

Weighted networks (continued)

Weighted Networks: Weight-Topology Correlations

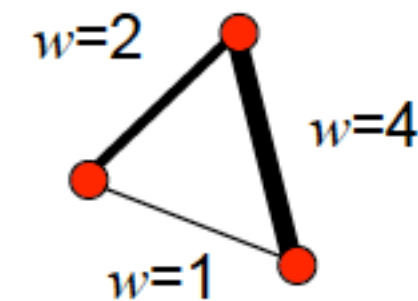
- Instead of simply attempting to generalize existing measures, it might be better to focus on **correlations between weights and topology**
- Question: What role do edges of different weight play in the network?
- E.g. transport networks: edge weights are high where capacity is needed, i.e. where betweenness centrality is high
- There are different scales to this problem: the global, macroscopic scale of overall connectivity and the mesoscopic scale of clusters and modules

Weighted Subgraphs: Intensity

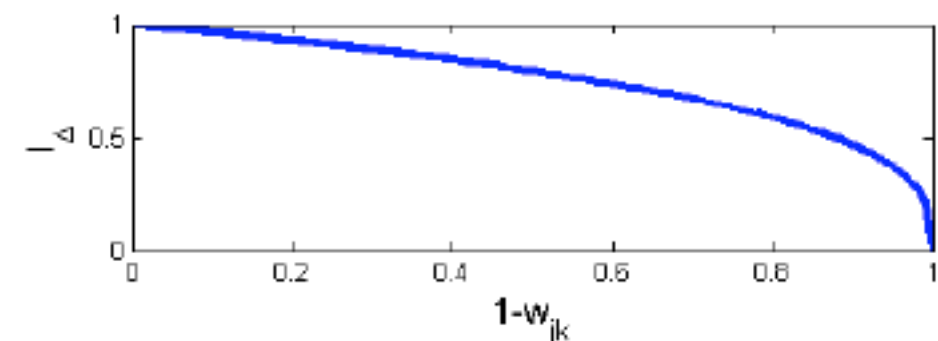
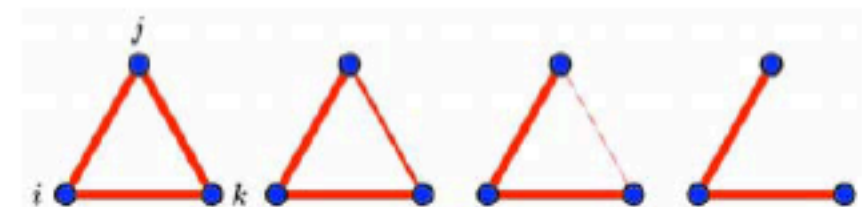
- The **intensity** I of a subgraph g with nodes v_g and links l_g , such that $|l_g|$ is the number of links in g , is defined as

$$I(g) = \left(\prod_{ij \in l_g} w_{ij} \right)^{1/|l_g|}$$

- Measures the “weight” of a subgraph
- Becomes low if any of the weights is low



$$I(\Delta) = (1 \times 2 \times 4)^{1/3} = 2$$

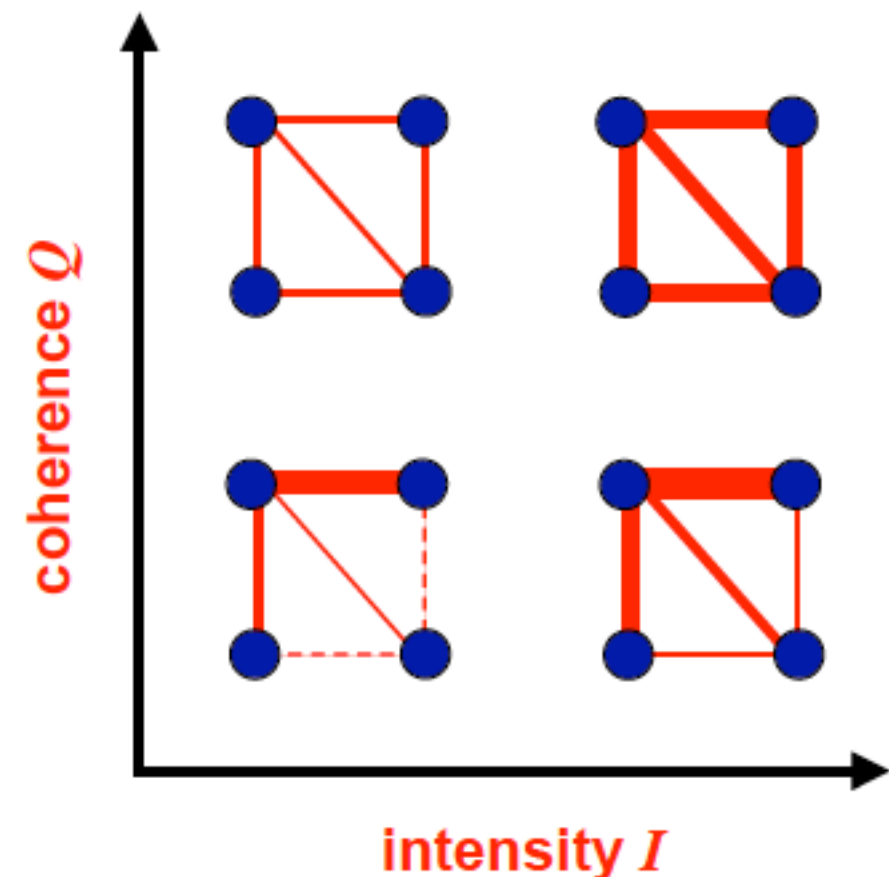


Weighted Subgraphs: Coherence

- The **coherence** Q of a subgraph g with nodes v_g and links l_g , such that $|l_g|$ is the number of links in g , is defined as

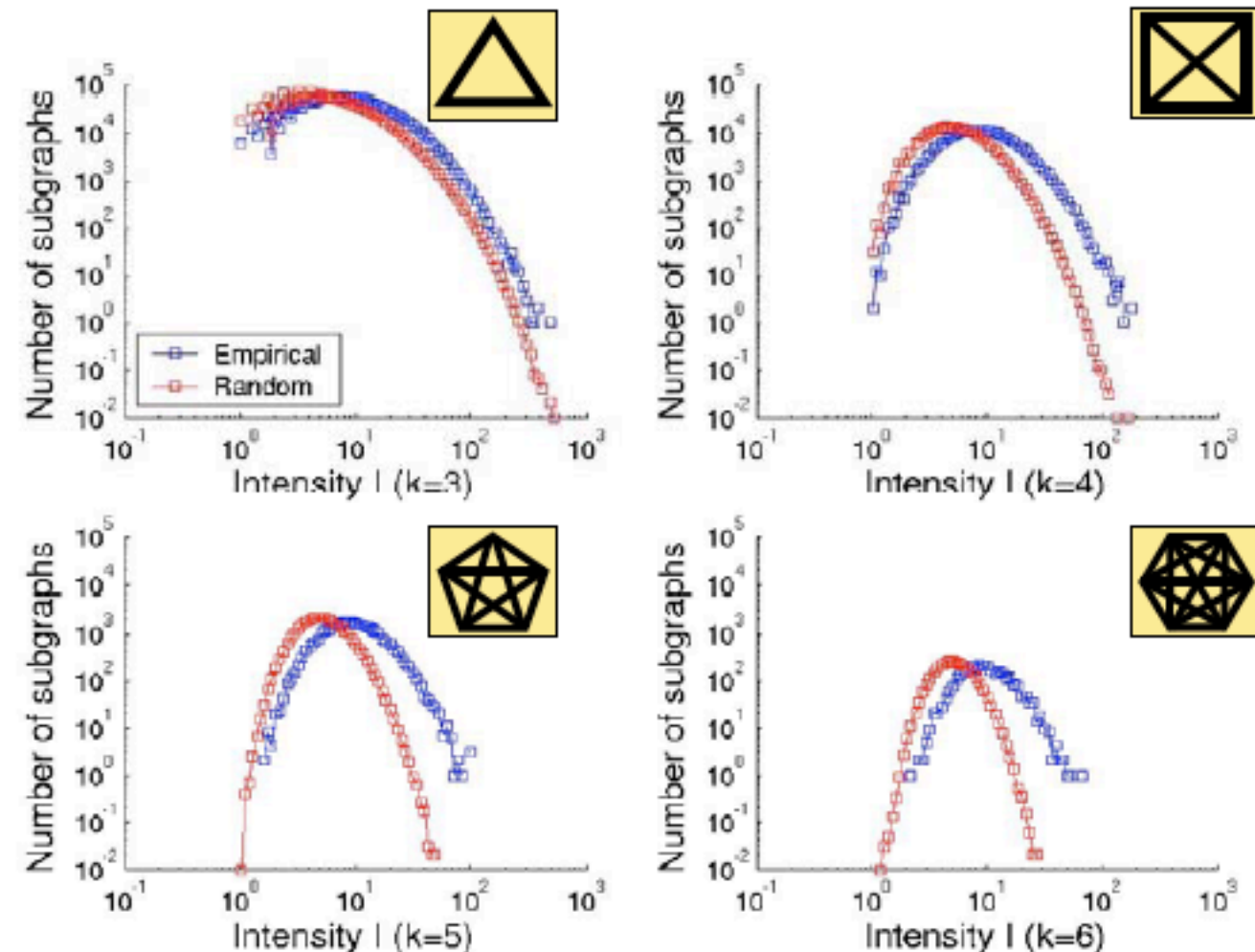
$$Q(g) = \frac{I(g)}{\frac{1}{|l_g|} \sum_{ij \in g} w_{ij}}$$

- Measures how equal (“coherent”) the weights are
- If all weights $w_{ij} = w$, $Q(g)=1$



Example: Intensity Distributions

- Data from a large social network inferred from mobile telephony call records
- Weight = total duration of calls between i and j in 18 weeks
- **Blue = original network, red = reference ensemble average**
- Reference ensemble: same network, weights permuted



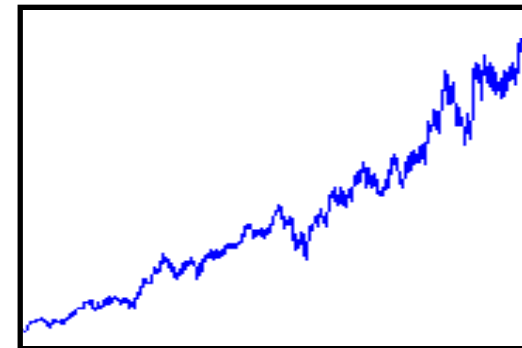
Onnela et al, New Journal of Physics 9, 179 (2007)

Weighted networks from time series

Example: stock networks

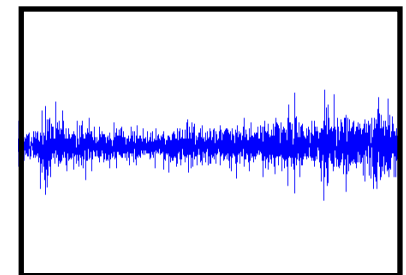
1. Starting point: time series of prices for N stocks

$$P_i(t)$$

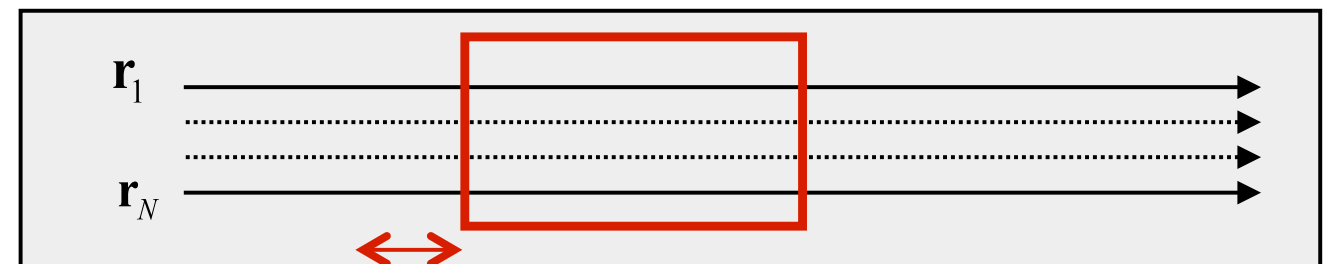


2. Calculate log-returns (usually done for stock prices, not feasible for all time series)

$$r_i(t) = \log \frac{P_i(t)}{P_i(t-1)}$$



3. Divide data into windows, or use the whole data length




(Note: time series length in data points must be $\gg N$)

time t

Weighted networks from time series

Example: stock networks

4. Calculate correlation coefficients between time series within your windows


$$\rho_{ij}^{\tau} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{\langle r_i^2 \rangle - \langle r_i \rangle^2} \sqrt{\langle r_j^2 \rangle - \langle r_j \rangle^2}}$$

$$-1 \leq \rho_{ij}^{\tau} \leq 1$$

5. If negative coefficients exist, take absolute values

6. This correlation matrix is your weight matrix W_{ij} !

7. Treat as a (full) weighted network - calculate MST, use thresholding, or similar

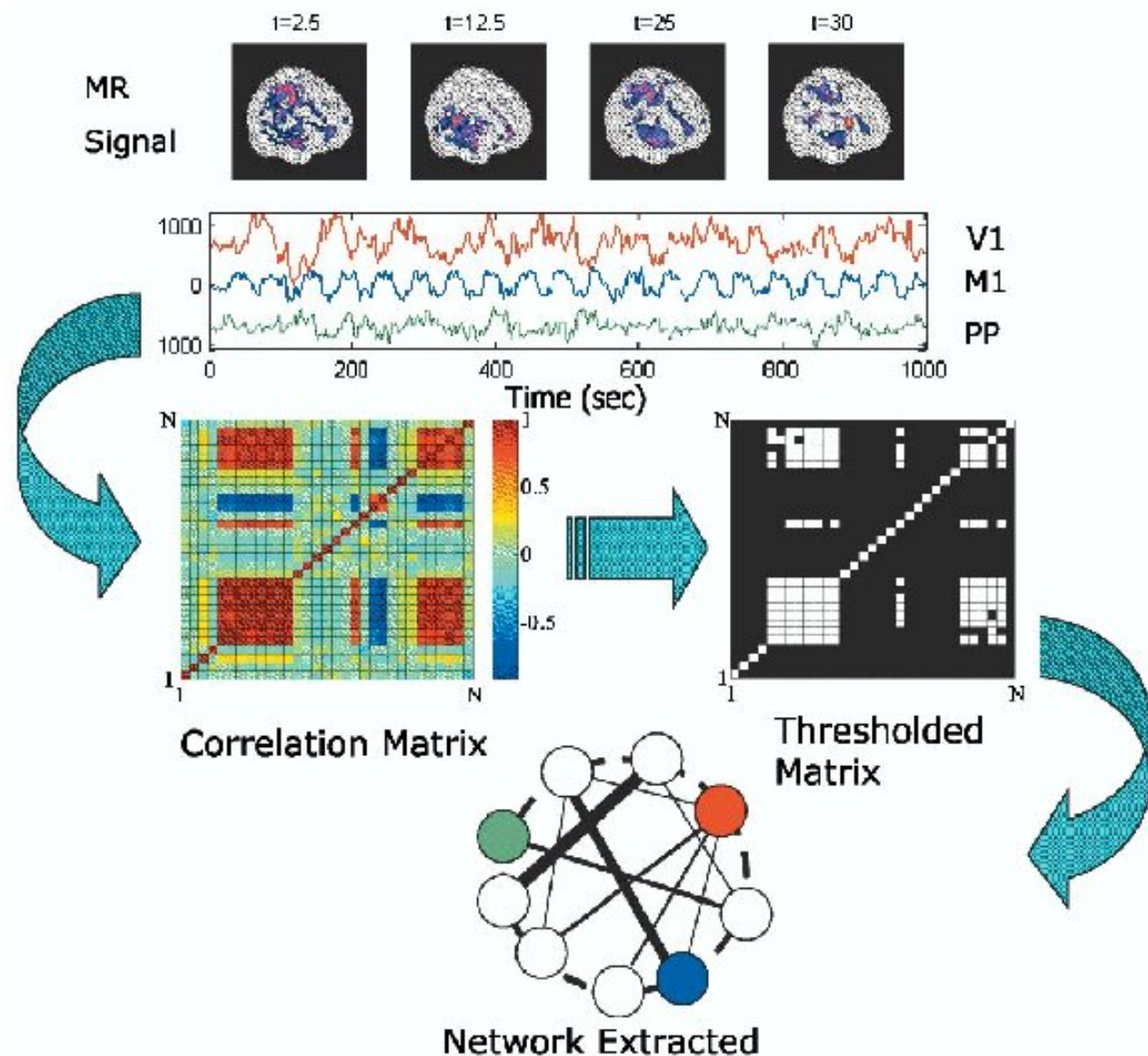
Weighted networks from time series

Example: brain functional networks

- Scale-free functional brain networks, Eguiluz et al, PRL **94**, 018102 (2005):

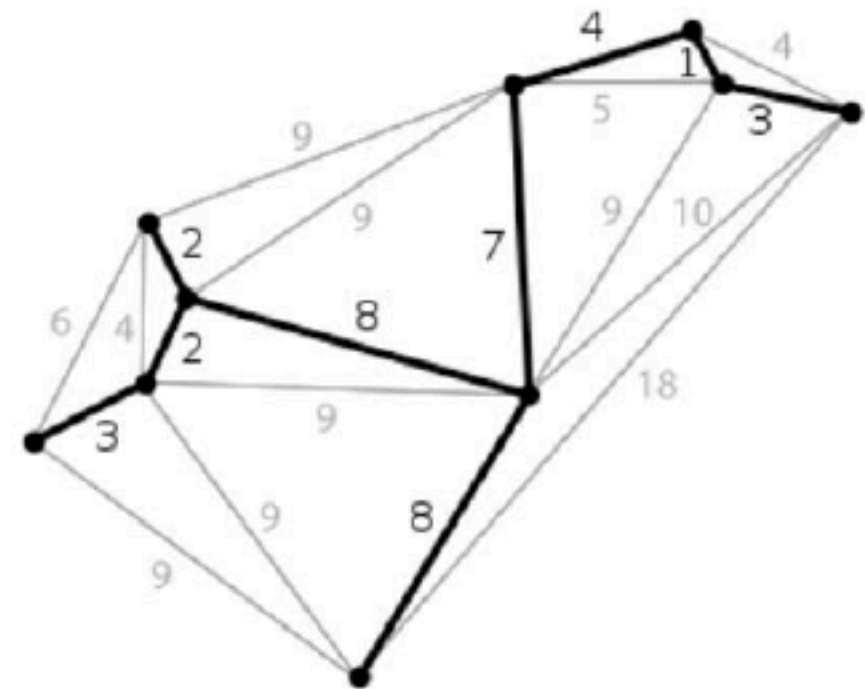
- Method:

- use fMRI time series on activity of small voxels
- construct correlation matrix
- leave only highest correlations
- construct network



Maximal/Minimal Spanning Trees

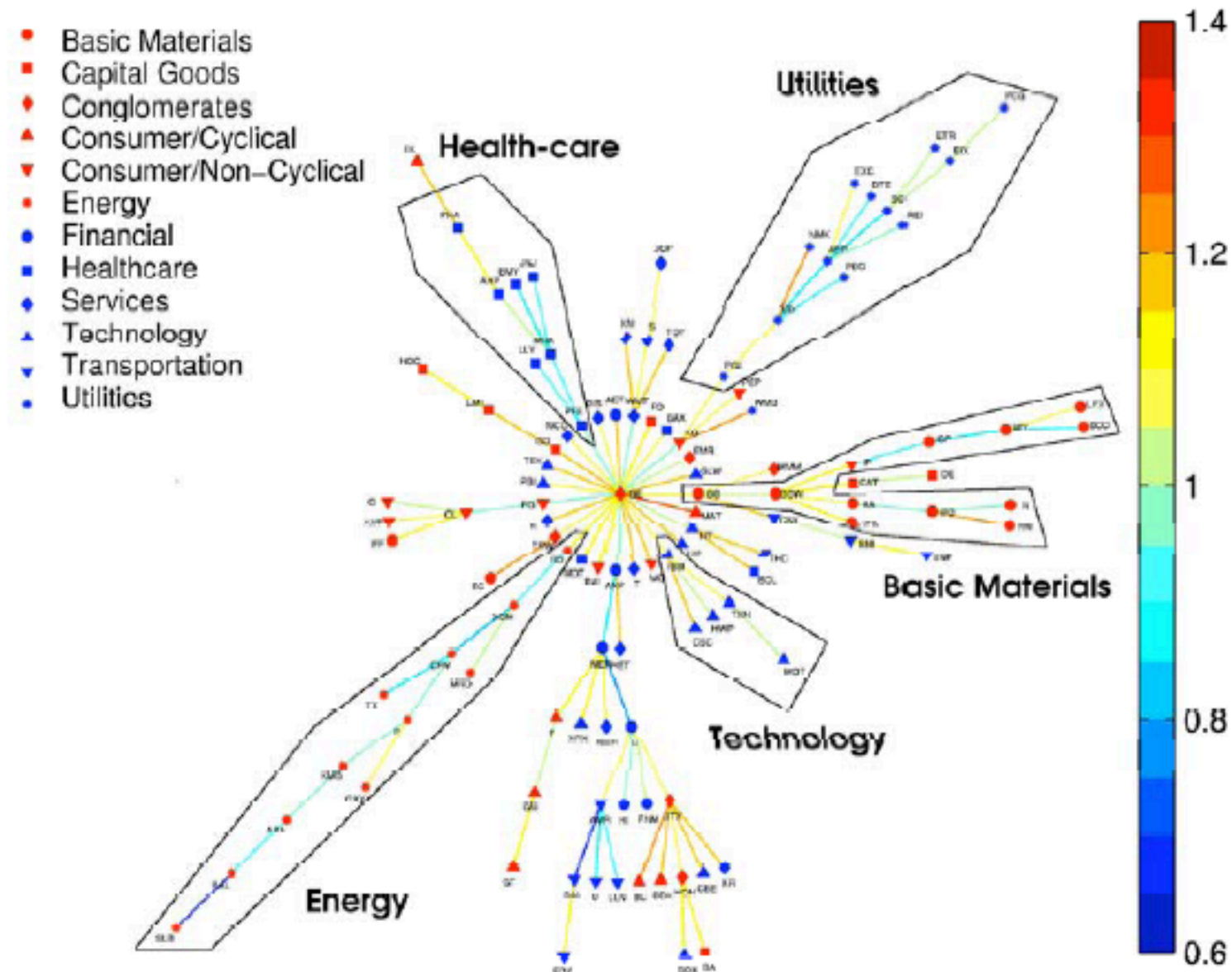
- Idea: to distill the “essential skeleton” of a weighted network
- Works as well for full matrices; can be used to transform a weight matrix into a tree
- Definition: a tree containing all the nodes in the network, such that the sum of weights of edges in the tree is minimized/maximized



Minimal/Maximal Spanning Trees: Interpretation

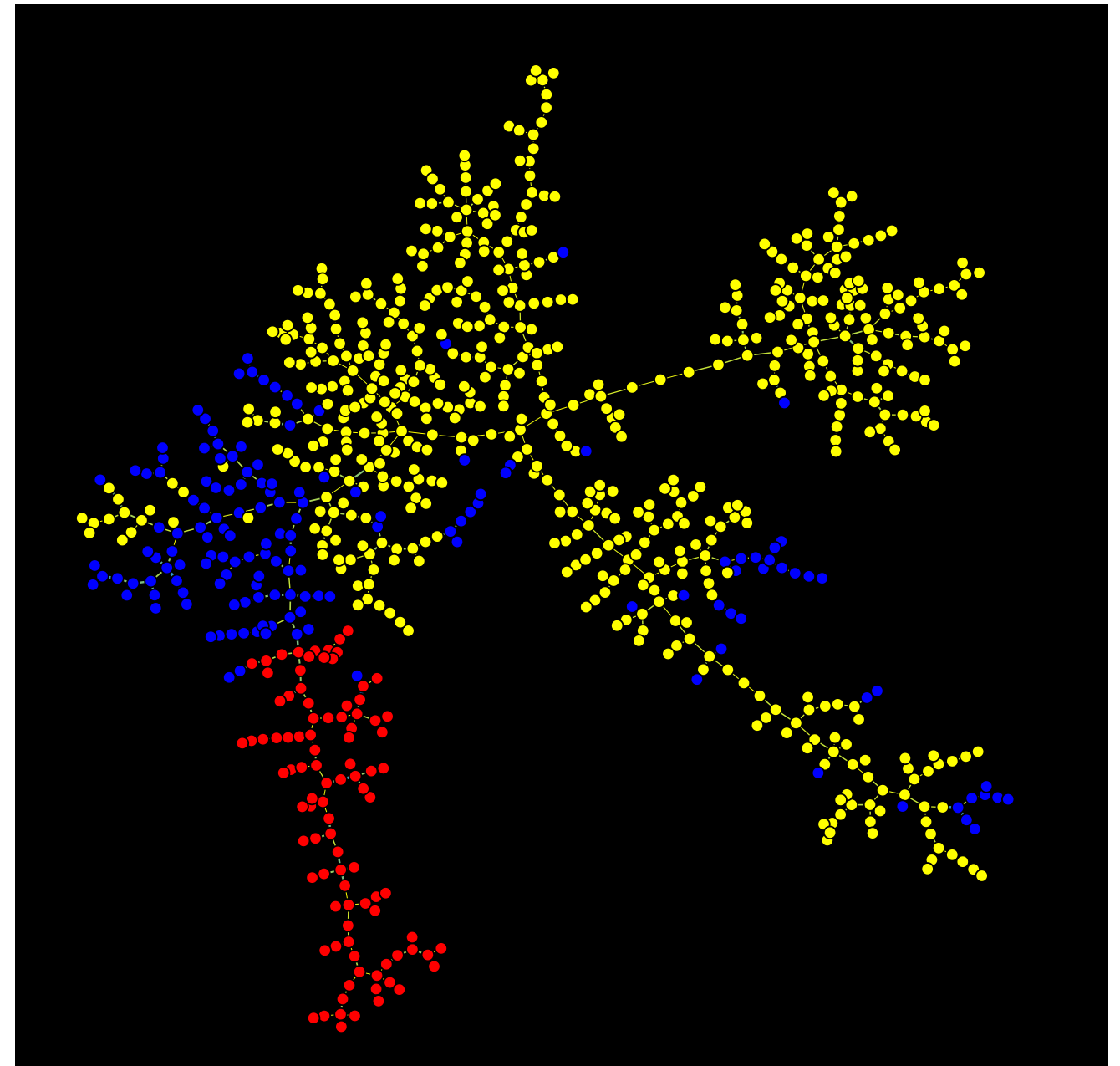
- Branches of MST's reflect clusters or “modules” in data
- One of the first proposed methods to analyze such structure
- But be careful: MSTs are very sensitive to noise & much information is discarded!

MST for correlation matrix of NYSE stocks



Maximal/minimal spanning trees

- In practice calculated using Kruskal's algorithm
 1. Sort original network's edges by decreasing weight
 2. Generate a network G with all original nodes but no links
 3. Assign each node to its own component
 4. Go through edges one by one, such that
 - 4.1. If endpoint nodes in different components, add edge to network G and merge components
 - 4.2. If endpoint nodes in same component, do nothing
 5. Stop when $N-1$ links have been added



MST of genetic distance matrix of approx 800 specimens of Mediterranean marine plants, colors = geographic area

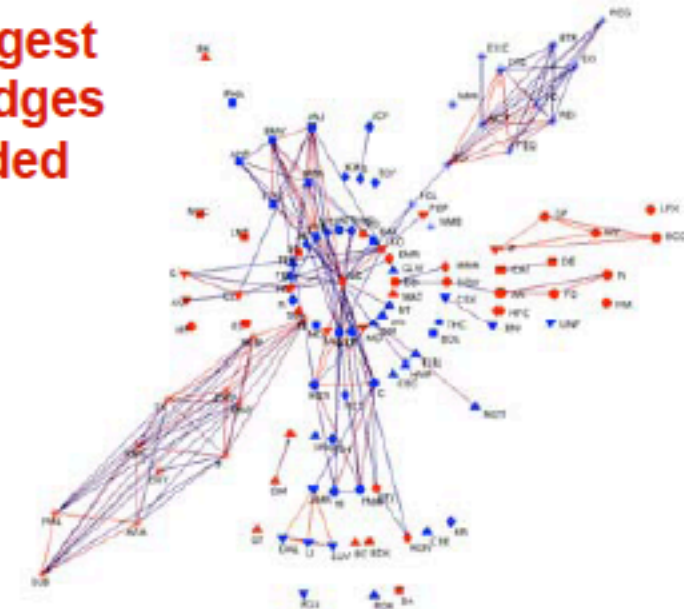
Matrices to Networks: Thresholding

- One can also transform full matrices to networks by **thresholding** them
- Just remove all links (weight matrix elements) below the weight of your choosing
- Again, makes clusters/modules/communities visible
- In any case, more information is retained than with MST's

Strongest
50 edges
included



Strongest
180 edges
included

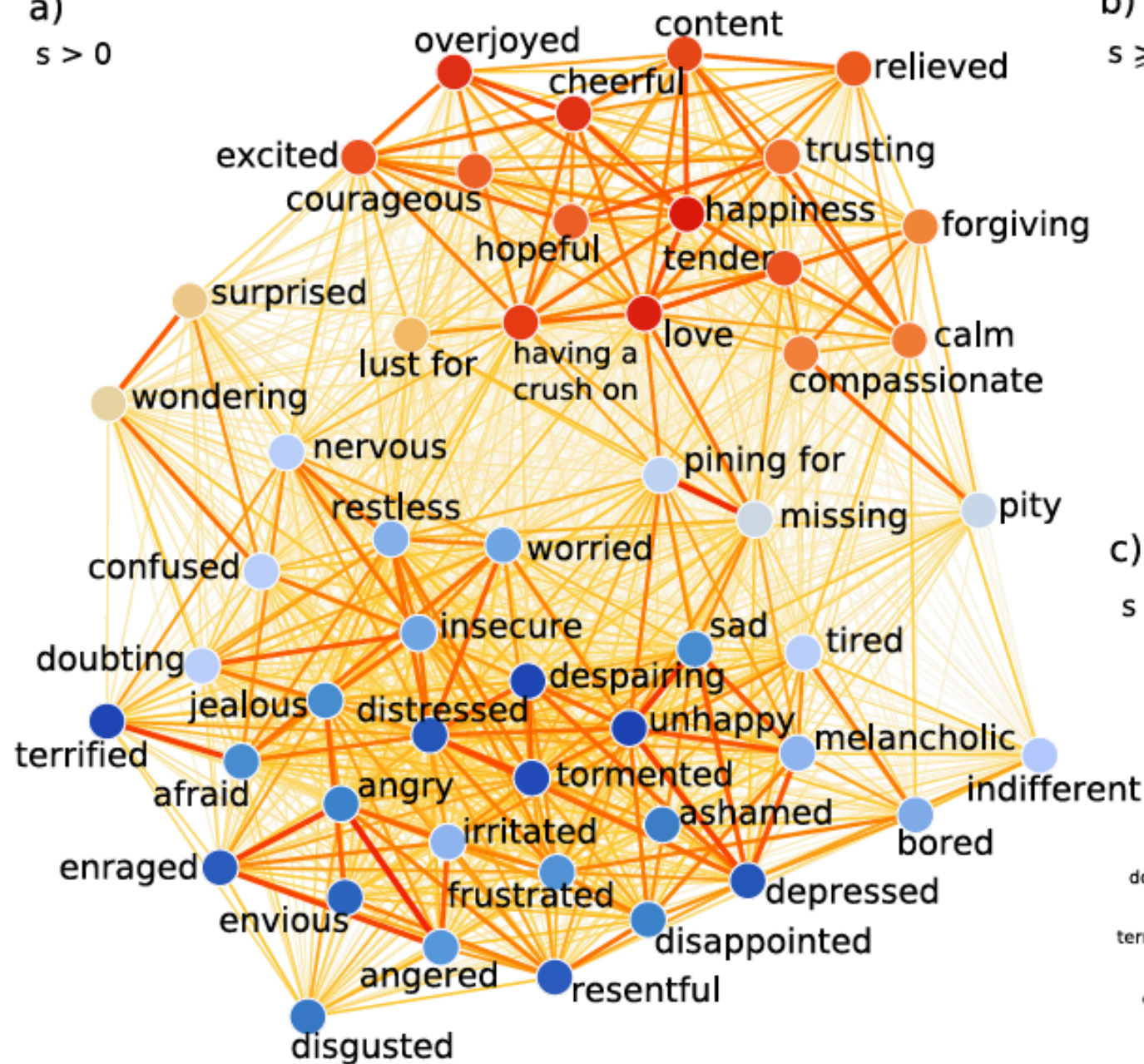


Thresholding: interview-based word association network

ASN Colored by valence

a)

$s > 0$



b)

$s \geq 2.0$



c)

$s \geq 3.75$



Social Networks

Social Networks Studies - Motivation

The social sciences point of view

- Man is a “social animal” - to the point that even our intellectual capability has likely evolved for being able to succeed in the social system of a small “tribe”
- Nowadays, (almost) everyone is part of an enormous social network spanning the entire world
- Micro-level social interactions (e.g. friendships) give rise to larger macro-level structures (social networks)
- Social networks are the “lattices” where information is transmitted, culture is formed, etc...

The network science point of view

- Social networks are self-organizing structures - no-one is designing or controlling them
- Individuals “see” only their immediate network neighbourhood
- Nevertheless there is clear emergent higher-level structure
- Are there simple rules or mechanisms which give rise to this structure?
- How does the structure affect various processes?

Other social animals



Wolf, *Canis lupus*

- Packs of 6-8 wolves
- Packs consist of offspring of the alpha couple



Bottle nose dolphin, *Tursiopsis truncatus*

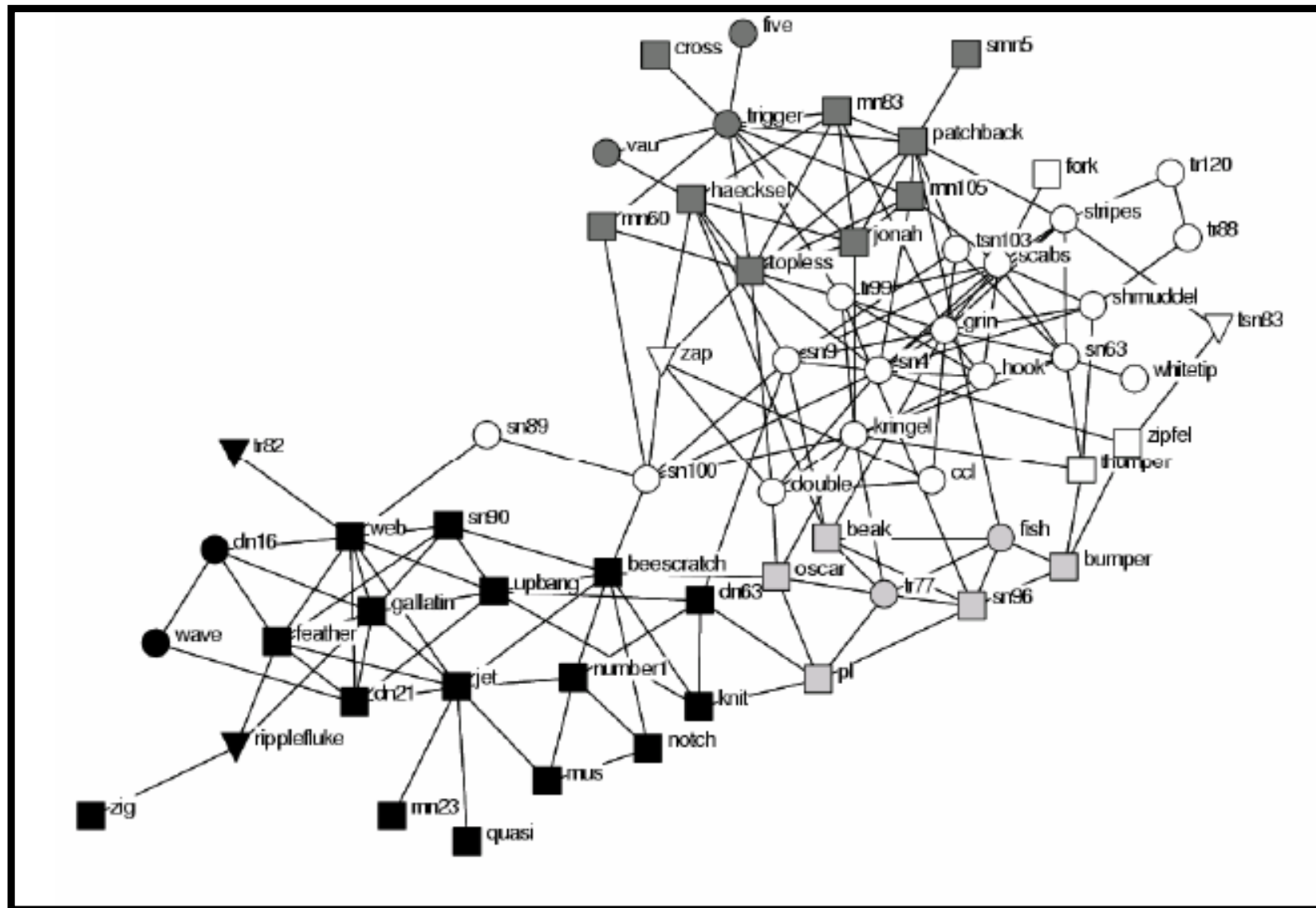
- Herds of ~100 dolphins
- Herd consists of smaller social groups



Chimpanzee, *Pan troglodytes*

- Around 100 members in a community
- The community consists of temporary, fluid groups of ~10 chimpanzees
- Strong hierarchy!

A dolphin social network



David Lusseau and M. E. J. Newman, *Proc. R. Soc. London B* **271**, S477-S481 (2004).

From friendships to societies

- Social networks consist of several (overlapping and fuzzy) levels

People



Friendships



Circles of friendship



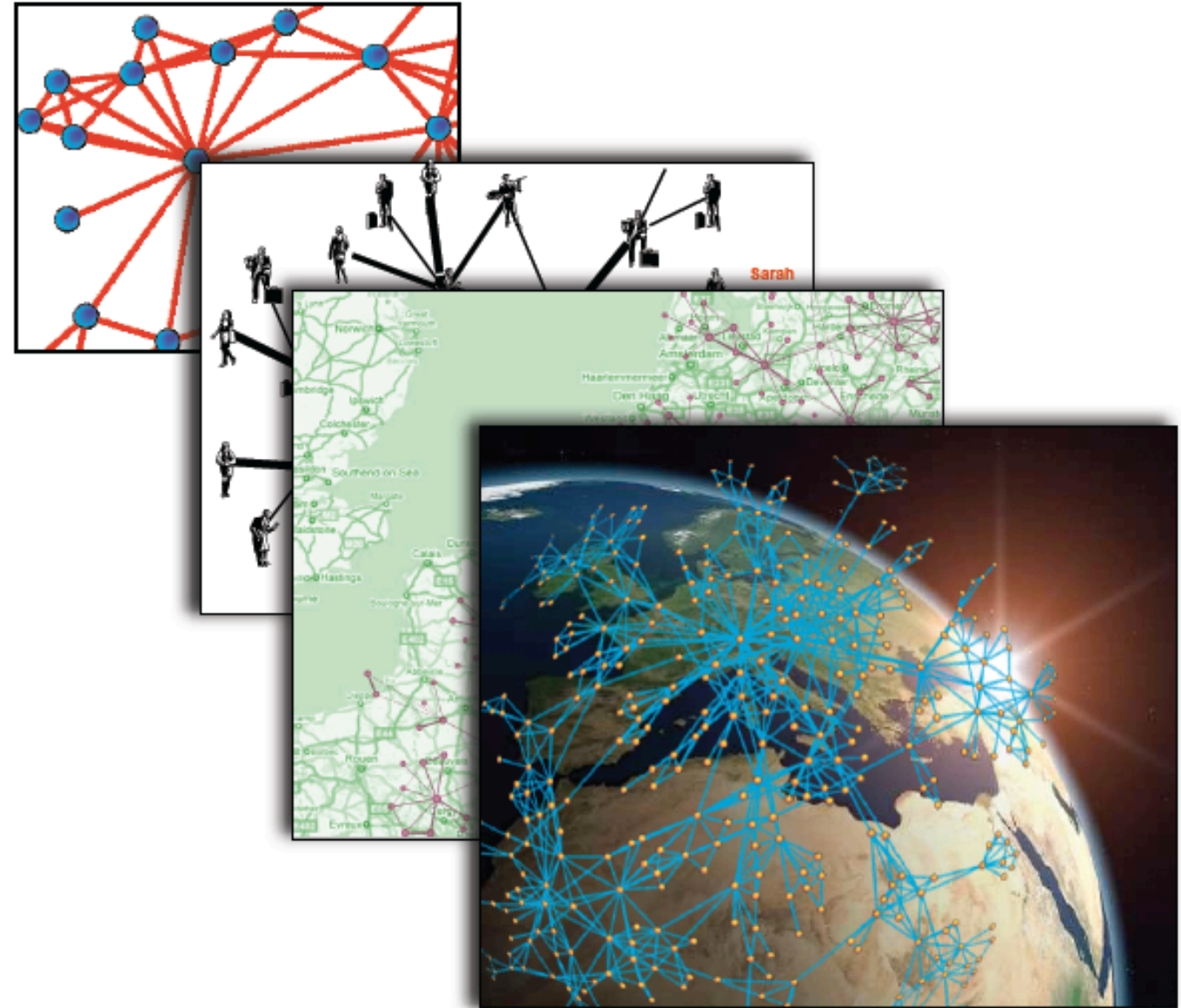
Social groups



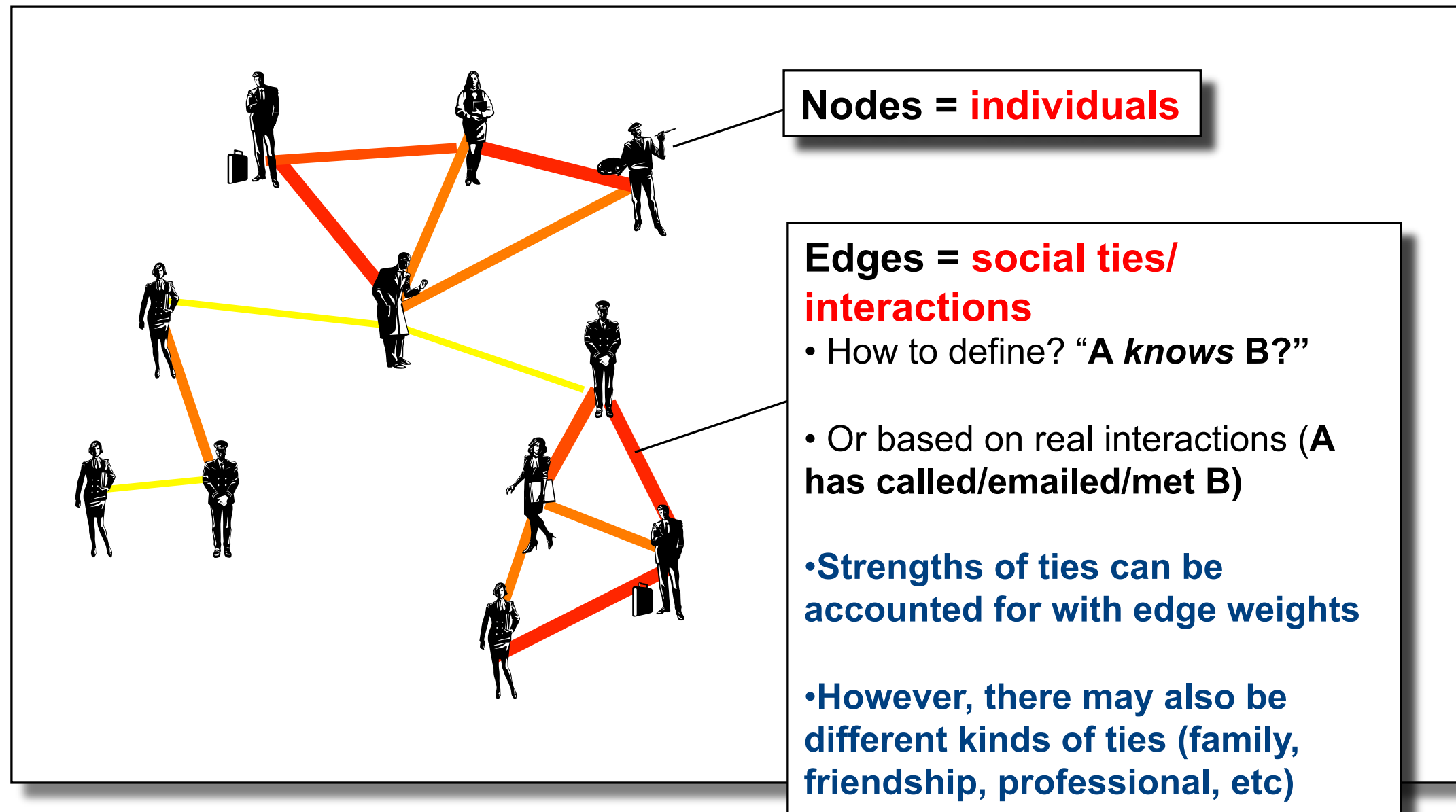
Communities



Society

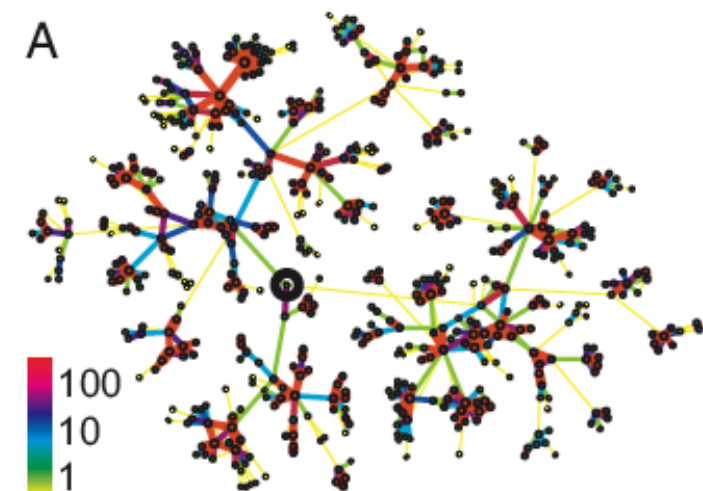
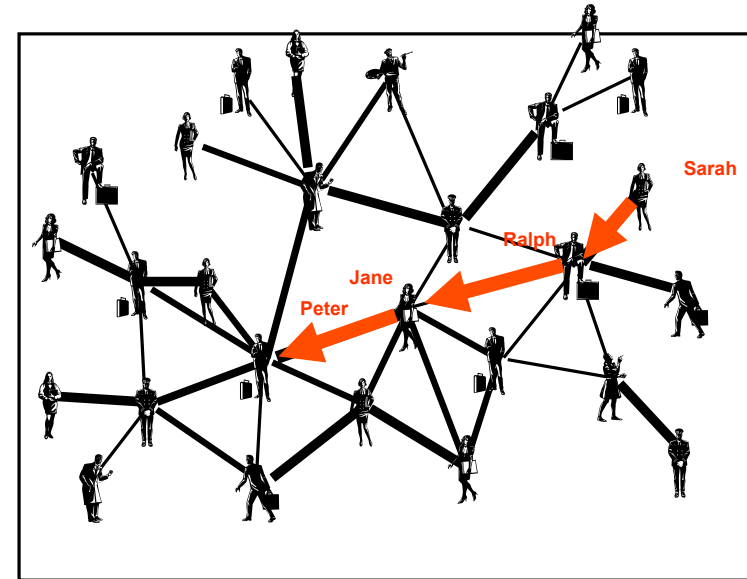


Social ties as networks



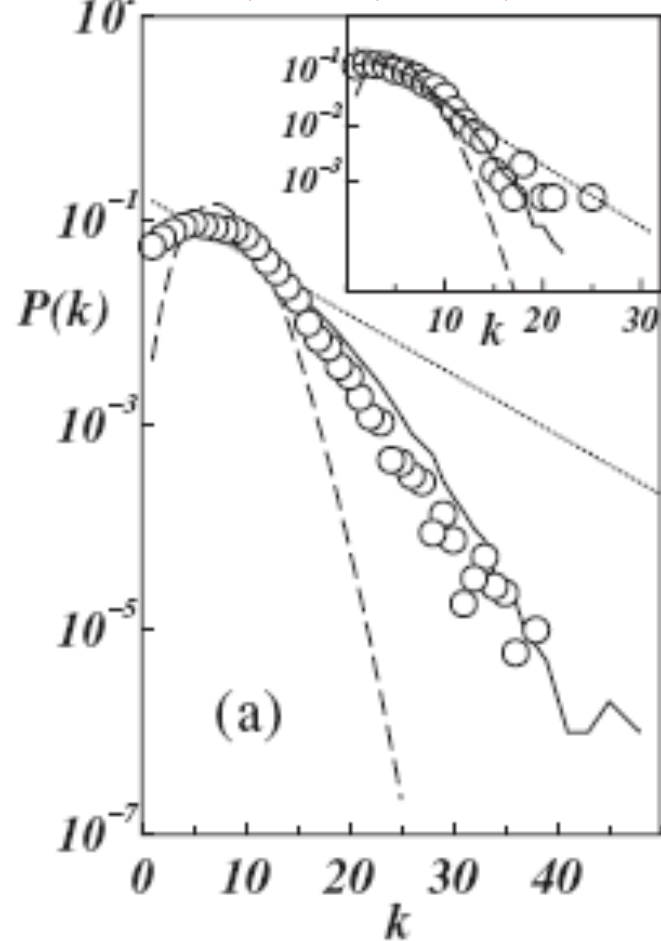
Social networks: known properties

- Short path lengths (“6 degrees”, “small world”)
- High clustering
- Assortativity: highly connected people friends with similar people
- Contain groups/cliques/communities/clusters



Degree distribution: no universal form

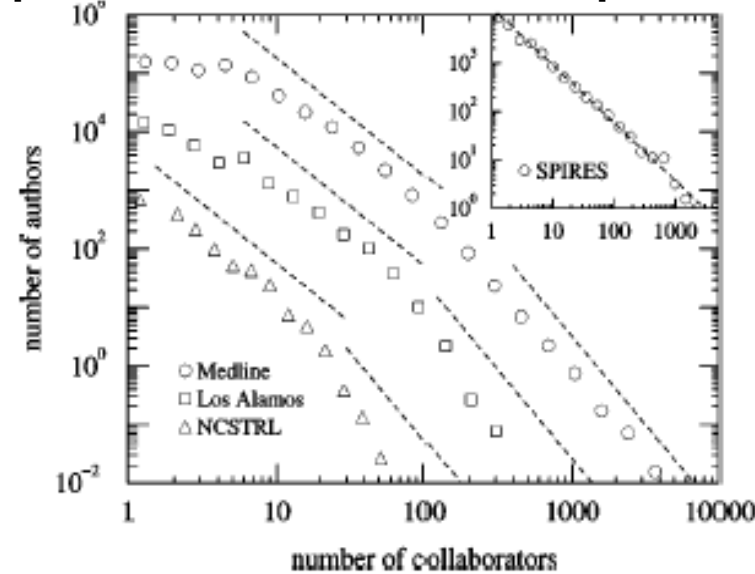
Gonzalez et al, PRL 96, 008702, 2006



U.S. schoolchildren:

$$p(k) \sim \exp(-k)$$

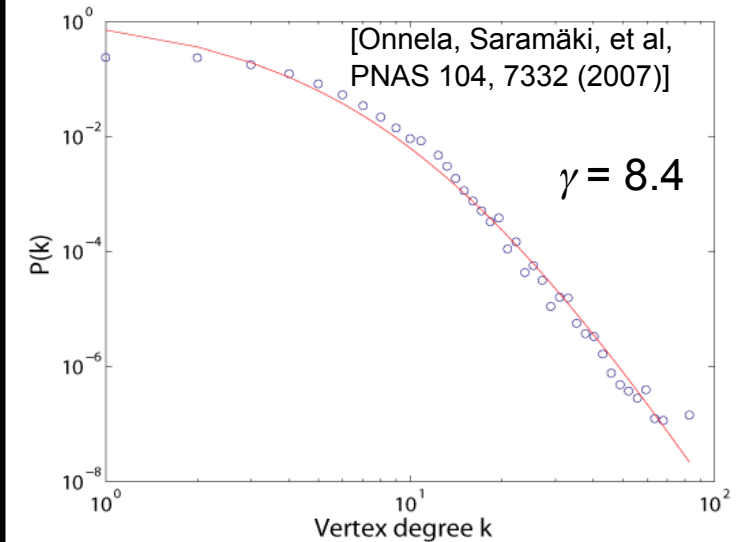
[M.E.J. Newman, PRE 64, 016131, 2001]



Collaboration networks

- Broad, might be a power law (or two power laws)

[Onnela, Saramäki, et al, PNAS 104, 7332 (2007)]



Mobile telephone call network

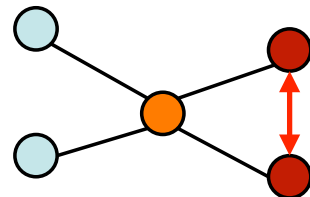
- tail looks like a power law but with a very large exponent

- Distributions generally broad
- Shape of distribution depends on network
- If power law, exponent has to be large (no-one can have 10000 friends)

Simple social network models

Davidson et al, Phys Rev Lett 88, 128701 (1999)

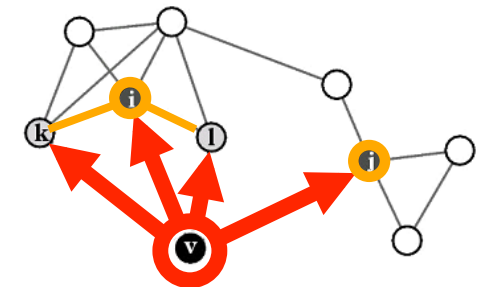
- First create a network of N nodes without any edges
- Repeat the following:
 - Pick a random node. If it has less than 2 neighbours, connect it to a random node. If it has 2 or more neighbours, randomly pick two of these and connect them.
 - With probability p remove the node and create a new one with a single random link.



- Correct: **clustered network, short pathlength, broad degree distribution**
- Incorrect: **no assortativity, no communities/groups**

Toivonen et al, Physica A 371, 88 (2005)

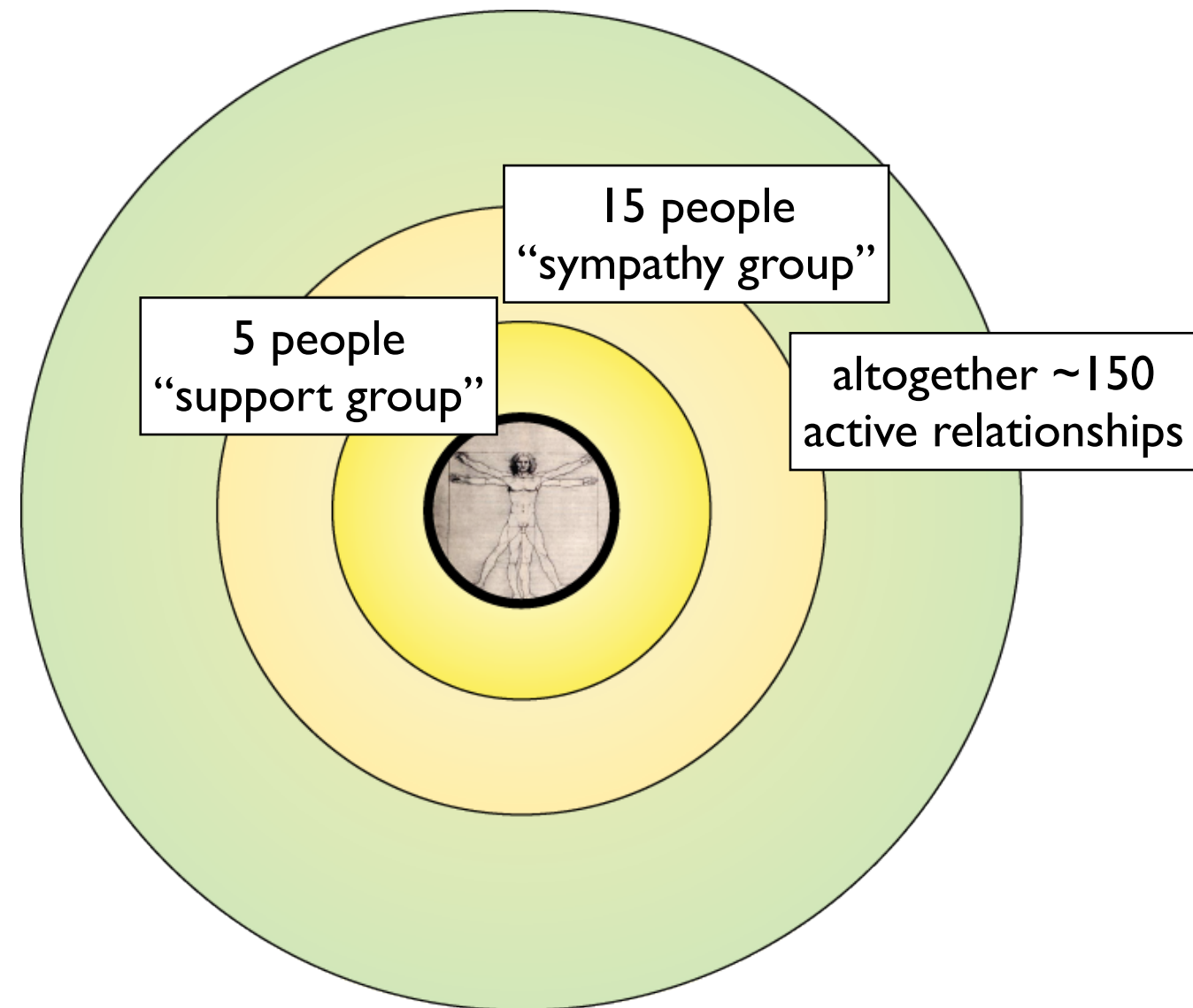
- Growth model
- Create a small initial seed, then repeat the following:
 - Randomly pick on the average m nodes as the “initial contacts”.
 - Pick on the average n of their neighbours.
 - Connect the new node to initial contacts and the chosen neighbours.



- Correct: **clustering, path lengths, degree distribution, assortativity, groups exist**
- Incorrect: **Group structure does not correspond to reality, hubs sit between groups**

The Dunbar Number

- “Egocentric” social networks, i.e. personal networks, are layered
- Robin Dunbar’s theory:
 - Core group of ~5 people (“support group”)
 - “Sympathy group” of ~15 people
 - Max ~150 active relationships - the “Dunbar Number”
- Evolutionary explanation: our cognitive capabilities do not allow for more
- Can technology increase this number? E.g. Orkut, Facebook, ?

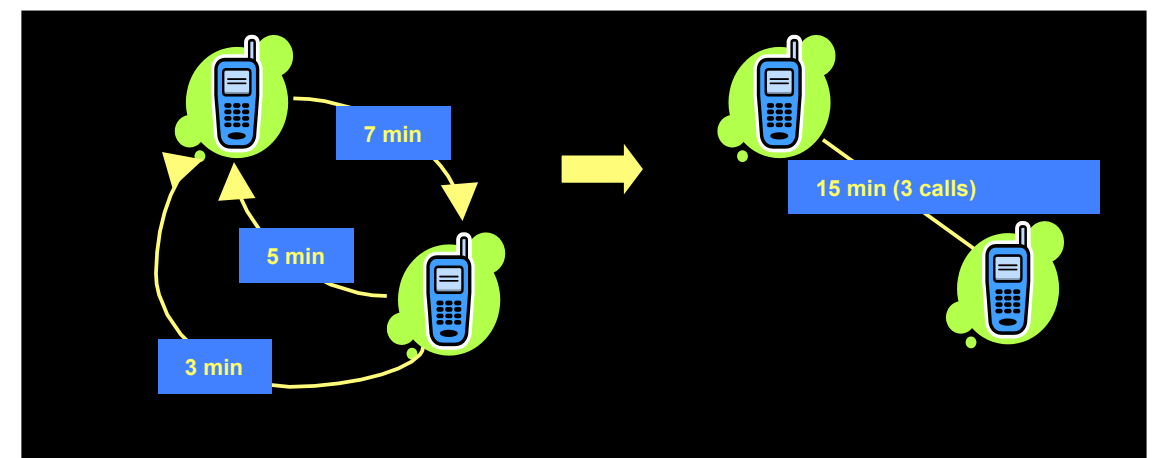


Social network analysis: mobile telephone call records

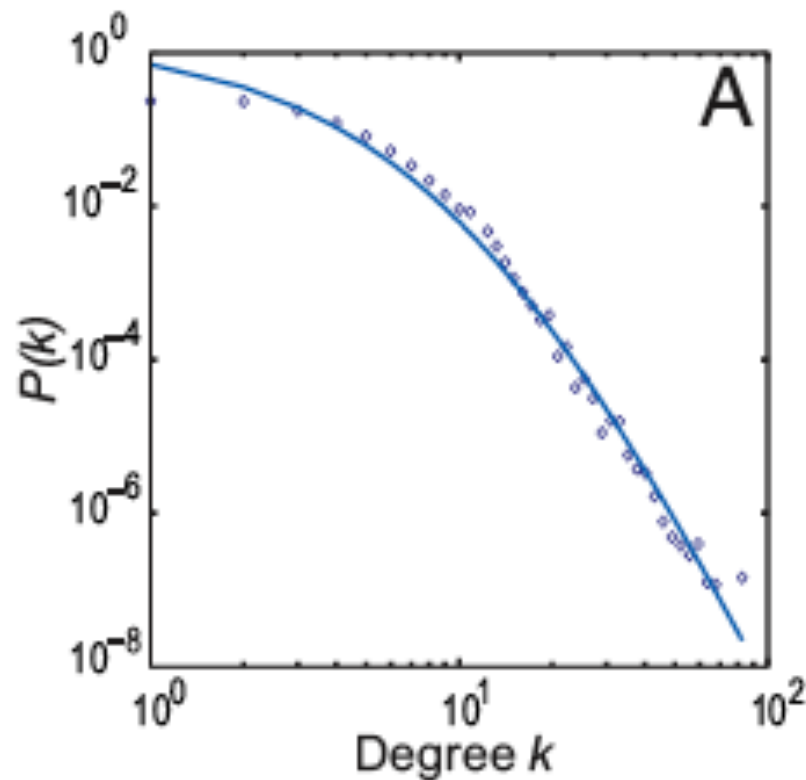
- Research published in
 - J.-P. Onnela, J. Saramäki, J. Hyvönen, G. Szabó, D. Lazer, K. Kaski, J. Kertész, A.-L. Barabási, *Proc. Natl. Acad. Sci. USA* **104**, 7332 (2007)
 - J.-P. Onnela, J. Saramäki, J. Hyvönen, G. Szabó, M. Argollo de Menezes, K. Kaski, A.-L. Barabási, and J. Kertész, *New Journal of Physics* **9**, 179 (2007)
- Target: to understand the structure, weight-topology-correlations and their consequences in a very large social network

Social network analysis: mobile telephone call records

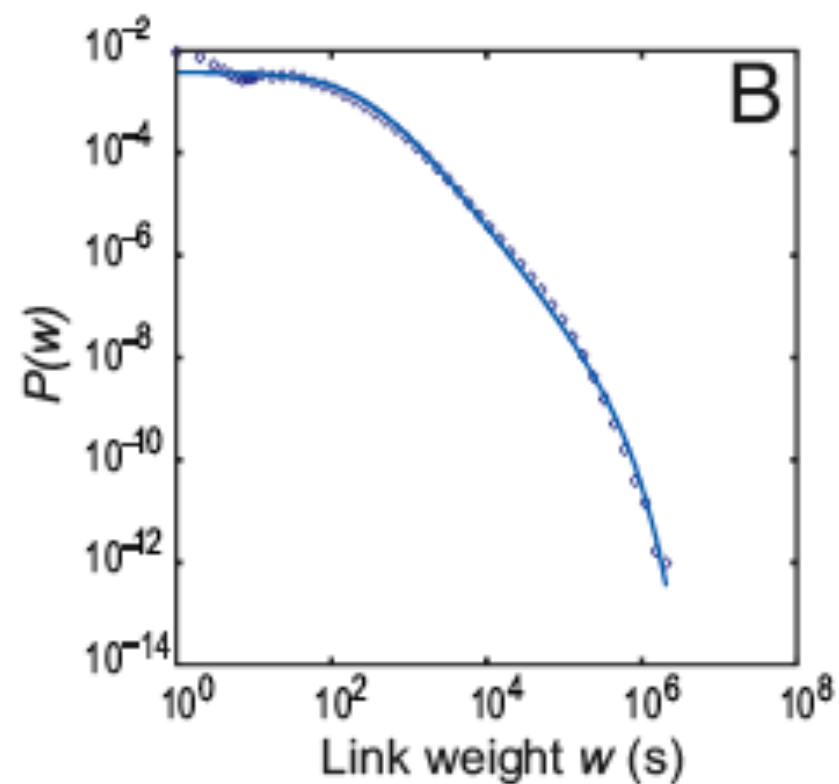
- Data: call records (caller, recipient) for 18 weeks for 7 million people within one operator's customer base
- Edge weights: total call minutes between two persons within 18 weeks
- Reciprocity filtering: we require that A has called B AND B has called A at least once
- After this, ~4 million people left in the network



Basic statistics



degree distribution: steep tail
which looks like a power law with
an exponent -8.4



weight distribution also broad

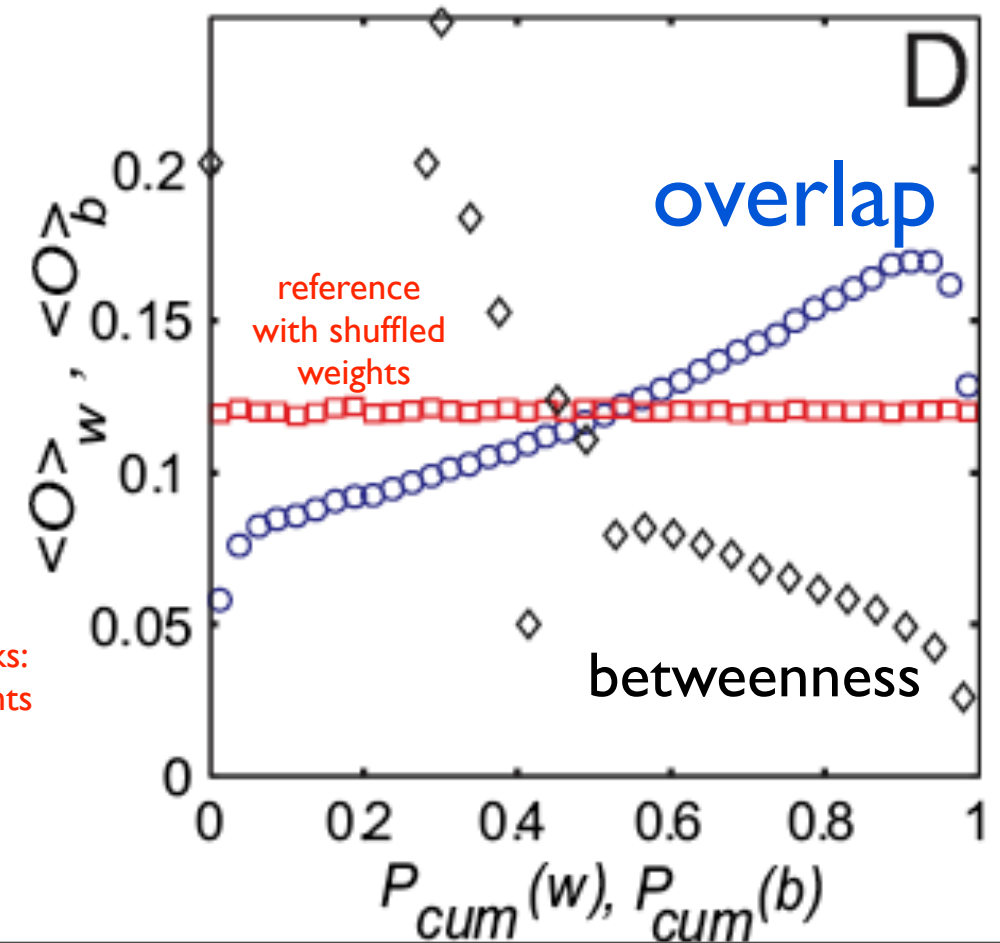
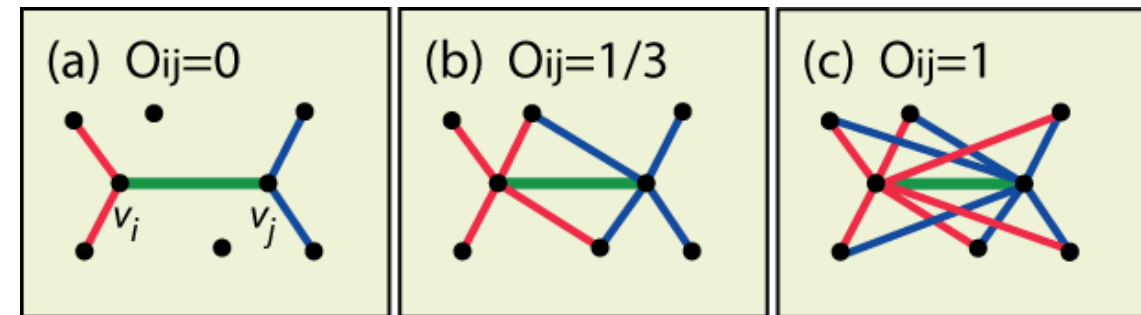
The Weak Ties Hypothesis

- ⑤ M. Granovetter, Am. J. Sociol. 78, 1360-1380, 1973.
- ⑤ "The strength of a tie is a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie."
- ⑤ The weak ties hypothesis:
The relative overlap of two individual's friendship networks varies directly with the strength of their tie to one another.
- ⑤ The cohesive power of weak ties: important in e.g. obtaining new information

Weak ties in real data

- Weak ties hypothesis: Relative overlap of friends varies with the tie strength
- Define **overlap** O_{ij} of edge (i,j) as the fraction of common neighbours
- Observation in the mobile telephone call network: Average overlap increases as a function of (cumulative) link weights

$$O_{ij} = \frac{n_{ij}}{(k_i - 1) + (k_j - 1) - n_{ij}}$$



(null hypotheses / reference systems for weighted networks: keep topology, shuffle all weights s.t. $w_{ij}=w_{lm}$, $w_{lm}=w_{ij}$ etc)

Role of weak ties on the network level

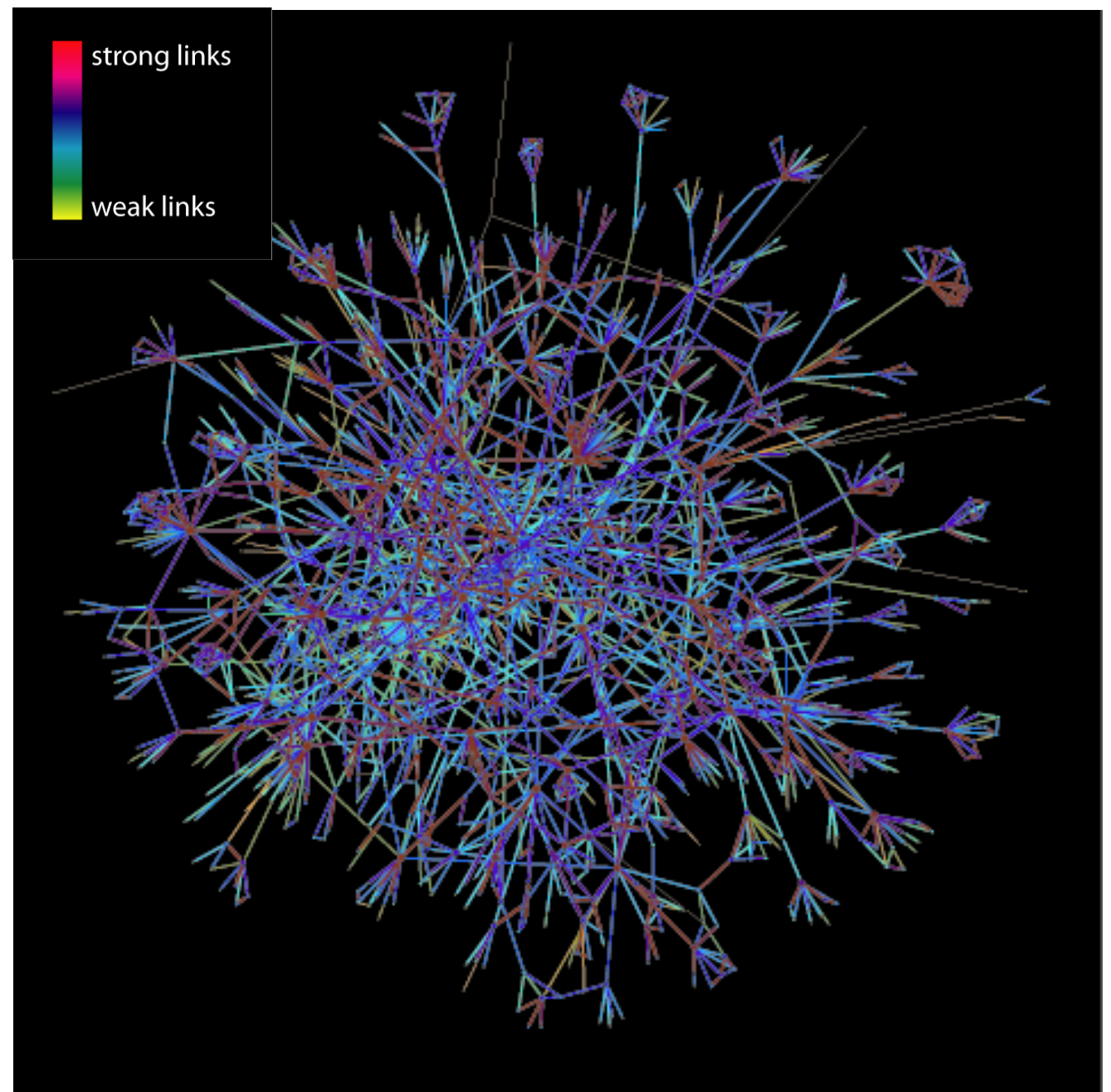
- Probe the global role of links of different weight and local topology
- Thresholding & percolation analysis: Remove links based on their weight (weak to strong, or strong to weak)
- Control parameter f is the fraction of removed links
 - Initial network ($f=0$); isolated nodes ($f=1$)

Role of weak ties on the network level

Initial connected network ($f=0$), small sample

\Rightarrow All links are intact, i.e. the network is in its initial

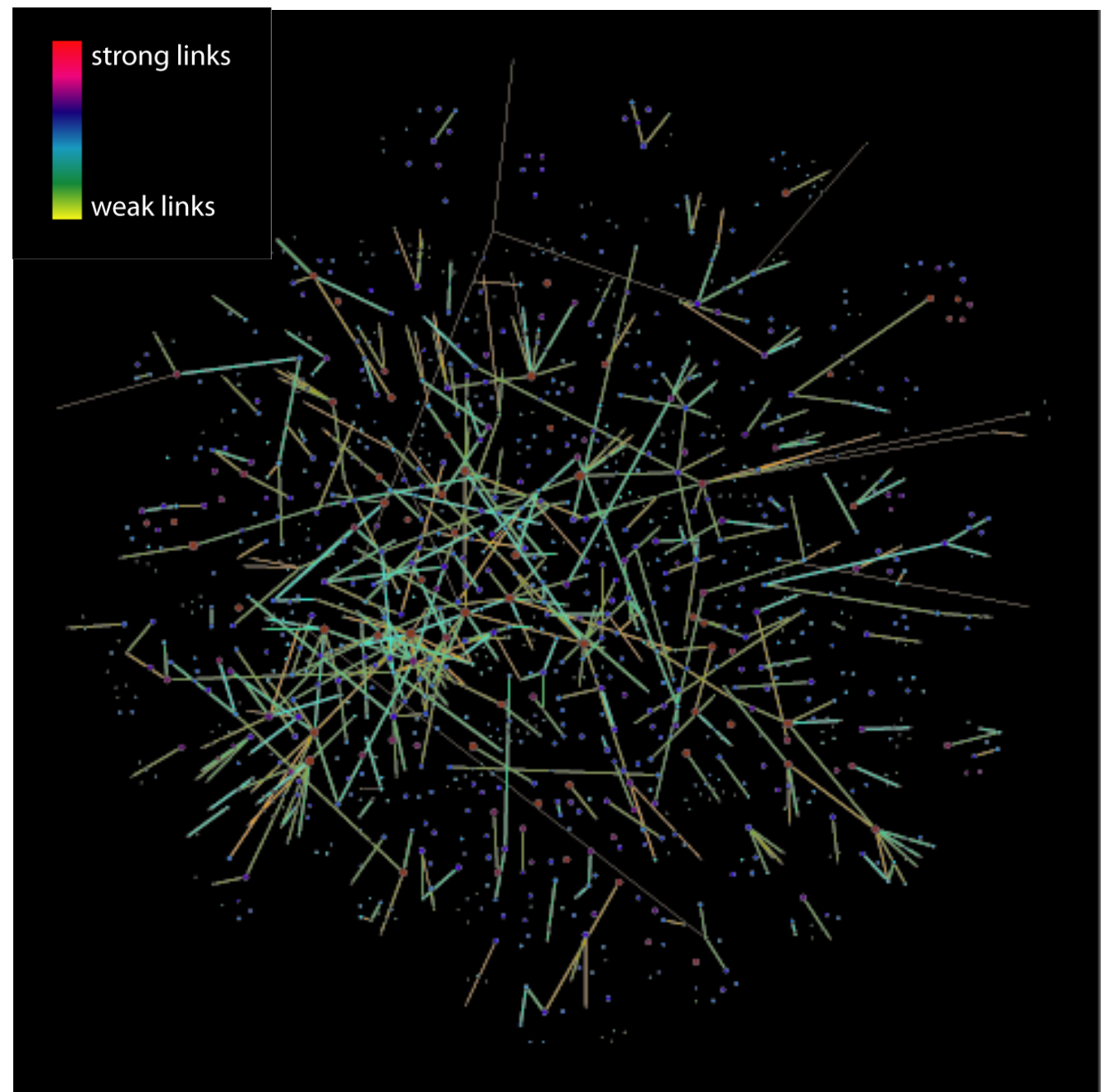
stage



Role of weak ties on the network level

Decreasing weight thresholded network ($f=0.8$)

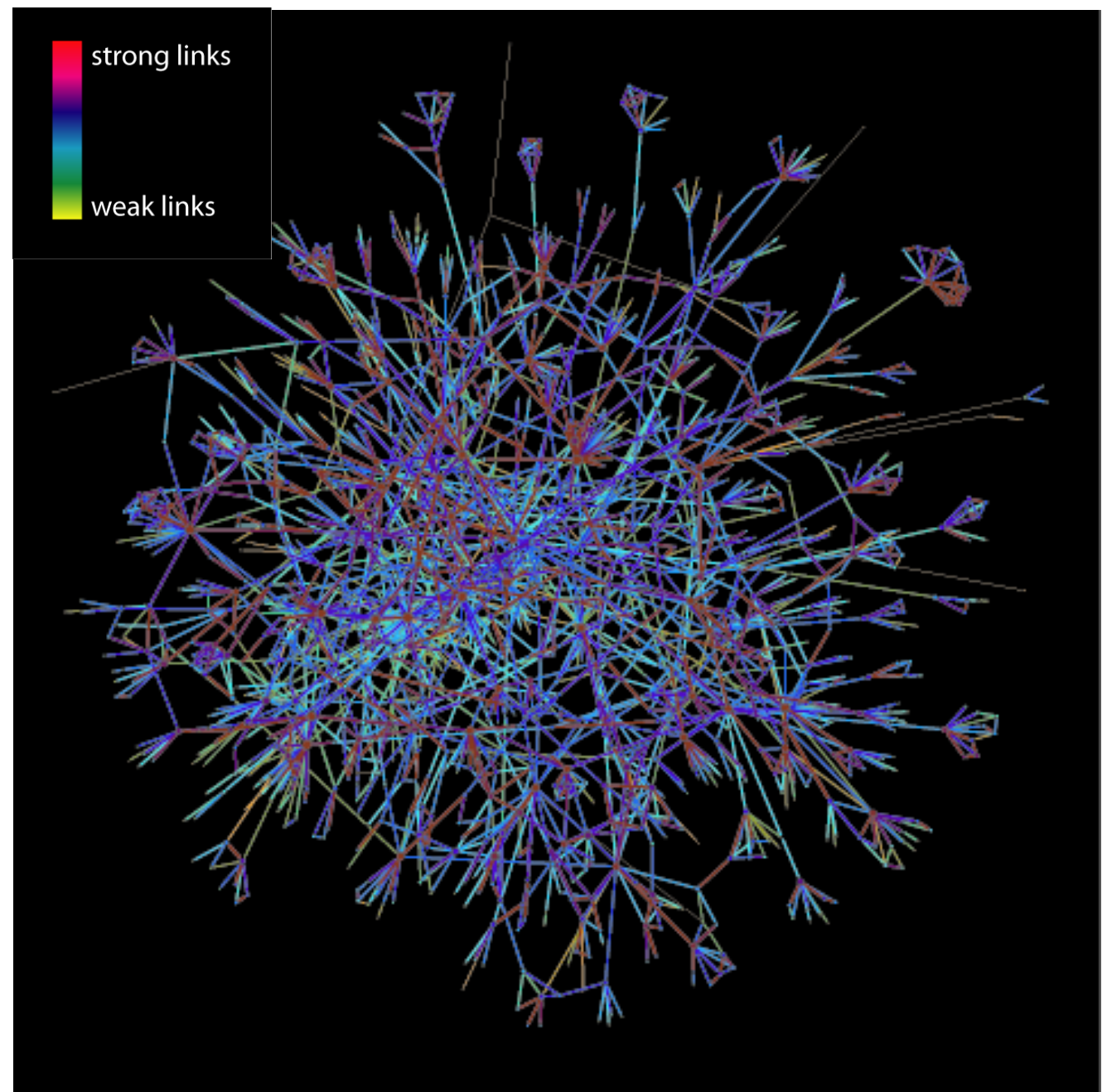
\Rightarrow 80% of the strongest links removed, weakest 20% remain



Role of weak ties on the network level

Initial connected network ($f=0$), small sample

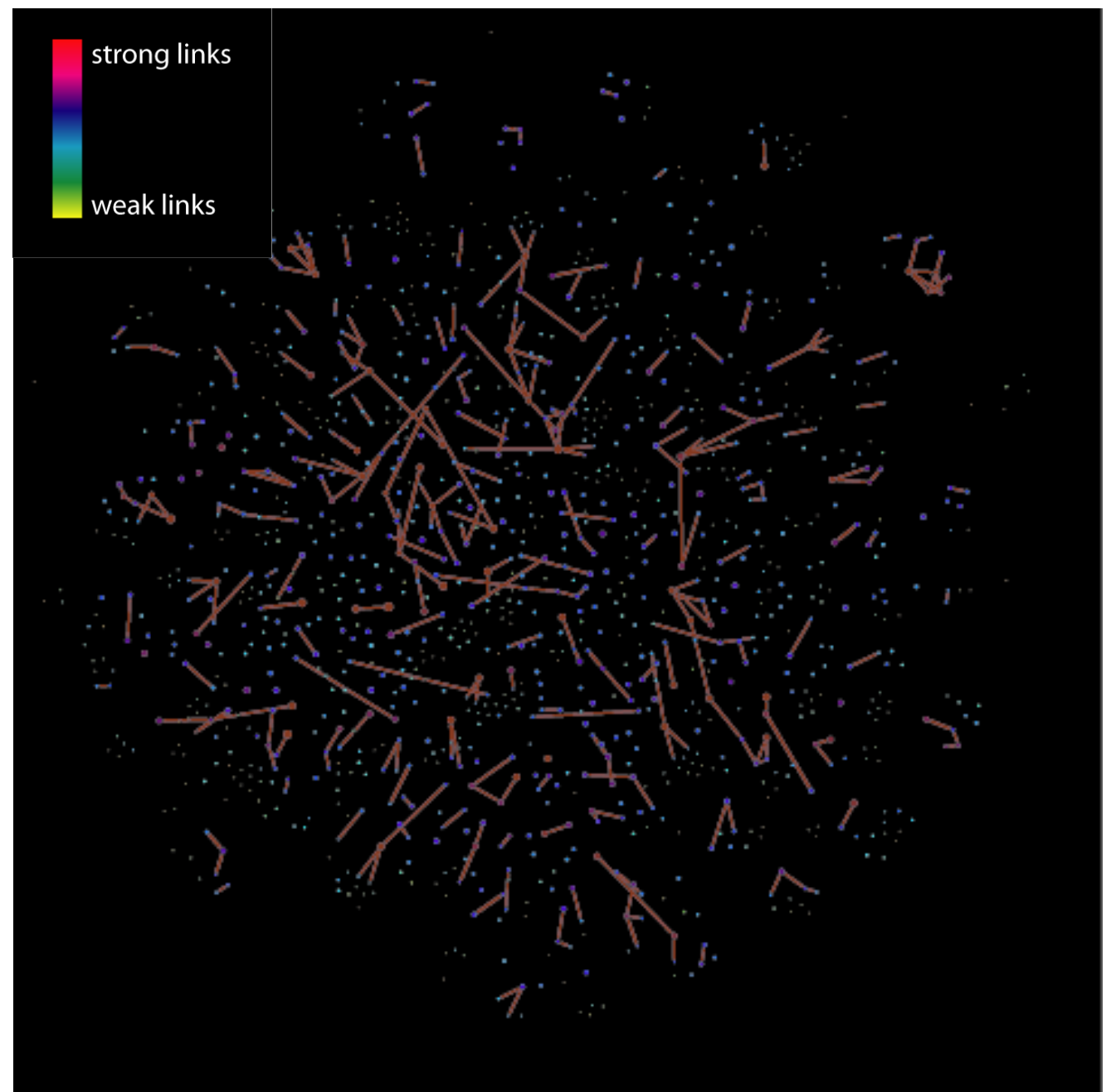
⇒ All links are intact, i.e. the network is in its initial stage



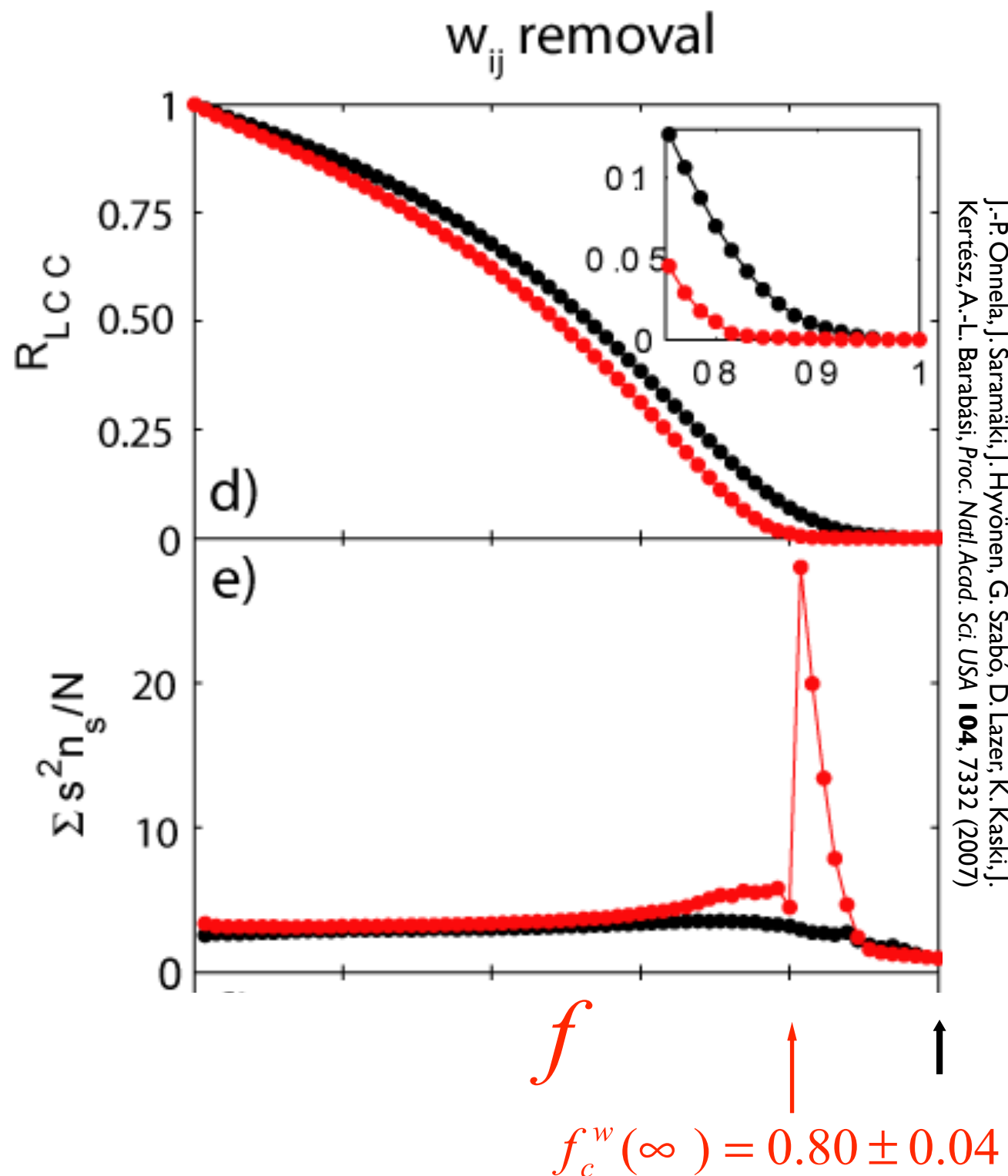
Role of weak ties on the network level

Increasing weight thresholded network ($f=0.8$)

⇒ 80% of the weakest links removed, strongest 20% remain



Role of weak ties on the network level



Weak links first:

- Network fragments at around $f=0.8$

Strong links first

- No evidence of fragmentation

R_{LCC} = fraction of nodes in largest connected component

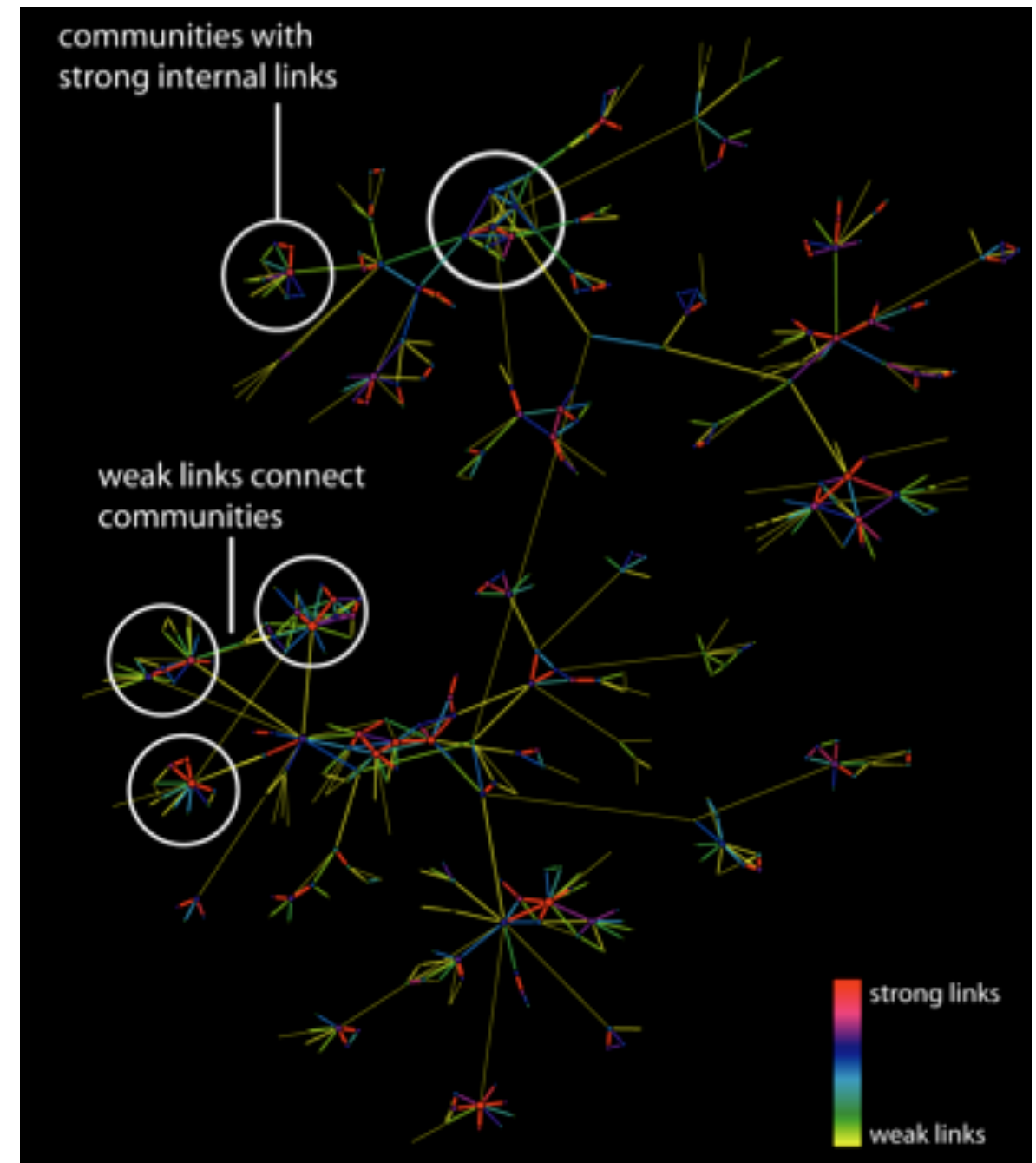
S = susceptibility

- Def: average cluster size (excl. LCC)

$$S = \frac{\sum_{s < S_{\max}} n_s s^2}{\sum_{s < S_{\max}} n_s s}$$

Mobile network: summary of observations

- Strong links associated with dense network neighbourhoods (triangles, cliques, etc)
- Weak links connect dense neighbourhoods
- I.e. social groups with strong ties are connected via bridges of weak links
- Weak links crucially important for connectivity of the whole network!



A weighted model based on observations

Kumpula, Onnela, Saramäki et al, Phys Rev Lett **99**, 228701 (2007)

Tie formation mechanisms known in social sciences

Cyclic closure:

- Getting to know people through own friends, their friends, etc
- Decreases exponentially with network distance*, hence one can only consider triangles (becoming friend of a friend's friend)

Focal closure:

- Connections which appear random regarding the network

Model

- Use these mechanisms, add tie reinforcement mechanism
- Network of fixed size N , initially random connections

* M. Kossinets et al., "Empirical Analysis of an Evolving Social Network", Science **311**, 88 (2006)

Microscopic rules

- Fixed number of nodes, **3 mechanisms for link creation & deletion**

- Rule 1/3: Local attachment + weight reinforcement**

- Pick a random node i
- Pick another (k) by weighted 2-step random walk

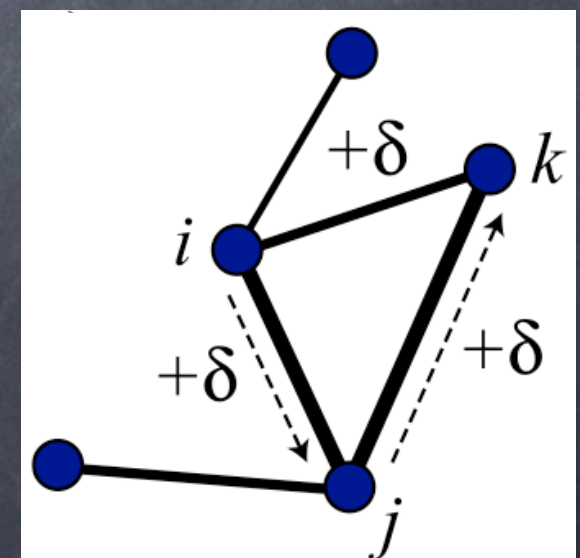
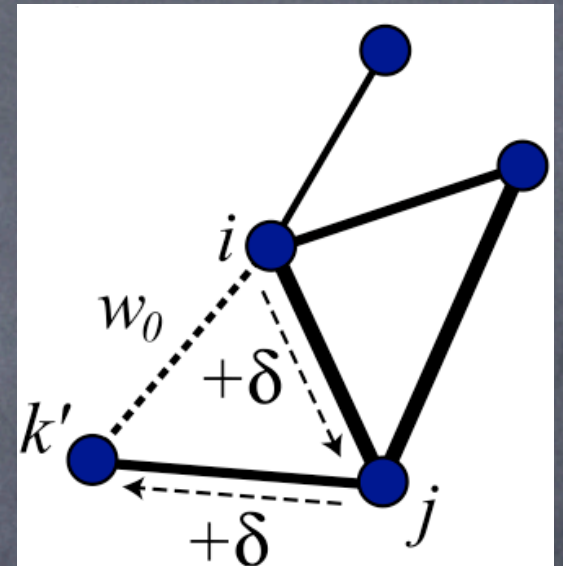
$$\begin{aligned}P(i \rightarrow j) &= w_{ij} / s_i \\P(j \rightarrow k) &= w_{jk} / (s_j - w_{ij}) \\w_{ij} &\rightarrow w_{ij} + \delta \\w_{jk} &\rightarrow w_{jk} + \delta\end{aligned}$$

- If no triangle $(i,j,k) \Rightarrow$ **Form triangle**

$$\begin{aligned}P(i, j, k) &= p_{\Delta} \\w_{ik} &= w_0 = 1\end{aligned}$$

- If triangle (i,j,k) exists \Rightarrow **Reinforce triangle**

$$w_{ik} \rightarrow w_{ik} + \delta$$



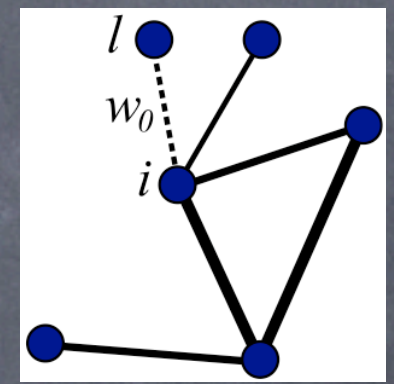
Microscopic rules

• Rule 2/3: Global (random) attachment

- Pick a random node, connect to a random node with probability p_r (or if its degree=0)

$$k_i = 0 \implies P(i, j) = 1; w_{ij} = w_o = 1$$

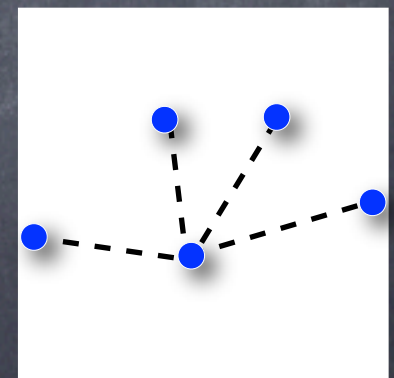
$$k_i > 0 \implies P(i, j) = p_r; w_{ij} = w_o$$



• Rule 3/3: Node deletion

- Pick a random node; delete it with probability p_d
- Adjacent links are removed
- Node is returned to the network

$$k_i > 0 \implies P(k_i = 0) = p_d$$



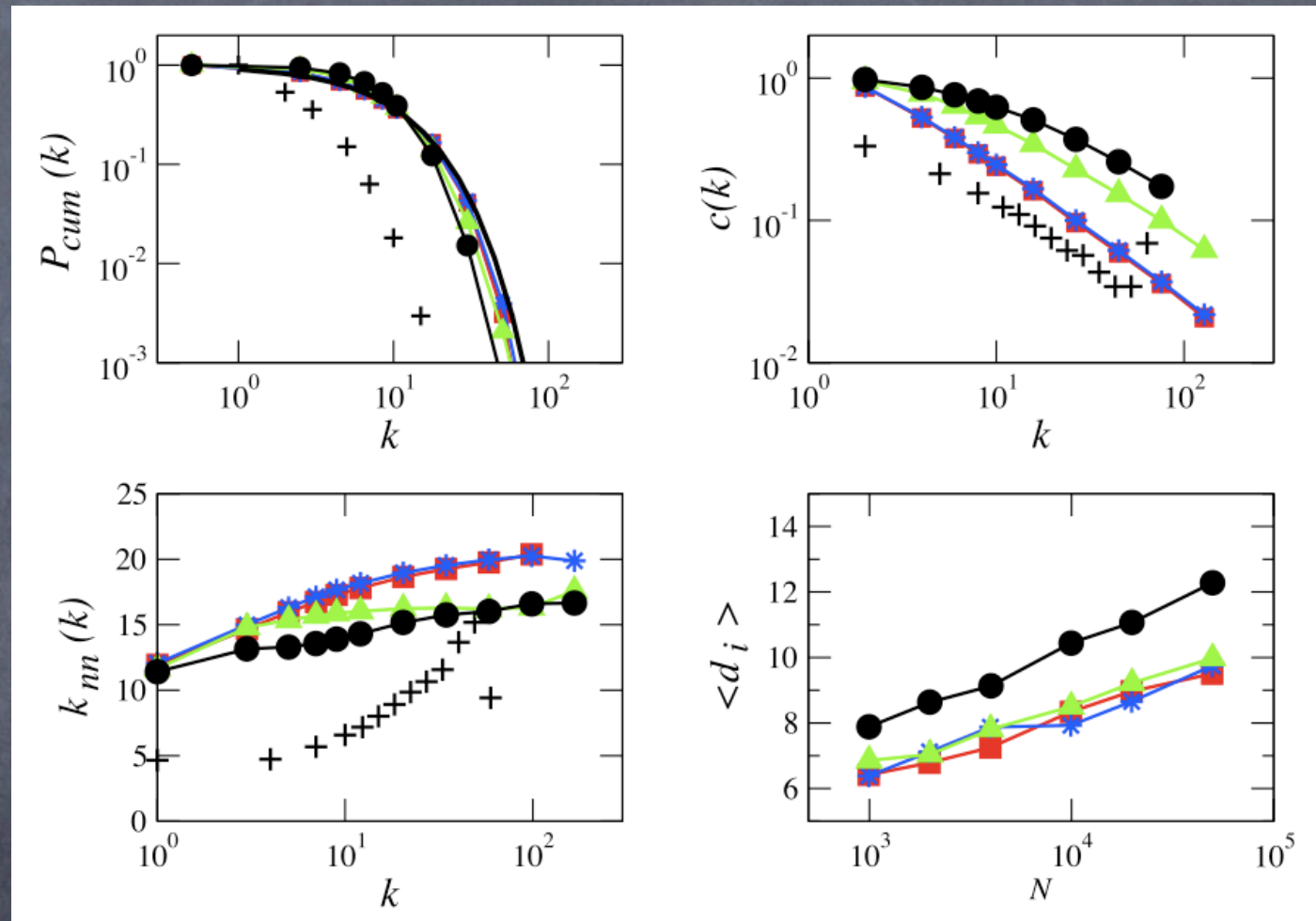
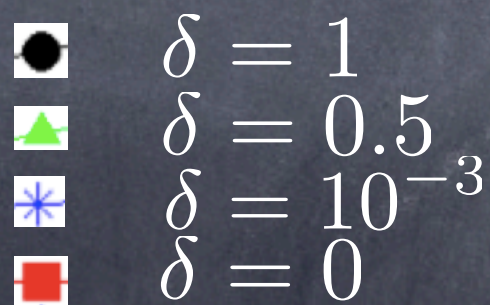
Basic characteristics

(a) Broad degree distribution

(b) High clustering

(c) Assortative

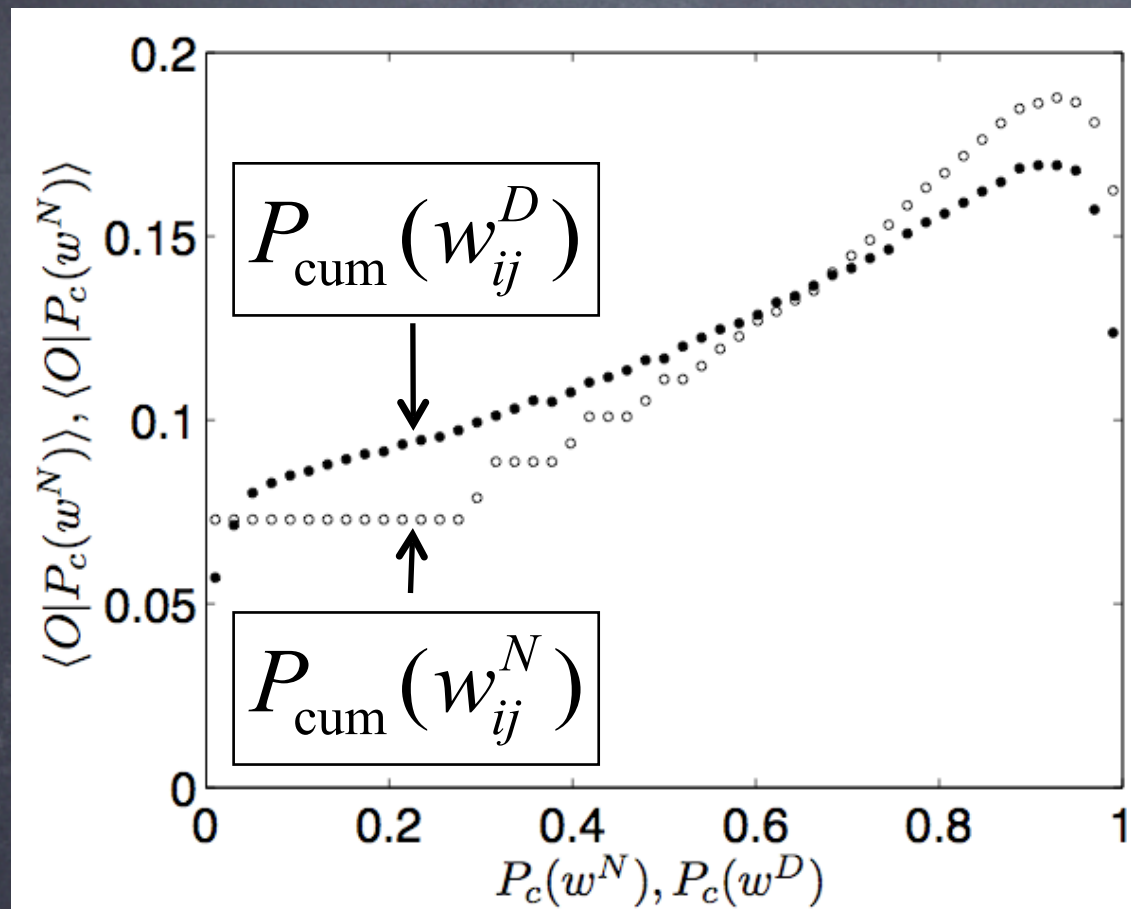
(d) Small world



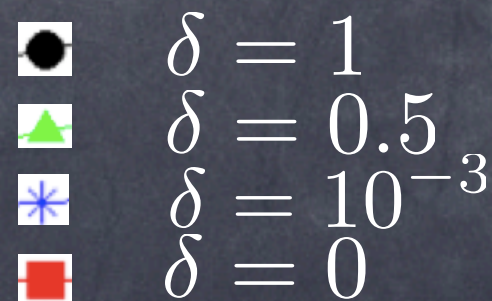
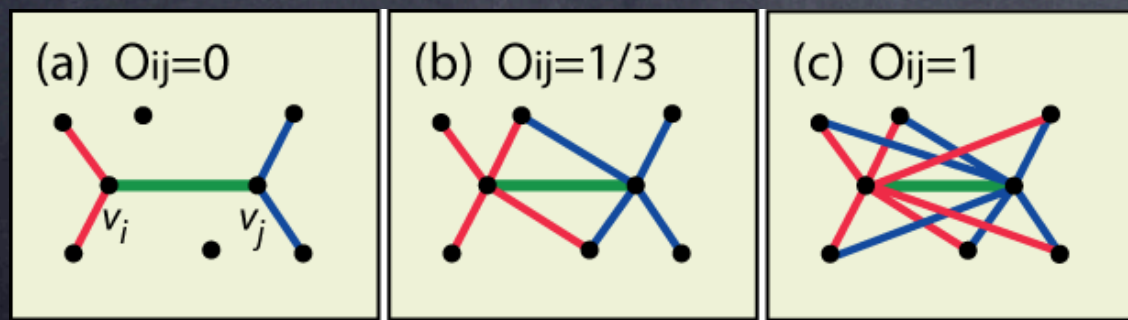
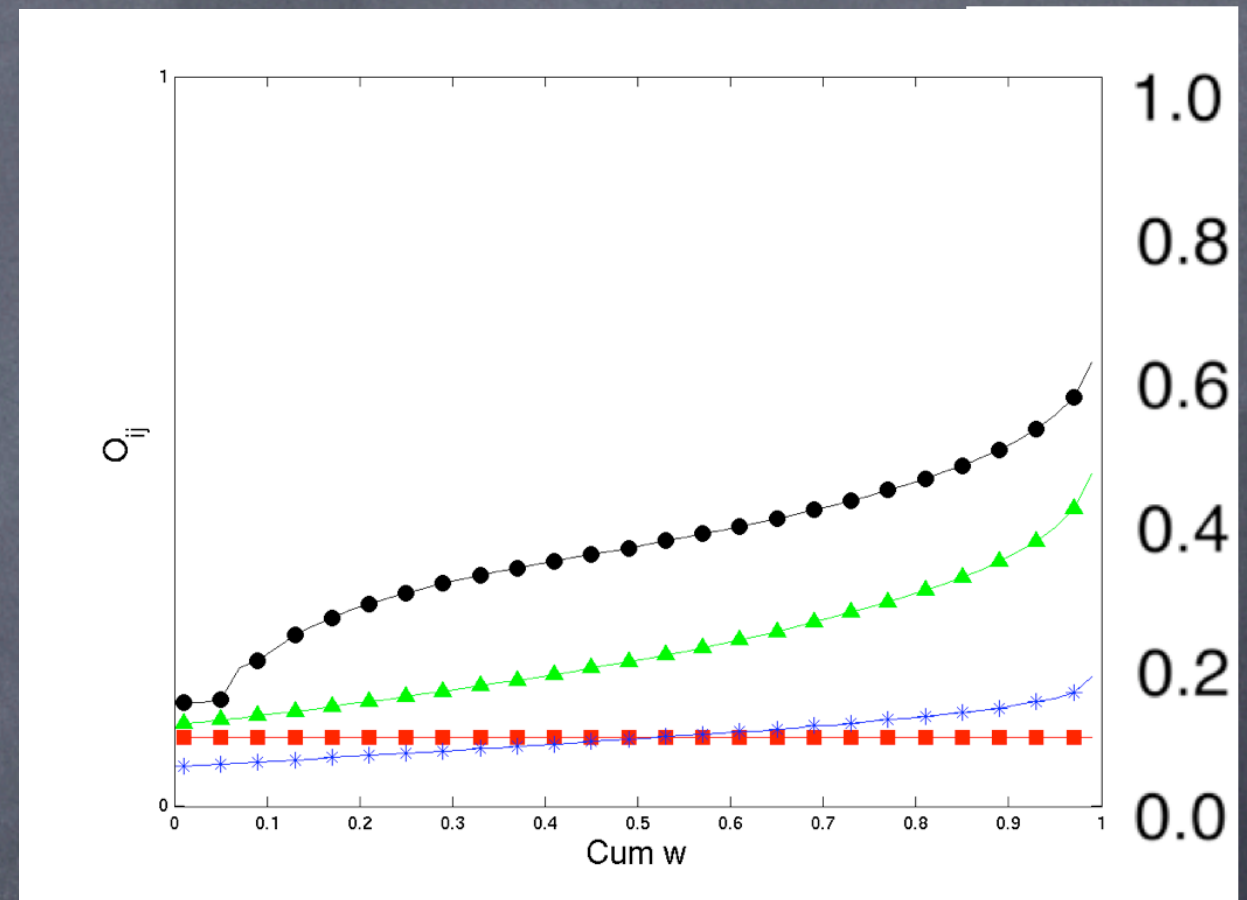
Values of δ are 0 (\square), 1×10^{-3} (*), 1×10^{-2} (\triangleright), 0.1 (\triangle), 0.5 (∇), and 1 (\circ).

Local structure (overlap)

Empirical



Model



Global structure (percolation)

Small $\delta < 0.1$ \star $\delta = 10^{-3}$
 \square $\delta = 0$

Network disintegrates at the same point for weak and strong link removal

Incompatible with WTH

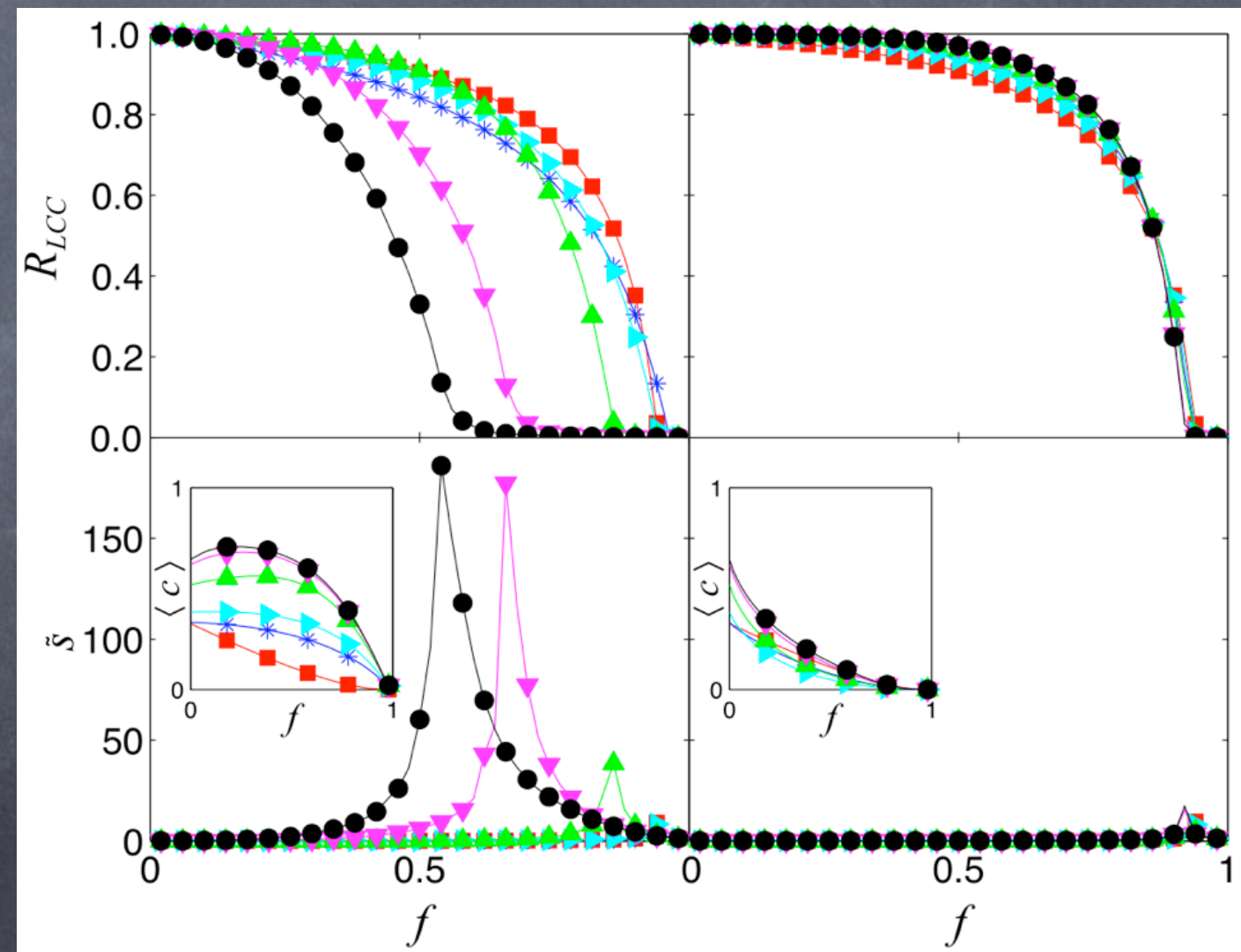
Large $\delta > 0.1$ \bullet $\delta = 1$
 ∇ $\delta = 0.5$

Network disintegrates at different points

Compatible with WTH

Weak go first

Strong go first



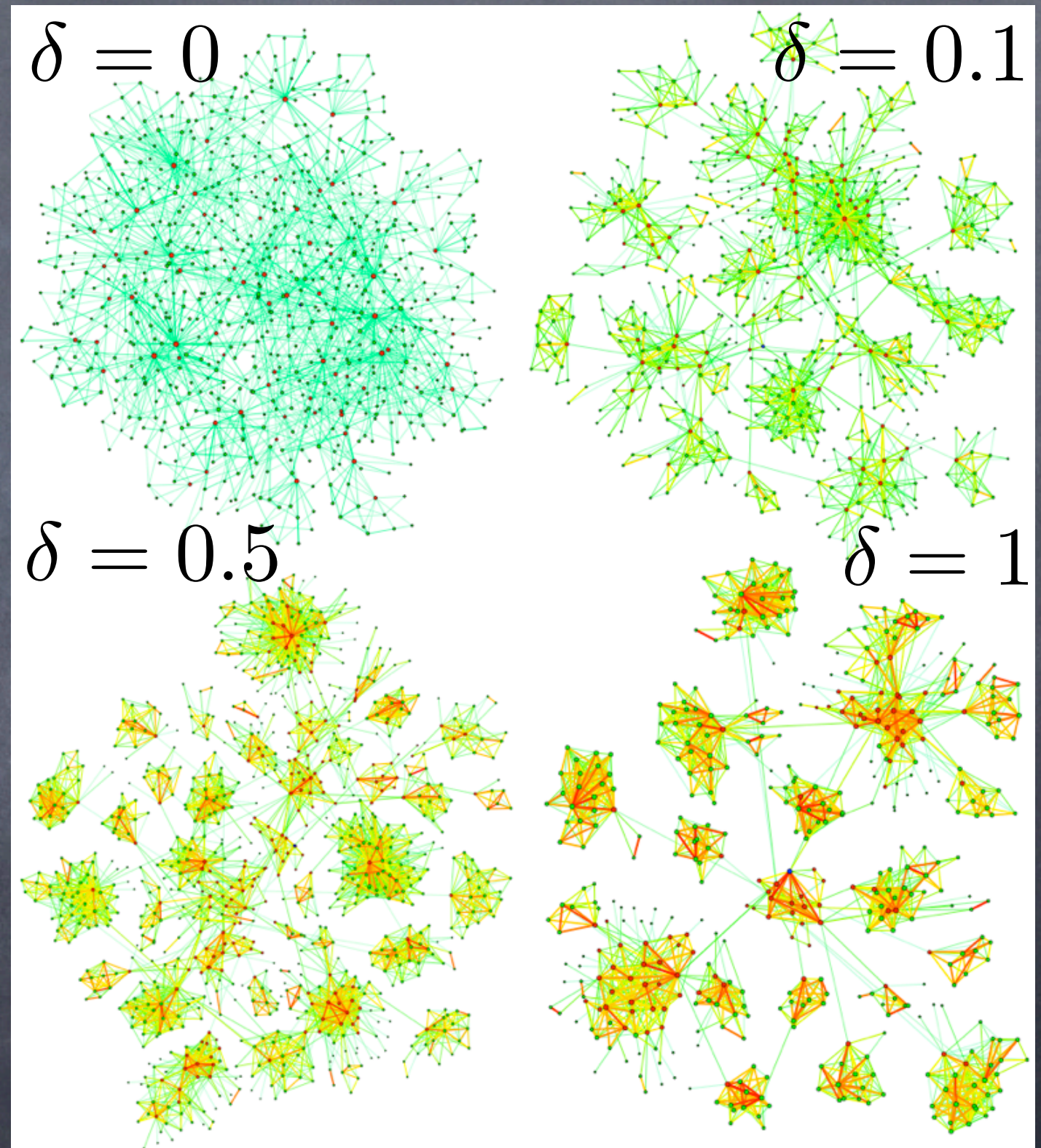
simulations of $N = 5 \times 10^4$ networks. Values of δ are 0 (\square), 1×10^{-3} (\star), 1×10^{-2} (\triangleright), 0.1 (\triangle), 0.5 (∇), and 1 (\circ).

Communities by inspection

- Increasing δ traps walks in communities, further enhancing trapping effect

=> Clear communities

- Triangles accumulate weight and act as nuclei for communities



Sociodynamic Models

- Mimick social processes taking place on networks
- Usually the outcome of dynamics is heavily affected by network structure
- Edge weights should affect interactions - however, only a few studies of soc. dyn. models on weighted networks exist.
- Examples:
 - SI, SIR (spreading processes) in the context of information/rumours
 - Threshold model (D.J.Watts, PNAS 99, 5766-577, 2002)
 - Opinion formation models: Voter, Majority Rule, Sznajd, language competition models, etc
 - See C. Castellano, S. Fortunato, V. Loreto: Statistical physics of social dynamics, Rev. Mod. Phys. 81, No. 2. (2009), pp. 591-646.