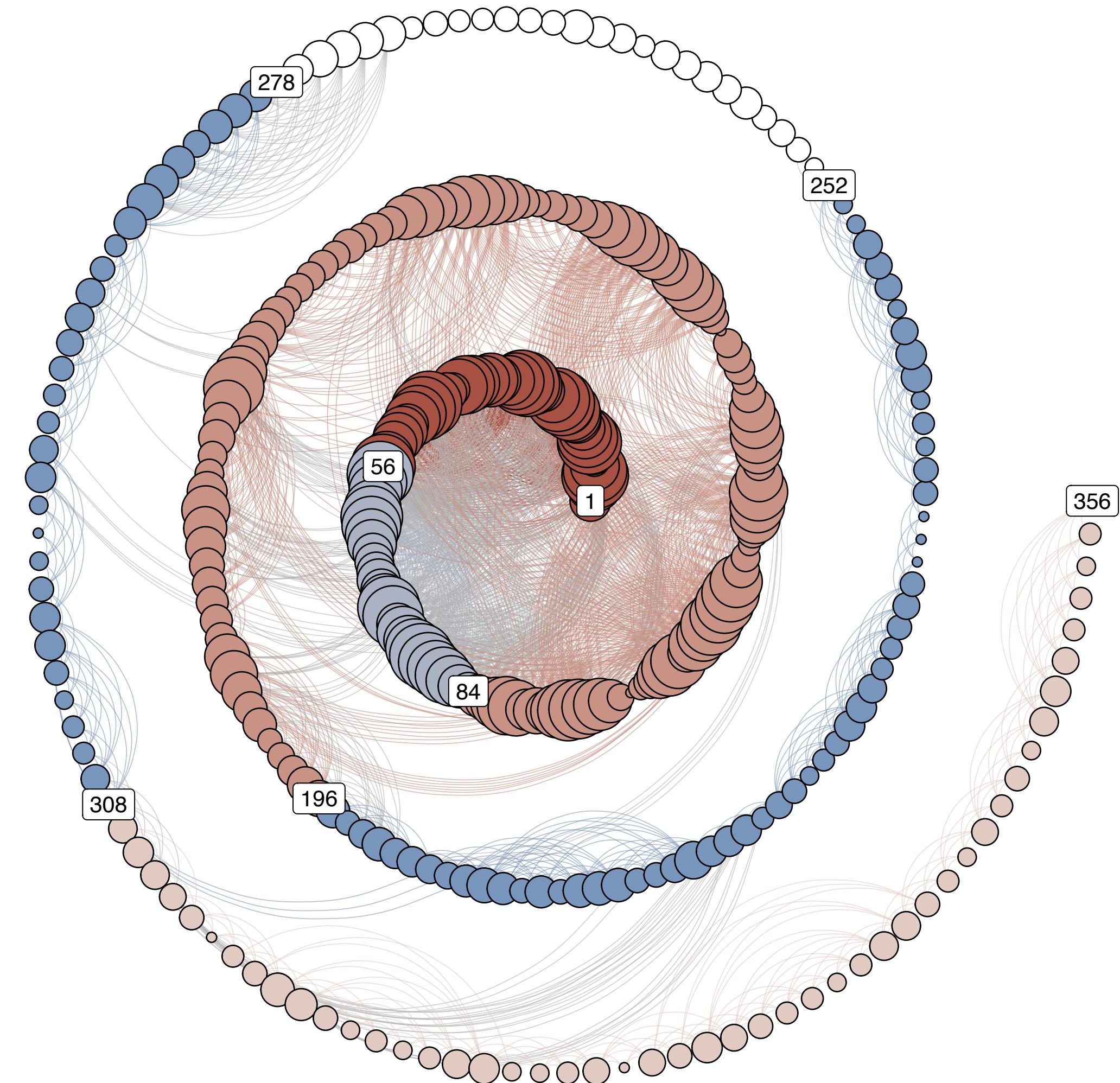
- baseline assessment
- start double blind period
- start actual reduction
- post reduction (planned)
- 'critical transition'
- post reduction (additional)



"I am looking forward to this day"

Phase in Experiment

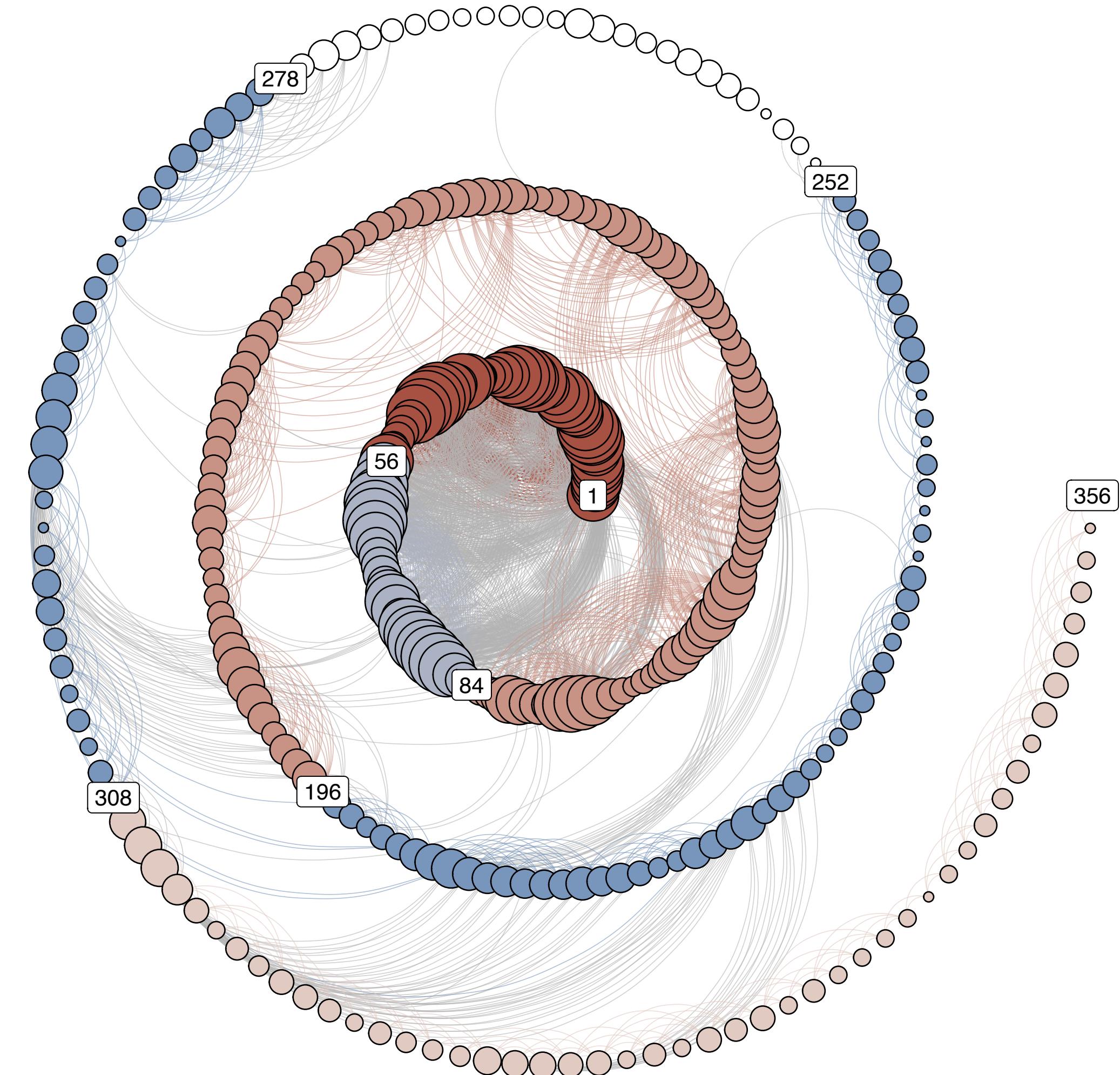
- baseline assessment
- start double blind period
- start actual reduction
- post reduction (planned)
- 'critical transition'
- post reduction (additional)



"I slept well"

Phase in Experiment

- baseline assessment ● start double blind period ● start actual reduction
- post reduction (planned) ○ 'critical transition' ○ post reduction (additional)



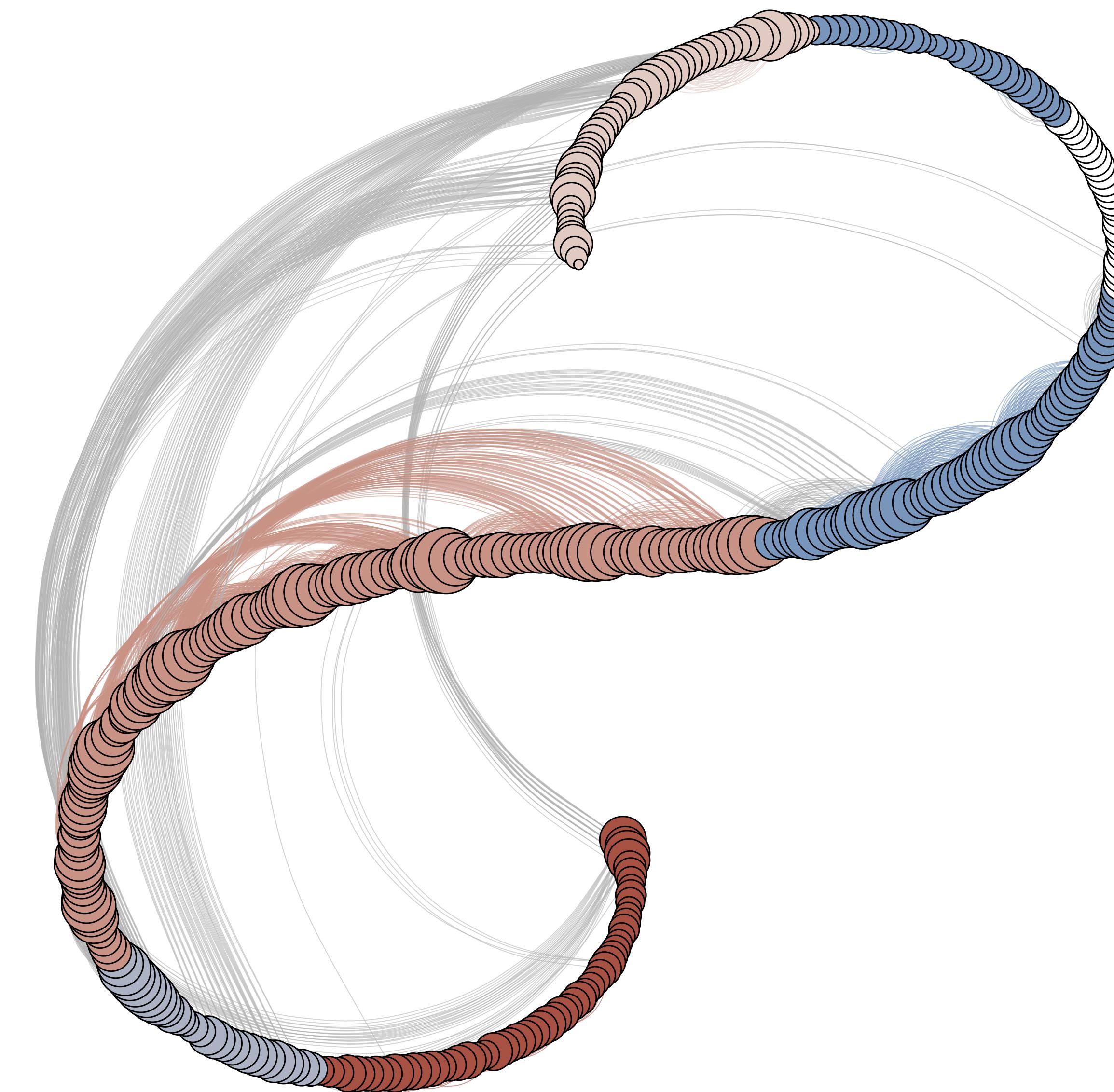
"I feel relaxed"

Node Degree

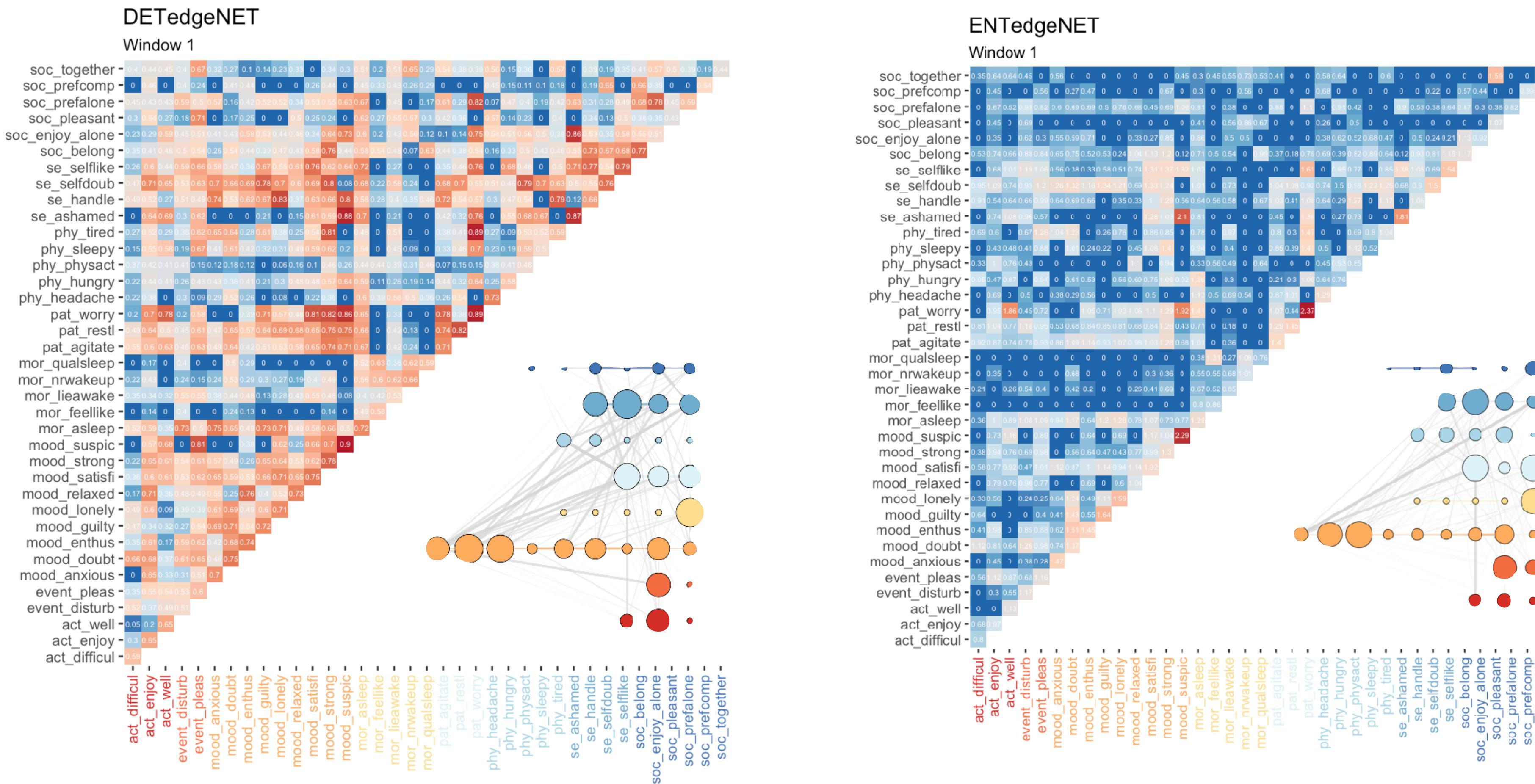


Phase in Experiment

- baseline assessment
- start double blind period
- start actual reduction
- post reduction (planned)
- 'critical transition'
- post reduction (additional)

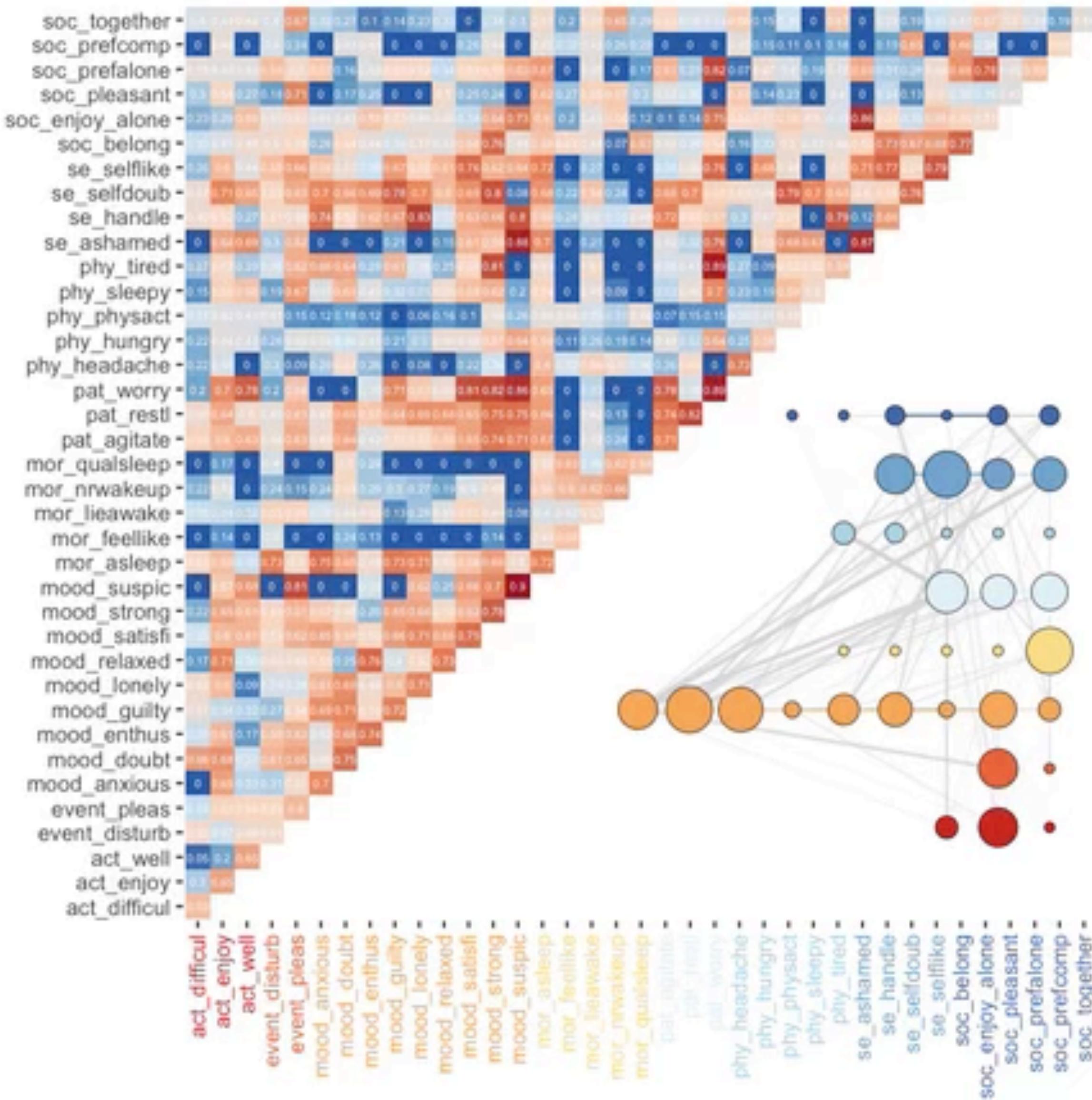


Multiplex Cross-Recurrence Network

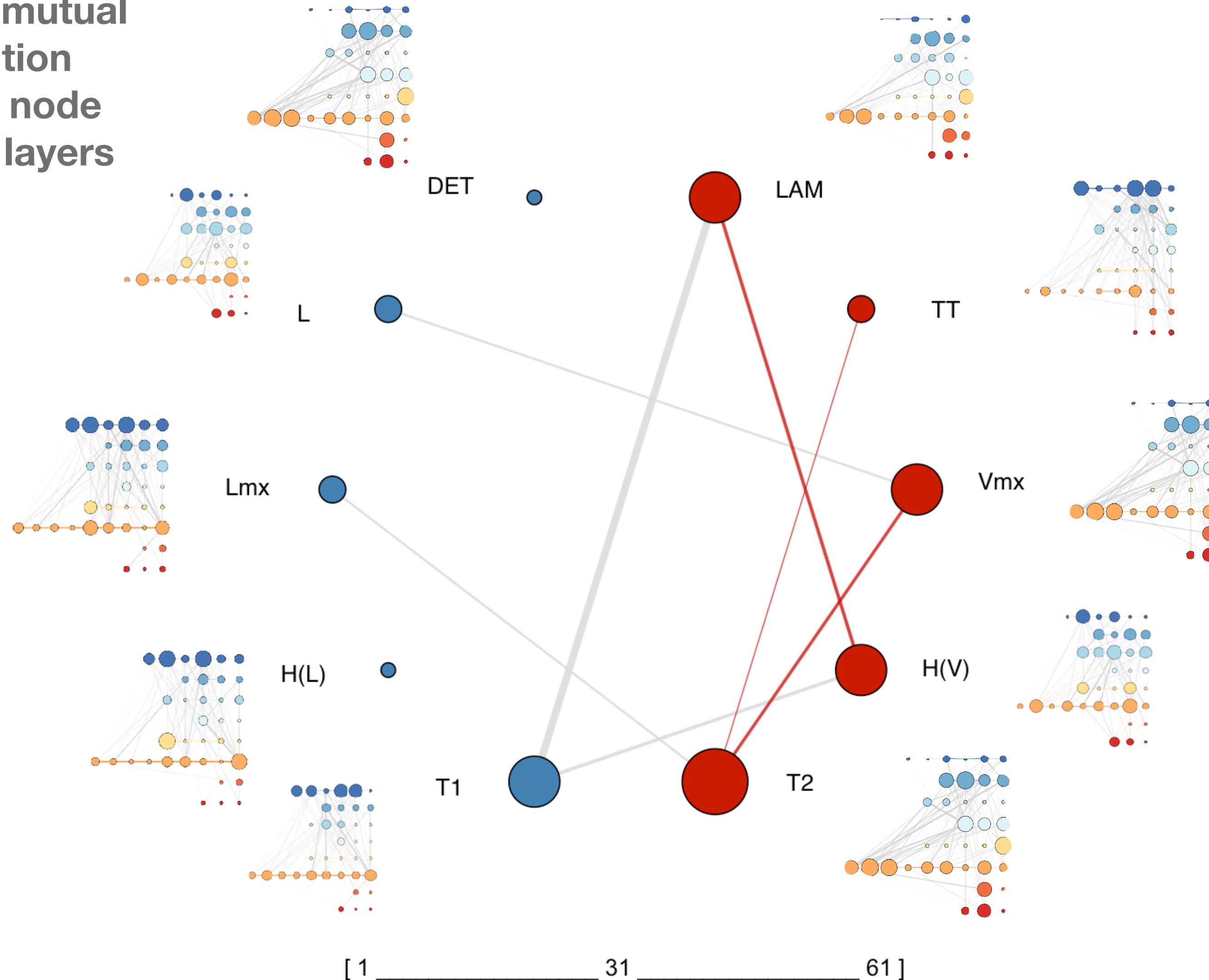


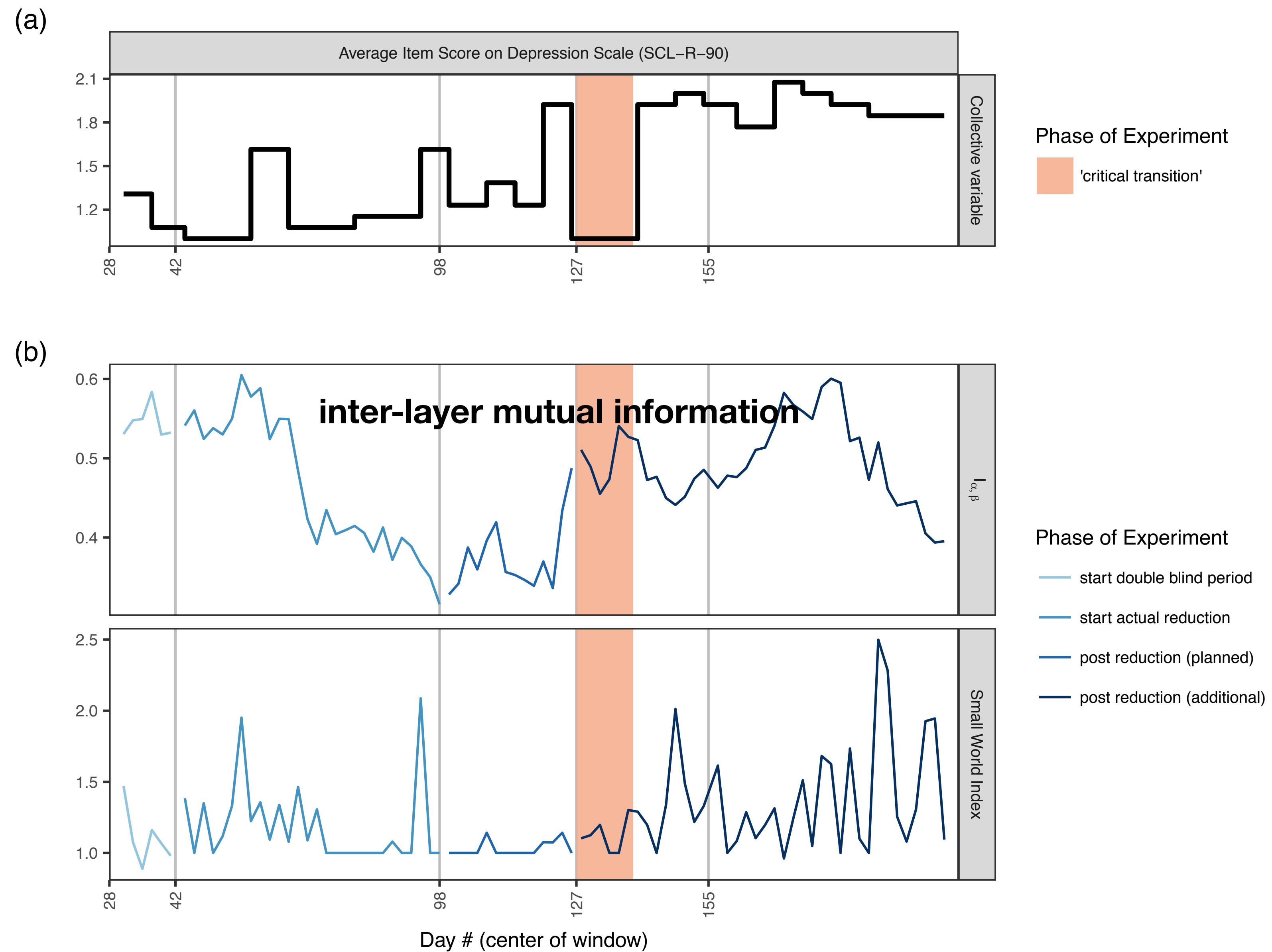
DETedgeNET

Window 1

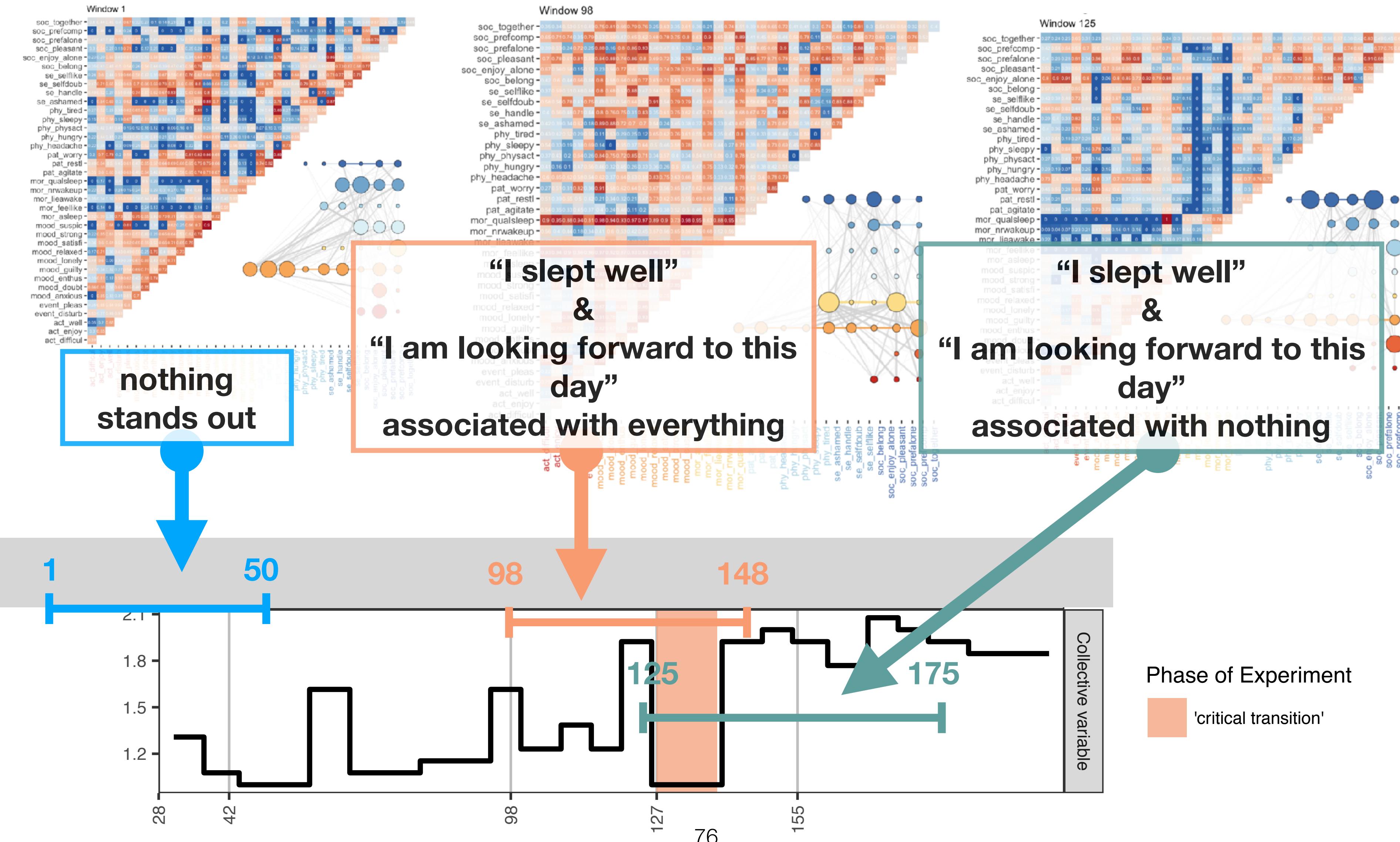


**edge weights:
inter-layer mutual
information
based on node
degree of layers**





Digging deeper ... into the ‘raw’ data: DETerminism-edge Network



Take Home Message

NO NEED TO REDUCE DIMENSION OF MULTIVARIATE
TIME SERIES DATA

USE MULTIPLEX RECURRENCE NETWORKS