

Network Science

Class 4: Scale-free property

Albert-László Barabási

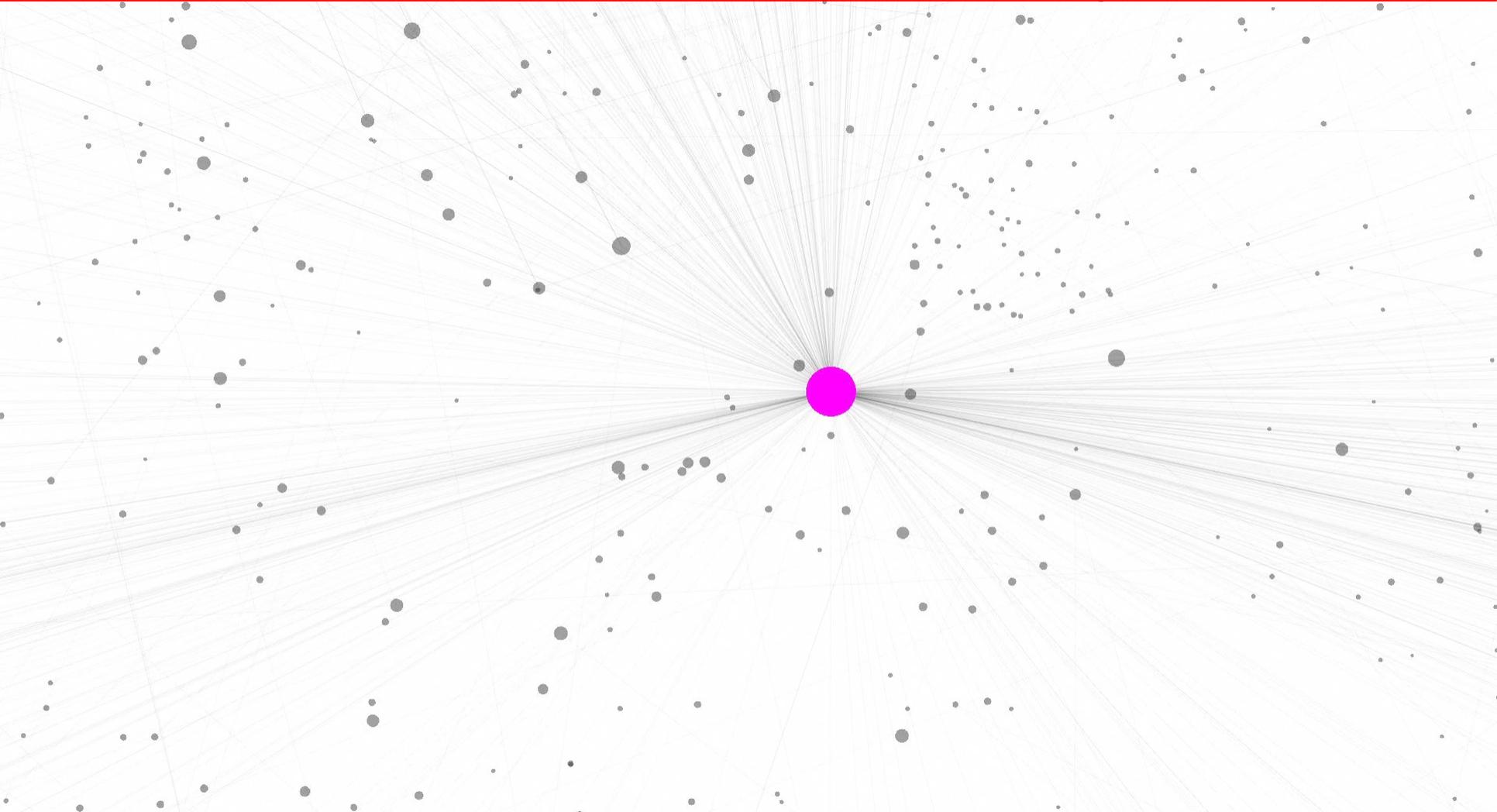
with Emma K. Towlson, Michael M. Danziger,
Sebastian Ruf and Louis Shekhtman

www.BarabasiLab.com

1. From the WWW to Scale-free networks. Definition.
2. Discrete and continuum formalism. Explain its meaning.
3. Hubs and the maximum degree.
4. What does 'scale-free' mean?
5. Universality. Are all networks scale-free?
6. From small worlds to ultra small worlds.
7. The role of the degree exponent.

Introduction

WORLD WIDE WEB



R. Albert, H. Jeong, A-L Barabasi, *Nature*, 401 130 (1999).

Power laws and scale-free networks

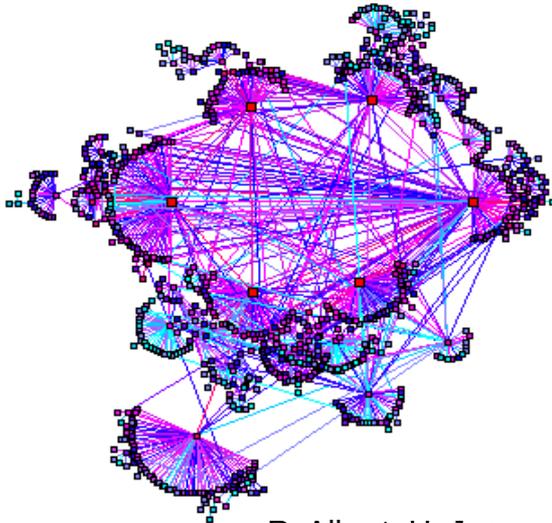
WORLD WIDE WEB

Nodes: **WWW documents**

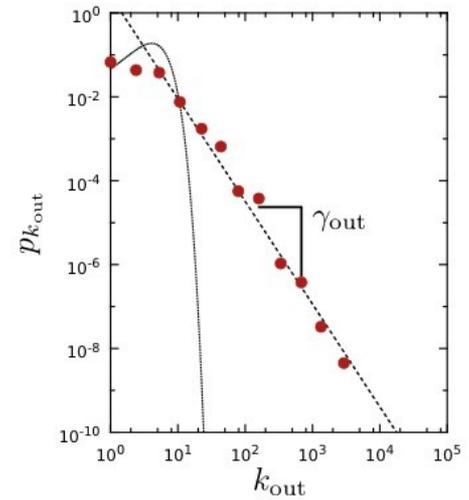
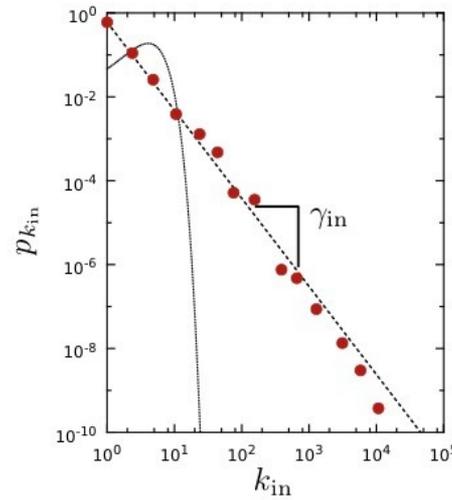
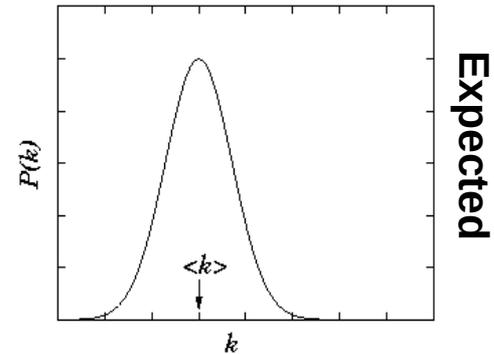
Links: **URL links**

Over 3 billion documents

ROBOT: collects all URL's found in a document and follows them recursively



R. Albert, H. Jeong, A-L Barabasi, *Nature*, 401 130 (1999).



Discrete vs. Continuum formalism

Discrete Formalism

As node degrees are always positive integers, the discrete formalism captures the probability that a node has exactly k links:

$$p_k = Ck^{-\gamma}.$$

$$\sum_{k=1}^{\infty} p_k = 1.$$

$$C \sum_{k=1}^{\infty} k^{-\gamma} = 1$$

$$C = \frac{1}{\sum_{k=1}^{\infty} k^{-\gamma}} = \frac{1}{\zeta(\gamma)},$$

$$p_k = \frac{k^{-\gamma}}{\zeta(\gamma)}$$

INTERPRETATION:

$$p_k$$

Continuum Formalism

In analytical calculations it is often convenient to assume that the degrees can take up any positive real value:

$$p(k) = Ck^{-\gamma}.$$

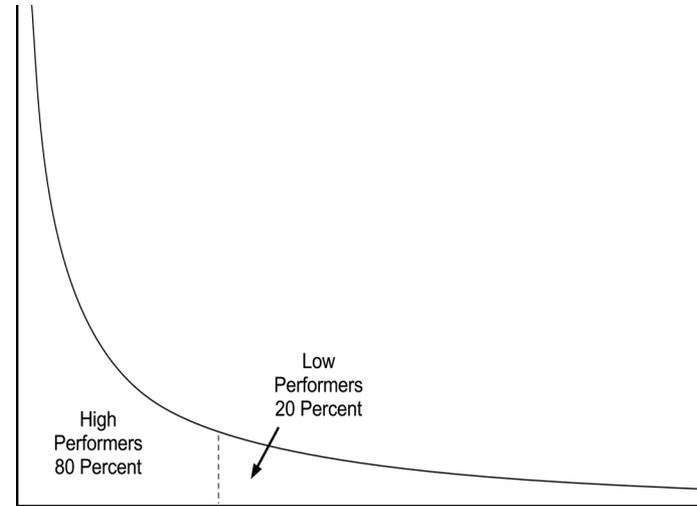
$$\int_{k_{\min}}^{\infty} p(k)dk = 1$$

$$C = \frac{1}{\int_{k_{\min}}^{\infty} k^{-\gamma} dk} = (\gamma - 1)k_{\min}^{\gamma-1}$$

$$p(k) = (\gamma - 1)k_{\min}^{\gamma-1}k^{-\gamma}.$$

$$\int_{k_1}^{k_2} p(k)dk$$

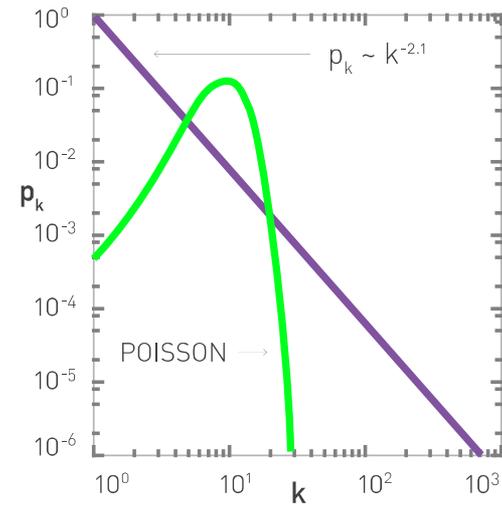
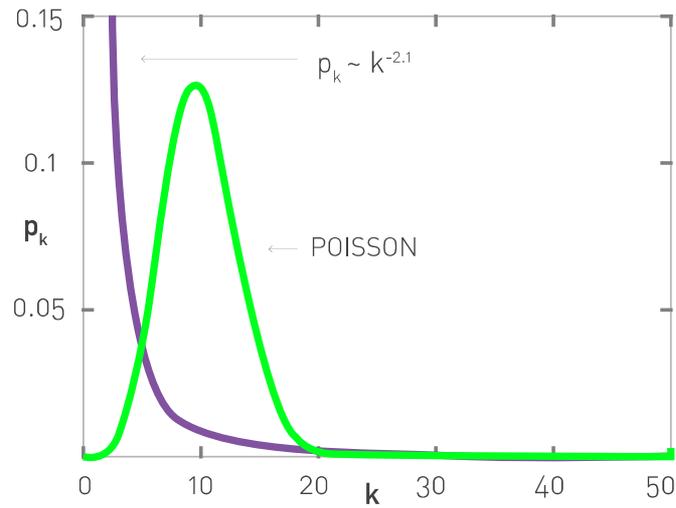
80/20 RULE



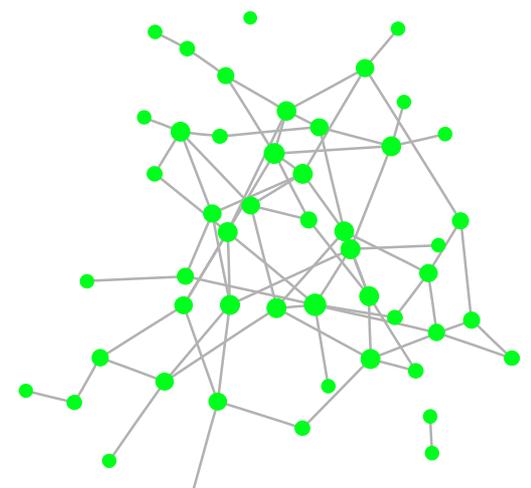
Vilfredo Federico Damaso Pareto (1848 – 1923), Italian economist, political scientist and philosopher, who had important contributions to our understanding of income distribution and to the analysis of individuals choices. A number of fundamental principles are named after him, like Pareto efficiency, Pareto distribution (another name for a power-law distribution), the Pareto principle (or 80/20 law).

Hubs

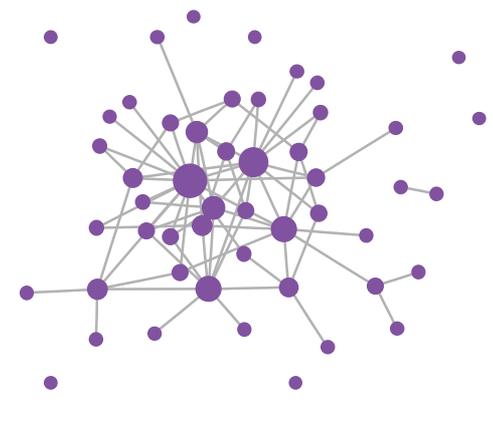
The difference between a power law and an exponential distribution



(c)



(d)



The difference between a power law and an exponential distribution

Let us use the WWW to illustrate the properties of the high- k regime.

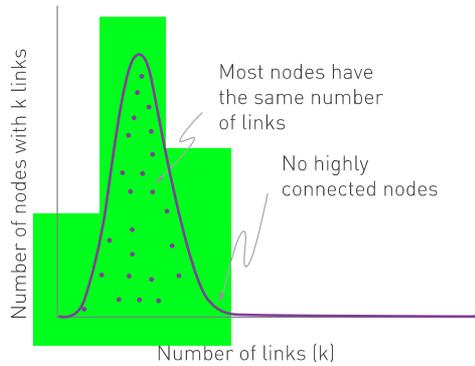
The probability to have a node with $k \sim 100$ is

- *About $p_{100} \simeq 10^{-30}$ in a Poisson distribution*
- *About $p_{100} \simeq 10^{-4}$ if p_k follows a power law.*
- *Consequently, if the WWW were to be a random network, according to the Poisson prediction we would expect 10^{-18} $k > 100$ degree nodes, or none.*

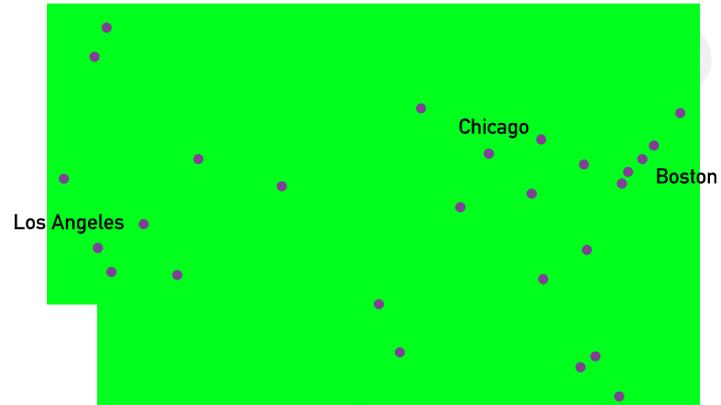
$$N_{k>100} = 10^9$$

- *For a power law degree distribution, we expect about $k > 100$ degree nodes*

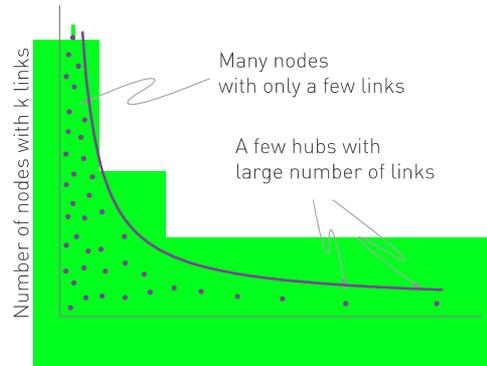
(a) POISSON



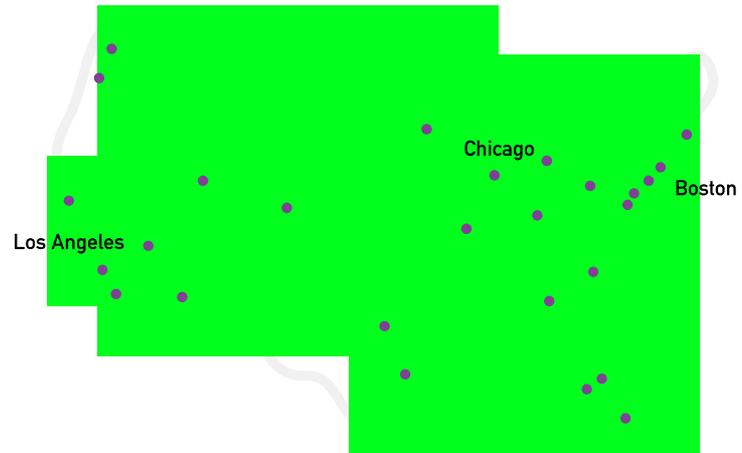
(b)



(c) POWER LAW



(d)



The size of the biggest hub

All real networks are finite \rightarrow let us explore its consequences.

\rightarrow We have an expected maximum degree, k_{\max}

Estimating k_{\max}

$$\int_{k_{\max}}^{\infty} P(k) dk \approx \frac{1}{N}$$

Why: the probability to have a node larger than k_{\max} should not exceed the prob. to have one node, i.e. $1/N$ fraction of all nodes

$$\int_{k_{\max}}^{\infty} P(k) dk = (\gamma - 1) k_{\min}^{\gamma-1} \int_{k_{\max}}^{\infty} k^{-\gamma} dk = \frac{(\gamma - 1)}{(-\gamma + 1)} k_{\min}^{\gamma-1} \left[k^{-\gamma+1} \right]_{k_{\max}}^{\infty} = \frac{k_{\min}^{\gamma-1}}{k_{\max}^{\gamma-1}} \approx \frac{1}{N}$$

$$k_{\max} = k_{\min} N^{\frac{1}{\gamma-1}}$$

The size of the biggest hub

$$k_{\max} = k_{\min} N^{\frac{1}{\gamma-1}}$$

To illustrate the difference in the maximum degree of an exponential and a scale-free network let us return to the WWW sample of [Figure 4.1](#), consisting of $N \approx 3 \times 10^5$ nodes. As $k_{\min} = 1$, if the degree distribution were to follow an exponential, [\(4.17\)](#) predicts that the maximum degree should be $k_{\max} \approx 13$. In a scale-free network of similar size and $\gamma = 2.1$, [\(4.18\)](#) predicts $k_{\max} \approx 85,000$, a remarkable difference. Note that the largest in-degree of the WWW map of [Figure 4.1](#) is 10,721, which is comparable to k_{\max} predicted by a scale-free network. This reinforces our conclusion that *in a random network hubs are effectivelly forbidden, while in scale-free networks they are naturally present.*

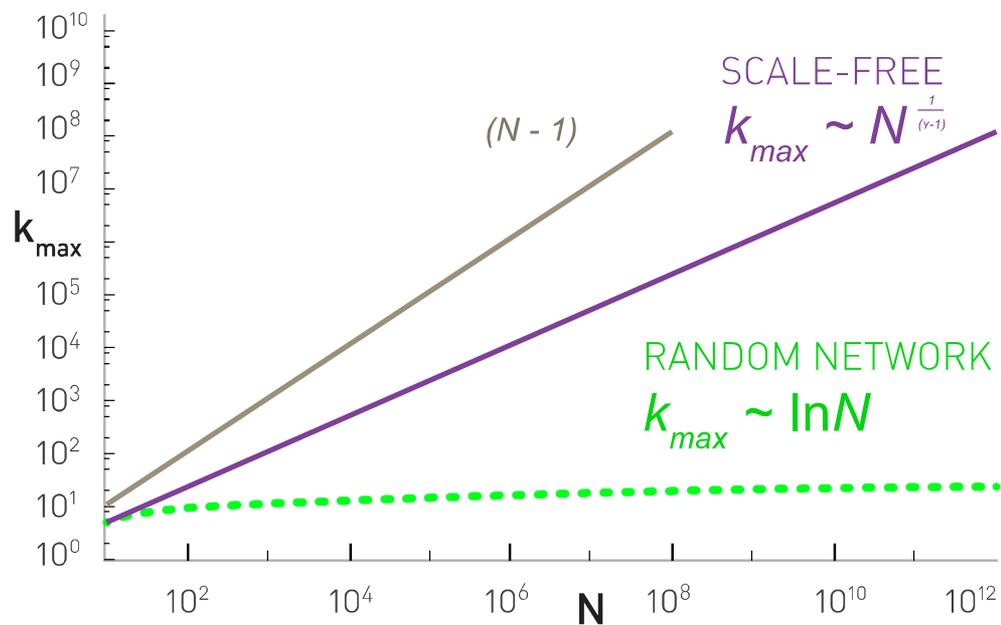
Finite scale-free networks

Expected maximum degree, k_{\max}

$$k_{\max} = k_{\min} N^{\frac{1}{\gamma-1}}$$

- k_{\max} , increases with the size of the network
→ the larger a system is, the larger its biggest hub
 - For $\gamma > 2$ k_{\max} increases slower than N
→ the largest hub will contain a decreasing fraction of links as N increases.
 - For $\gamma = 2$ $k_{\max} \sim N$.
→ The size of the biggest hub is $O(N)$
 - For $\gamma < 2$ k_{\max} increases faster than N : condensation phenomena
→ the largest hub will grab an increasing fraction of links. Anomaly!

The size of the largest hub



$$k_{\max} = k_{\min} N^{\frac{1}{\gamma-1}}$$

The meaning of scale-free

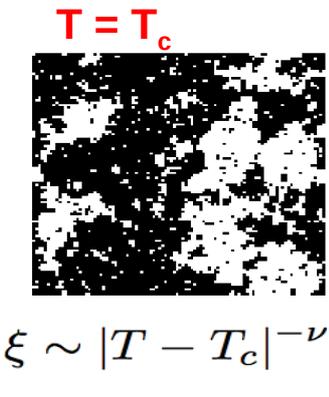
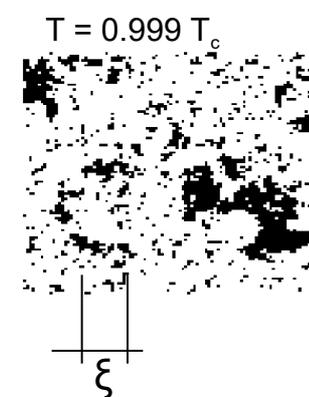
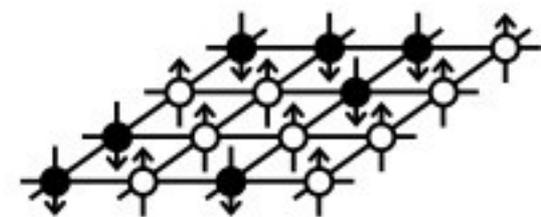
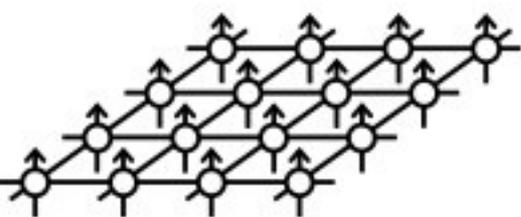
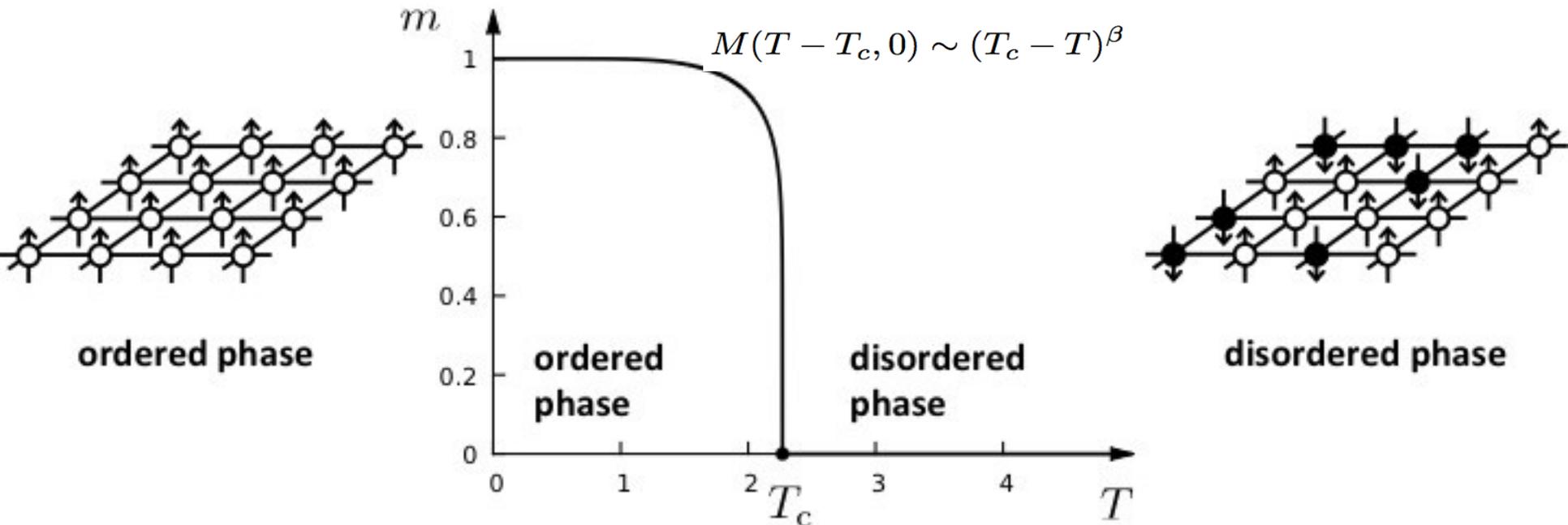
Definition:

Networks with a power law tail in their degree distribution are called 'scale-free networks'

Where does the name come from?

Critical Phenomena and scale-invariance
(a detour)

Phase transitions in complex systems I: Magnetism



$$\xi \sim |T - T_c|^{-\nu}$$

Kinetically Constrained



At $T = T_c$:

correlation length
diverges

Fluctuations emerge at
all scales:

scale-free behavior

Scale invariance at the critical point

by Douglas Ashton

www.kineticallyconstrained.com

- Correlation length diverges at the critical point: the whole system is correlated!
- **Scale invariance:** there is no characteristic scale for the fluctuation (**scale-free behavior**).
- **Universality:** exponents are independent of the system's details.

Divergences in scale-free distributions

$$P(k) = Ck^{-\gamma} \quad k = [k_{\min}, \infty) \quad \int_{k_{\min}}^{\infty} P(k)dk = 1 \quad C = \frac{1}{\int_{k_{\min}}^{\infty} k^{-\gamma} dk} = (\gamma - 1)k_{\min}^{\gamma-1}$$

$$P(k) = (\gamma - 1)k_{\min}^{\gamma-1}k^{-\gamma}$$

$$\langle k^m \rangle = \int_{k_{\min}}^{\infty} k^m P(k) dk \quad \langle k^m \rangle = (\gamma - 1)k_{\min}^{\gamma-1} \int_{k_{\min}}^{\infty} k^{m-\gamma} dk = \frac{(\gamma - 1)}{(m - \gamma + 1)} k_{\min}^{\gamma-1} \left[k^{m-\gamma+1} \right]_{k_{\min}}^{\infty}$$

$$\text{If } m-\gamma+1 < 0: \quad \langle k^m \rangle = -\frac{(\gamma - 1)}{(m - \gamma + 1)} k_{\min}^m$$

If $m-\gamma+1 > 0$, the integral diverges.

For a fixed γ this means that all moments with $m > \gamma - 1$ diverge.

DIVERGENCE OF THE HIGHER MOMENTS

$$\langle k^m \rangle = (\gamma - 1) k_{\min}^{\gamma-1} \int_{k_{\min}}^{\infty} k^{m-\lambda} dk = \frac{(\gamma - 1)}{(m - \gamma + 1)} k_{\min}^{\gamma-1} \left[k^{m-\gamma+1} \right]_{k_{\min}}^{\infty}$$

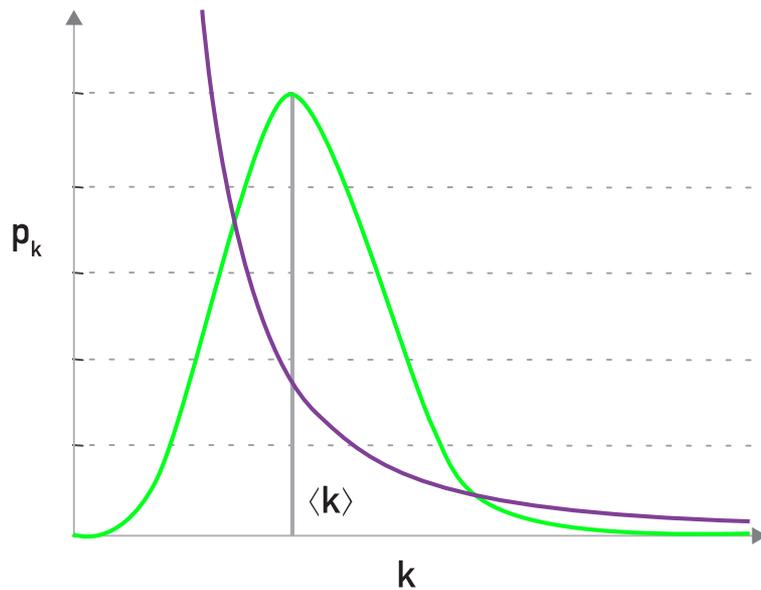
For a fixed λ this means all moments $m > \gamma - 1$ diverge.

Network	Size	$\langle k \rangle$	κ	γ_{out}	γ_{in}
WWW	325 729	4.51	900	2.45	2.1
WWW	4×10^7	7		2.38	2.1
WWW	2×10^8	7.5	4000	2.72	2.1
WWW, site	260 000				1.94
Internet, domain*	3015-4389	3.42-3.76	30-40	2.1-2.2	2.1-2.2
Internet, router*	3888	2.57	30	2.48	2.48
Internet, router*	150 000	2.66	60	2.4	2.4
Movie actors*	212 250	28.78	900	2.3	2.3
Co-authors, SPIRES*	56 627	173	1100	1.2	1.2
Co-authors, neuro.*	209 293	11.54	400	2.1	2.1
Co-authors, math.*	70 975	3.9	120	2.5	2.5
Sexual contacts*	2810			3.4	3.4
Metabolic, <i>E. coli</i>	778	7.4	110	2.2	2.2
Protein, <i>S. cerev.</i> *	1870	2.39		2.4	2.4
Ythan estuary*	134	8.7	35	1.05	1.05
Silwood Park*	154	4.75	27	1.13	1.13
Citation	783 339	8.57			3
Phone call	53×10^5	3.16		2.1	2.1
Words, co-occurrence*	460 902	70.13		2.7	2.7
Words, synonyms*	22 311	13.48		2.8	2.8

Many degree exponents are smaller than 3

→ $\langle k^2 \rangle$ diverges in the $N \rightarrow \infty$ limit!!!

The meaning of scale-free



Random Network

Randomly chosen node: $k = \langle k \rangle \pm \langle k \rangle^{1/2}$

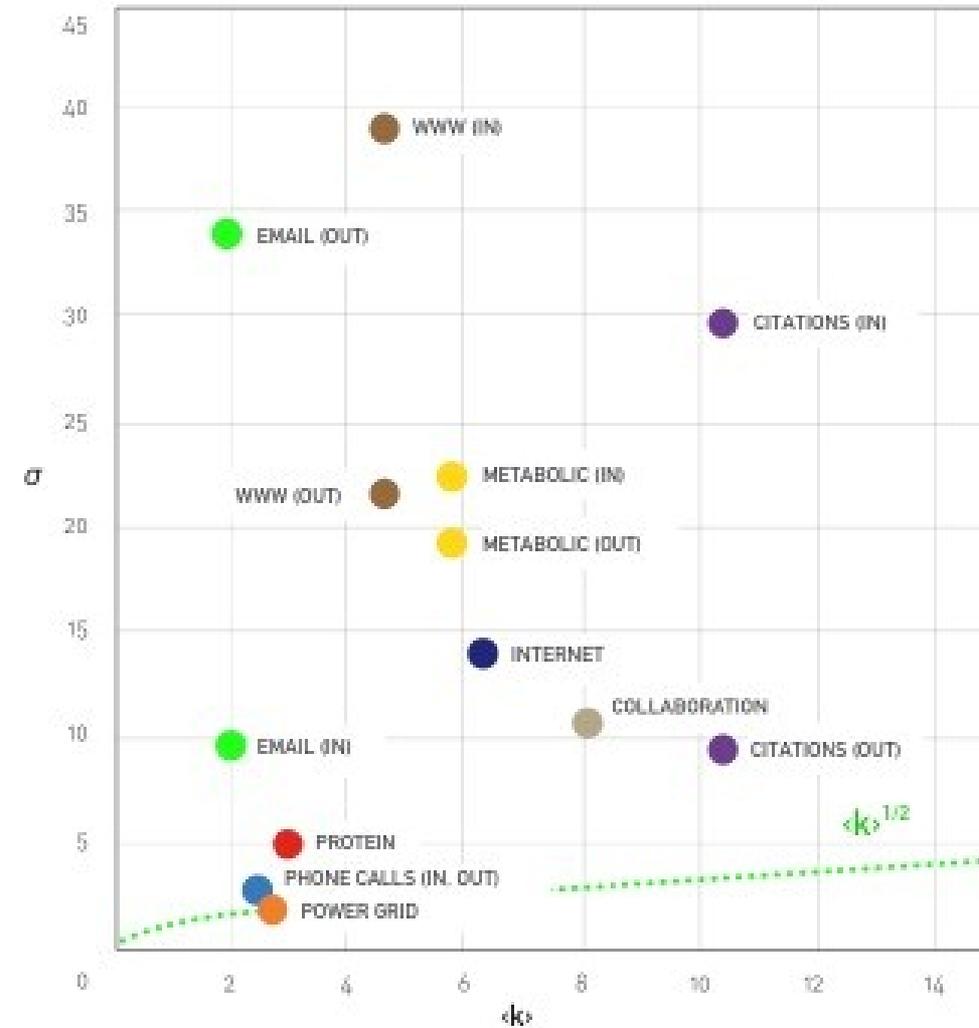
Scale: $\langle k \rangle$

Scale-Free Network

Randomly chosen node: $k = \langle k \rangle \pm \infty$

Scale: none

The meaning of scale-free



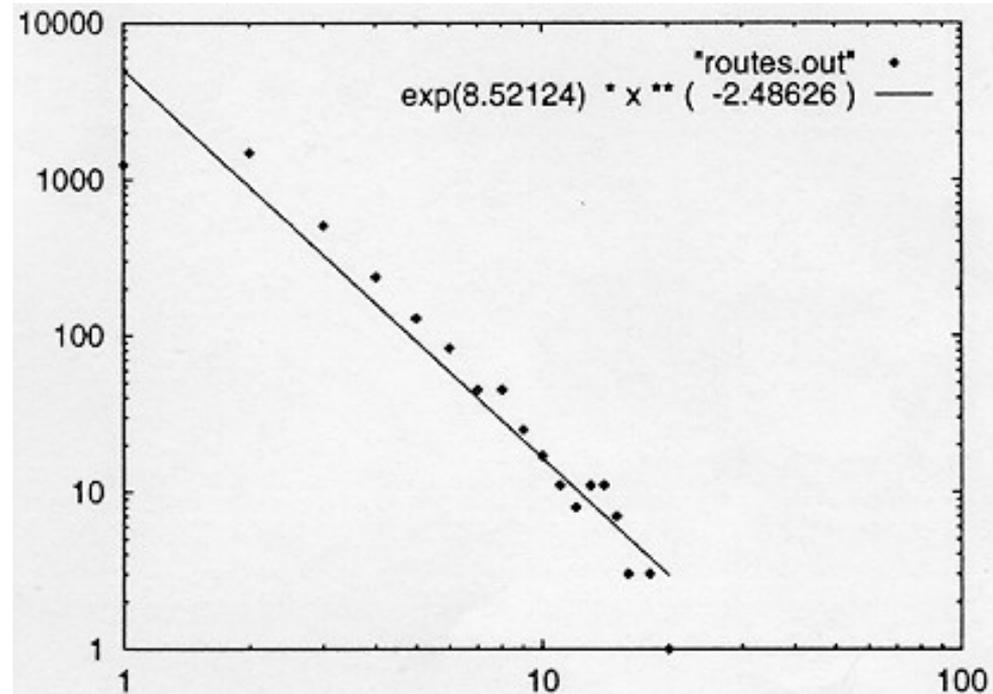
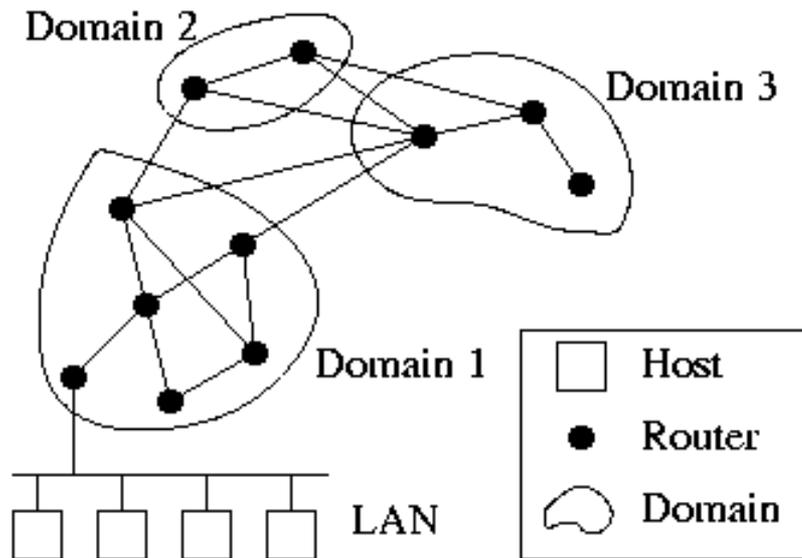
$$k = \langle k \rangle \pm \sigma_k$$

universality

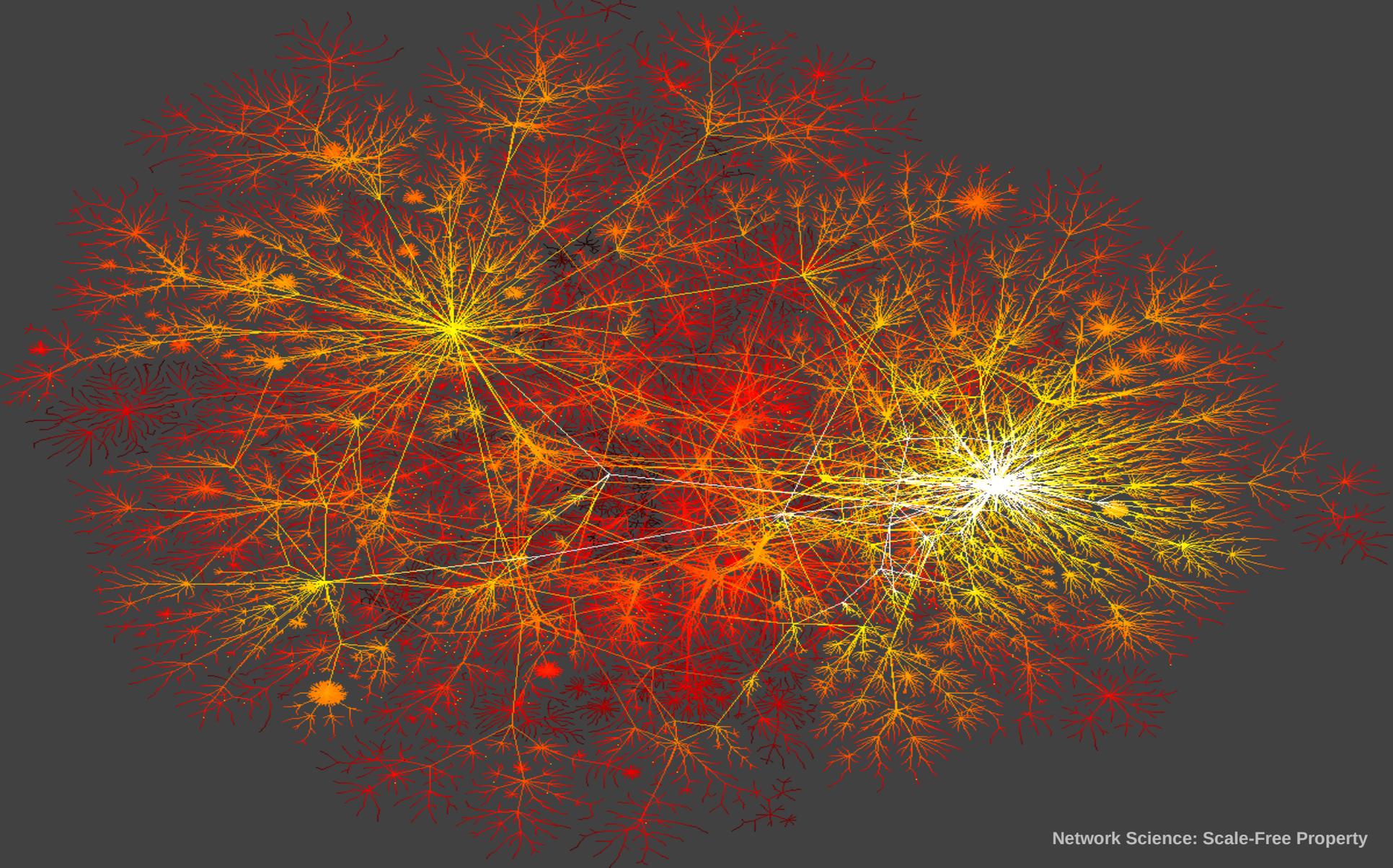
INTERNET BACKBONE

Nodes: computers, routers

Links: physical lines



(Faloutsos, Faloutsos and Faloutsos, 1999)

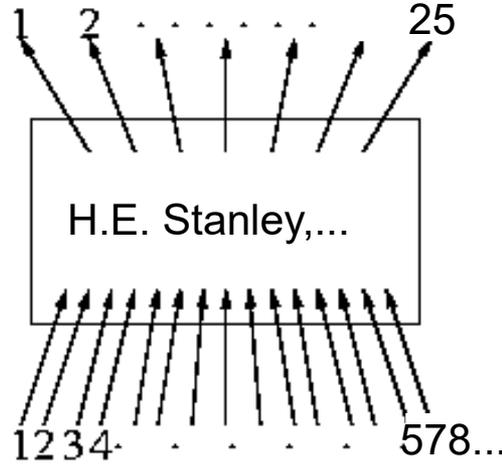


SCIENCE CITATION INDEX

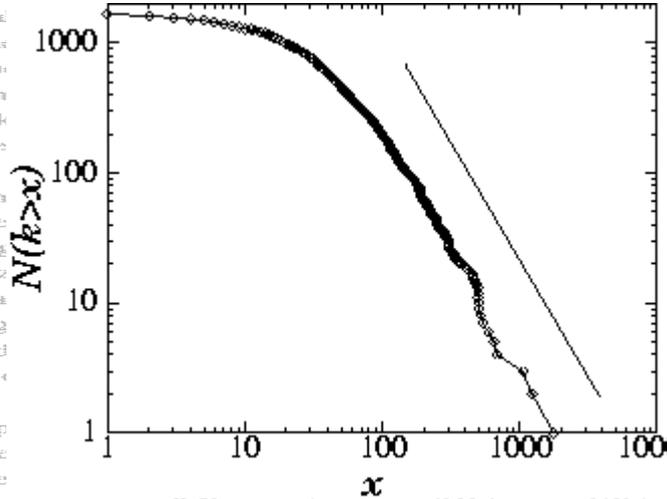
Out of over 500,000 Examined
(see <http://www.sst.nrel.gov>)

Nodes: papers
Links: citations

Author	Institute	Country	Field	avg. cites	total art.	total cites	rank by total cit.
Witten	Princeton (U)	USA, NJ	High-energy (P)	168	138	23235	1
Essler	UCSB (U)	USA, CA	Semie				2
Cava	Bell Labs (I)	USA, NJ	Supern				3
Batlogg	Bell Labs (I)	USA, NJ	Supern				4
Floog	Max-Planck (NL)	Germany	Semie				5
Ellis	Euro Nuclear Cent.	Switzerland	Astroph				6
Fisk	Florida State (U)	USA, FL	Solid S				7
Cardona	Max Planck (NL)	Germany	Semie				8
Nanopoulos	Texas A&M (U)	USA, TX	High-e				9
Heeger	UCSB (U)	USA, CA	Polym				10
Lee*							11
Suzuki*							12
Anderson							13
Suzuki*							14
Freeman							15
Tani							16
Mull							17
Schn							18
Chen							19
Mork							19
Mille							21
Chu				44	213	9453	22
Bedn				46	85	9311	23
Cobe				47	284	9311	23
Metz				86	108	9300	25
Wasz				57	162	9170	26
Shira				33	269	8841	27
Wieg				85	104	8822	28
Vand				67	129	8686	29
Uchi				28	301	8520	30
Hor				72	119	8512	31
Murp				111	76	8439	32
Birge				41	286	8375	33
Jorge				50	167	8298	34
Hinks	Argonne (NL)	USA, IL	Supetconductivity (E)	37	223	8263	35



1736 PRL papers (1988)



$P(k) \sim k^{-\gamma}$
 $(\gamma = 3)$

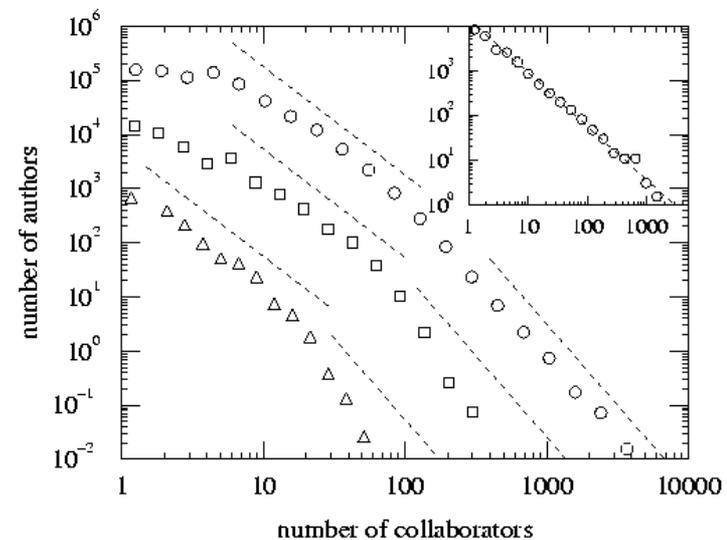
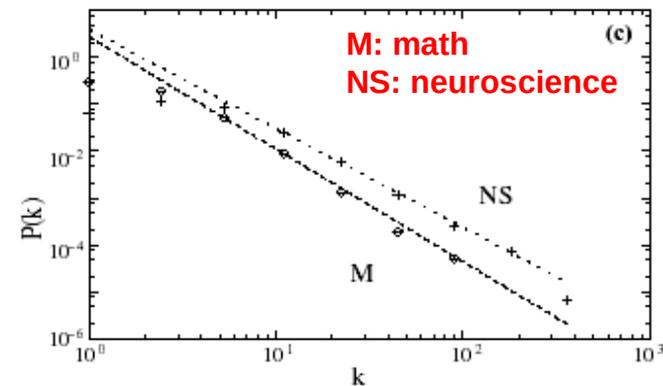
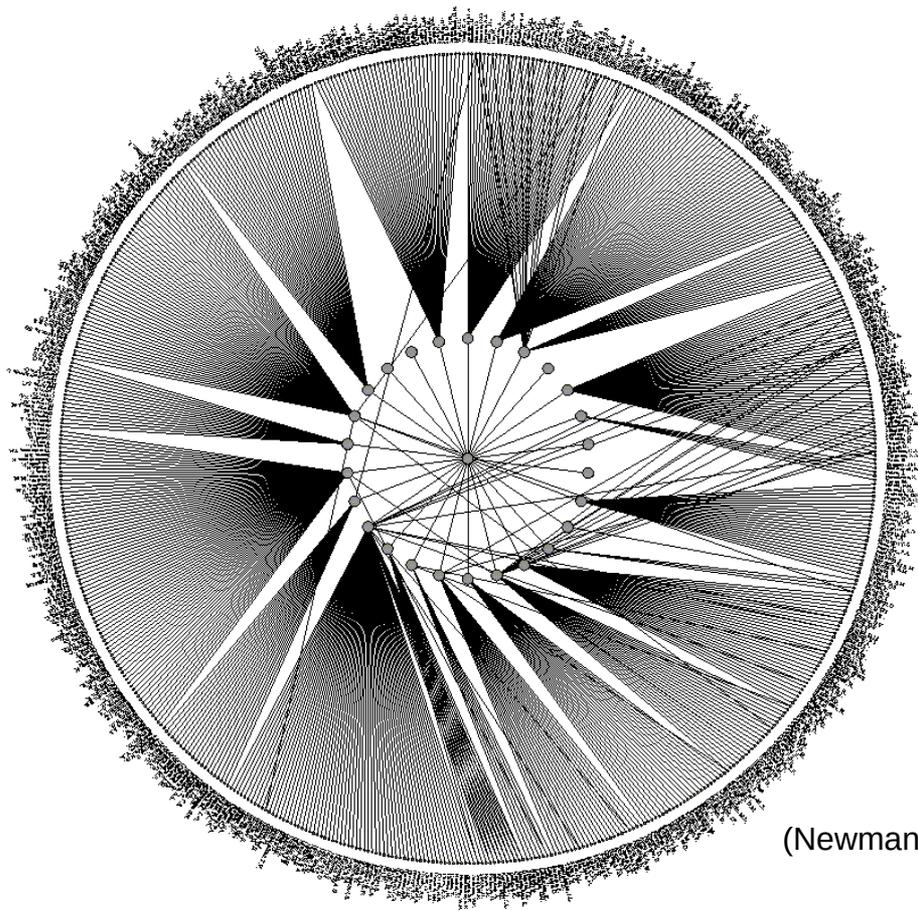
(S. Redner, 1998)

* citation total may be skewed because of multiple authors with the same name

SCIENCE COAUTHORSHIP

Nodes: scientist (authors)

Links: joint publication

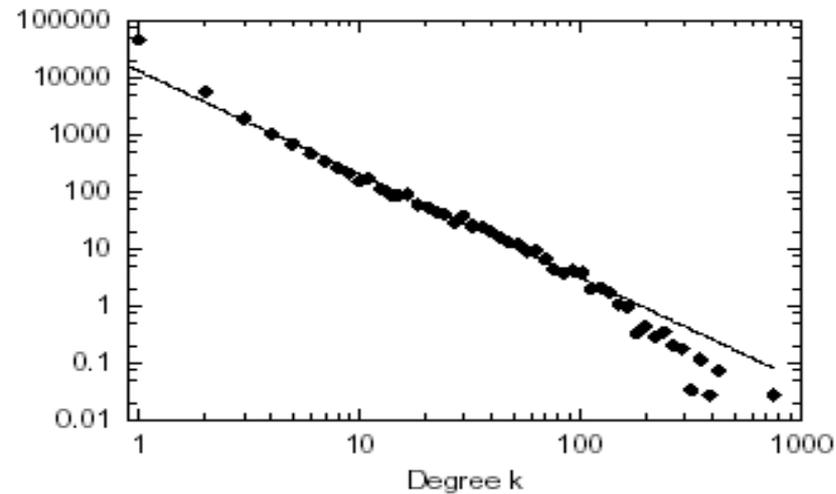


(Newman, 2000, Barabasi et al 2001)

ONLINE COMMUNITIES

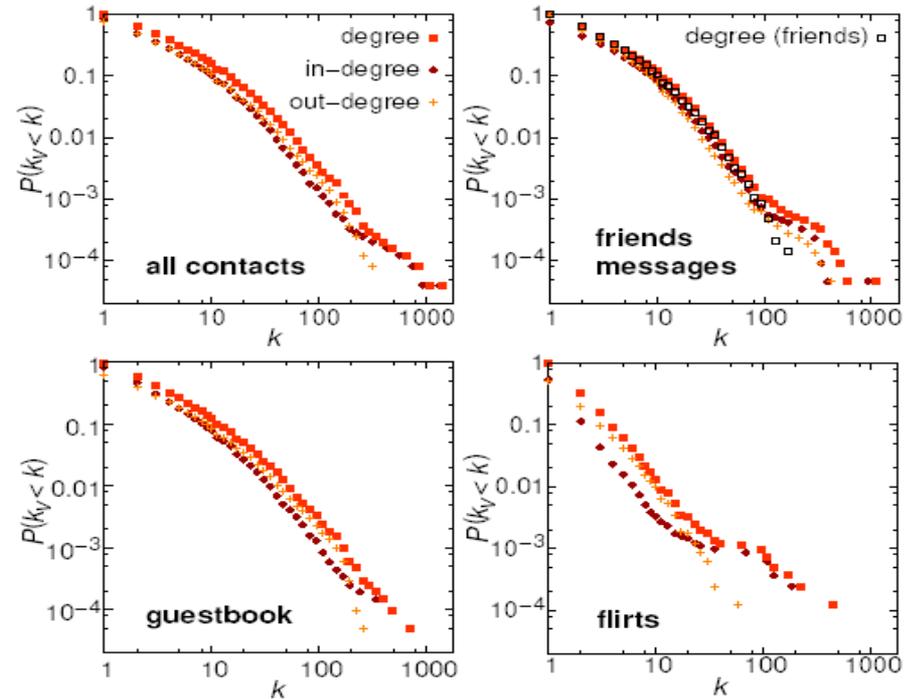
Nodes: online user
Links: email contact

Kiel University log files
112 days, N=59,912 nodes



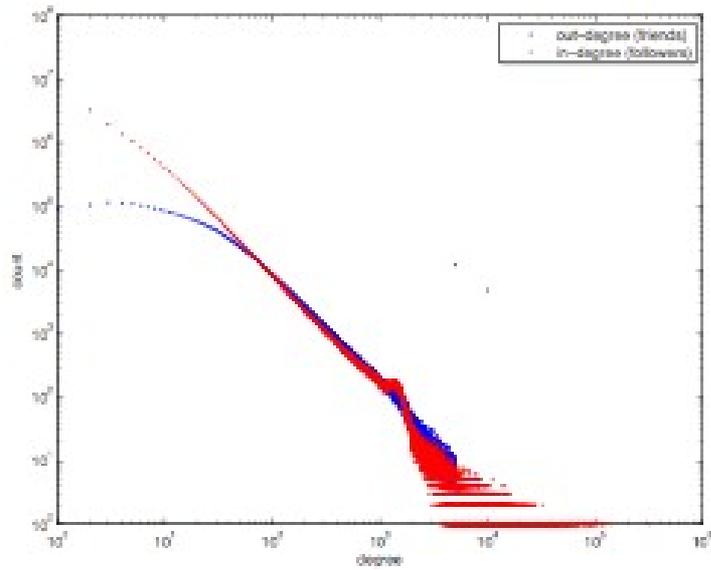
Ebel, Mielsch, Bornholdtz, PRE 2002.

Pussokram.com online community;
512 days, 25,000 users.

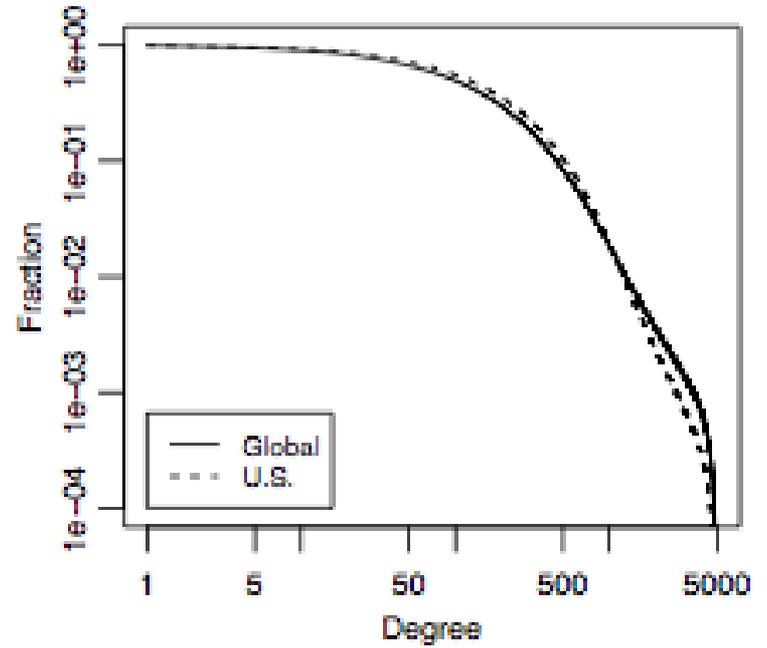


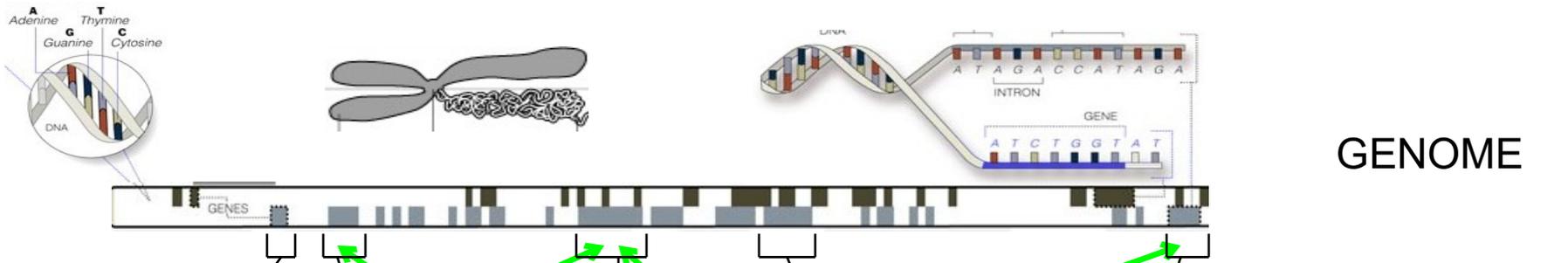
Holme, Edling, Liljeros, 2002.

Twitter:



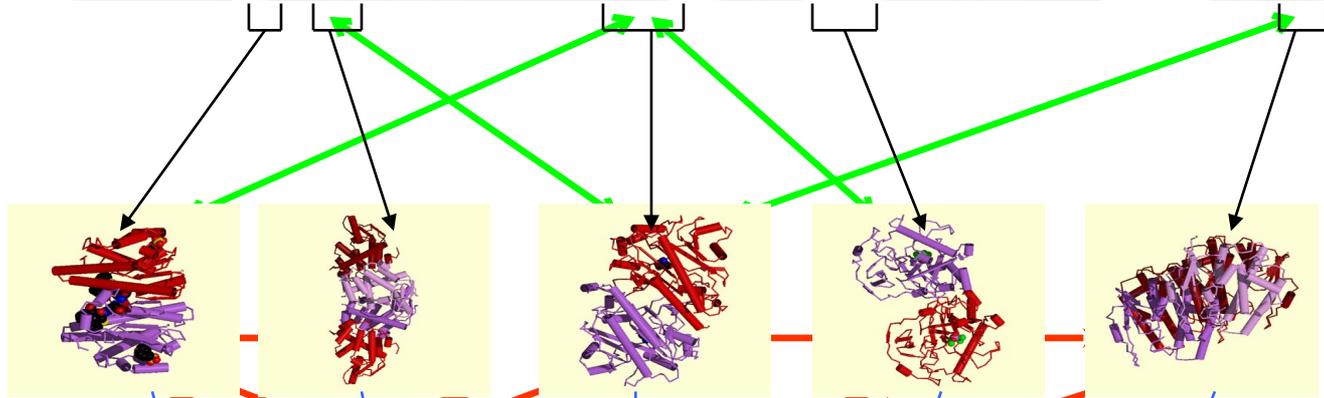
Facebook





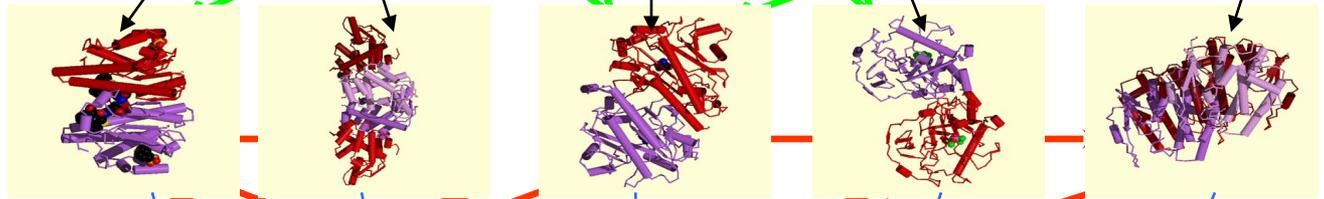
GENOME

protein-gene interactions



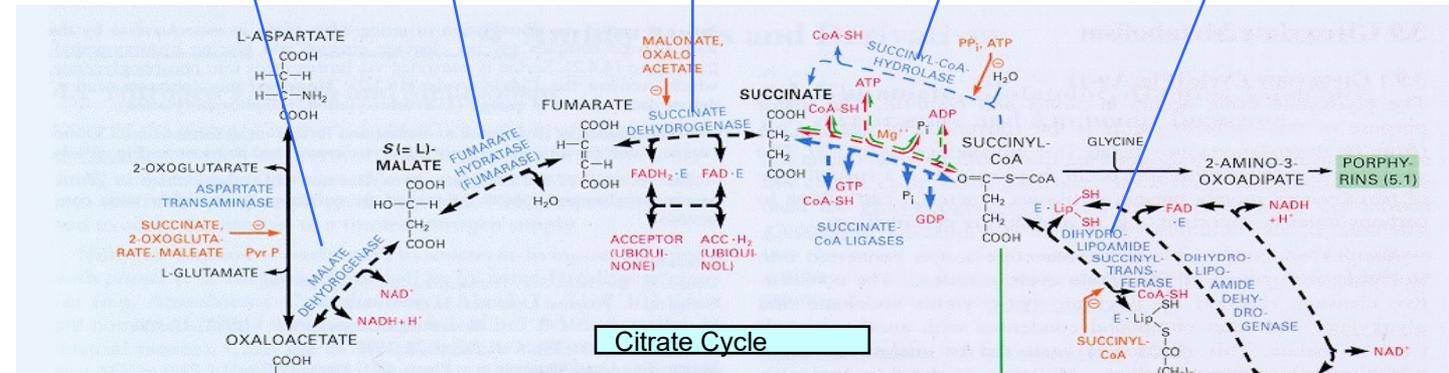
PROTEOME

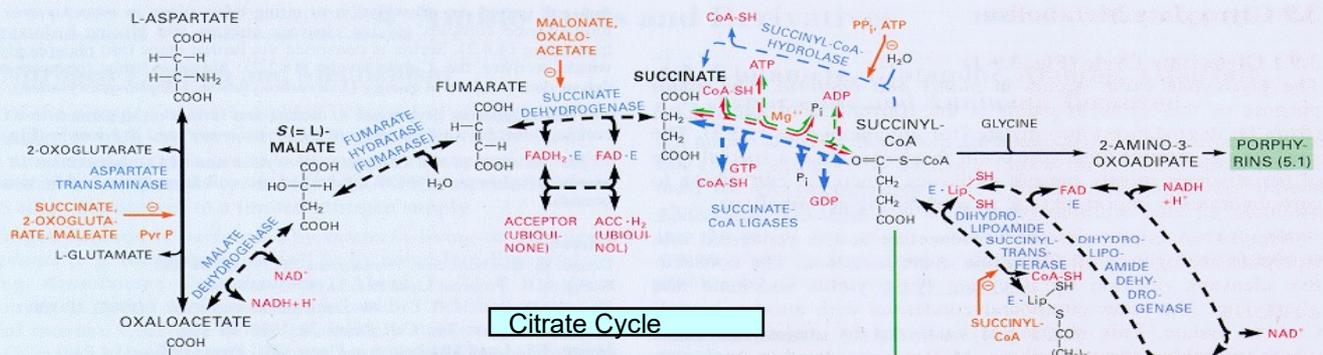
protein-protein interactions



METABOLISM

Bio-chemical reactions

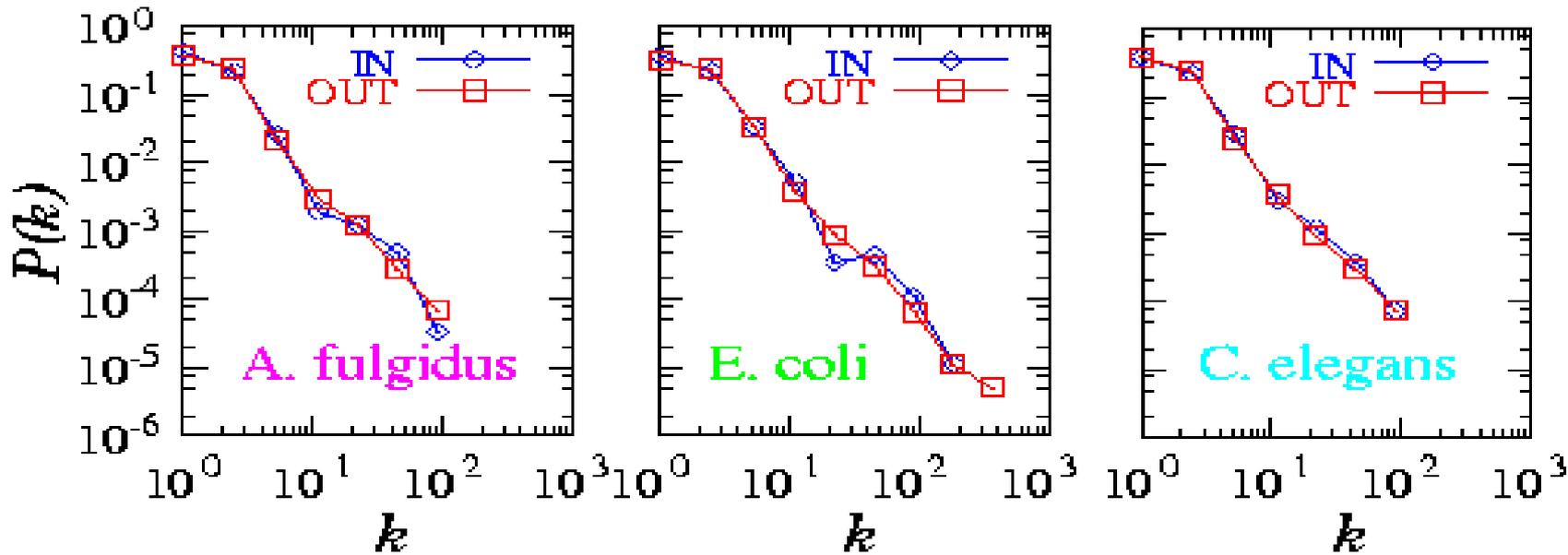




METABOLISM

Bio-chemical reactions

METABOLIC NETWORK



Archaea

Bacteria

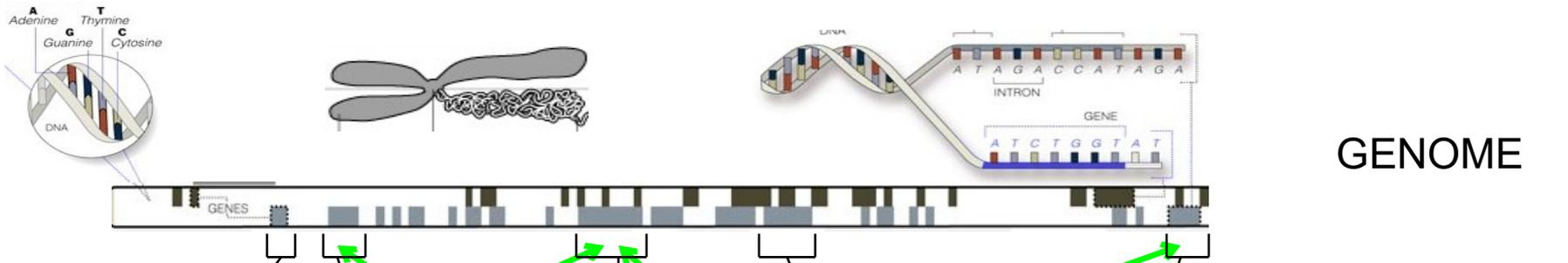
Eukaryotes

Organisms from all three domains of life are **scale-free!**

$$P_{in}(k) \approx k^{-2.2}$$

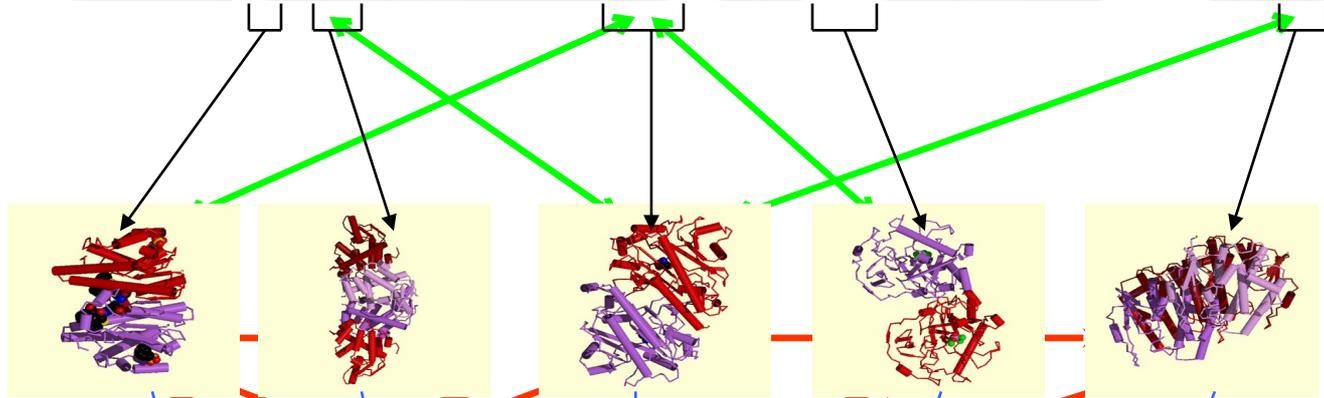
$$P_{out}(k) \approx k^{-2.2}$$

H. Jeong, B. Tombor, R. Albert, Z.N. Oltvai, and A.L. Barabasi, *Nature*, 407 651 (2000)



GENOME

protein-gene interactions

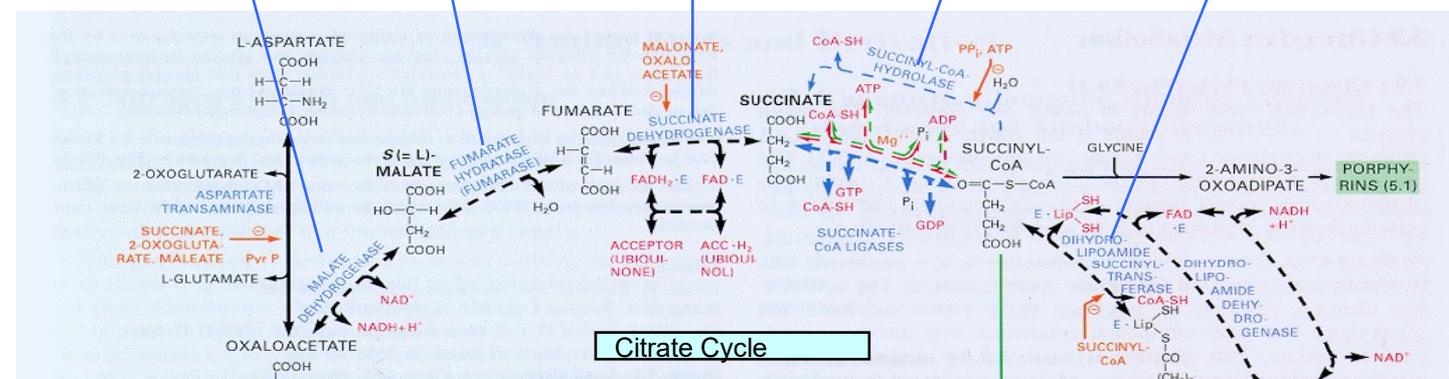


PROTEOME

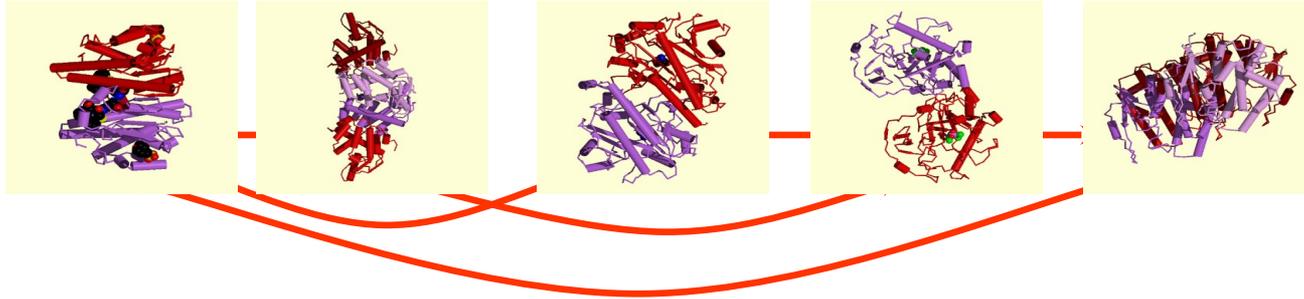
protein-protein interactions

METABOLISM

Bio-chemical reactions



METABOLIC NETWORK

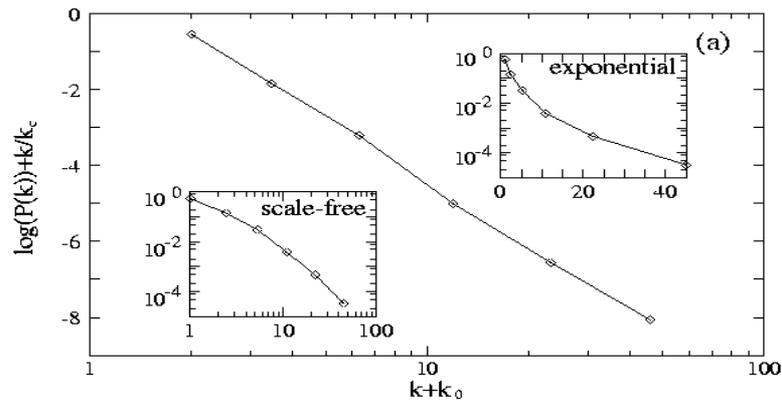


PROTEOME

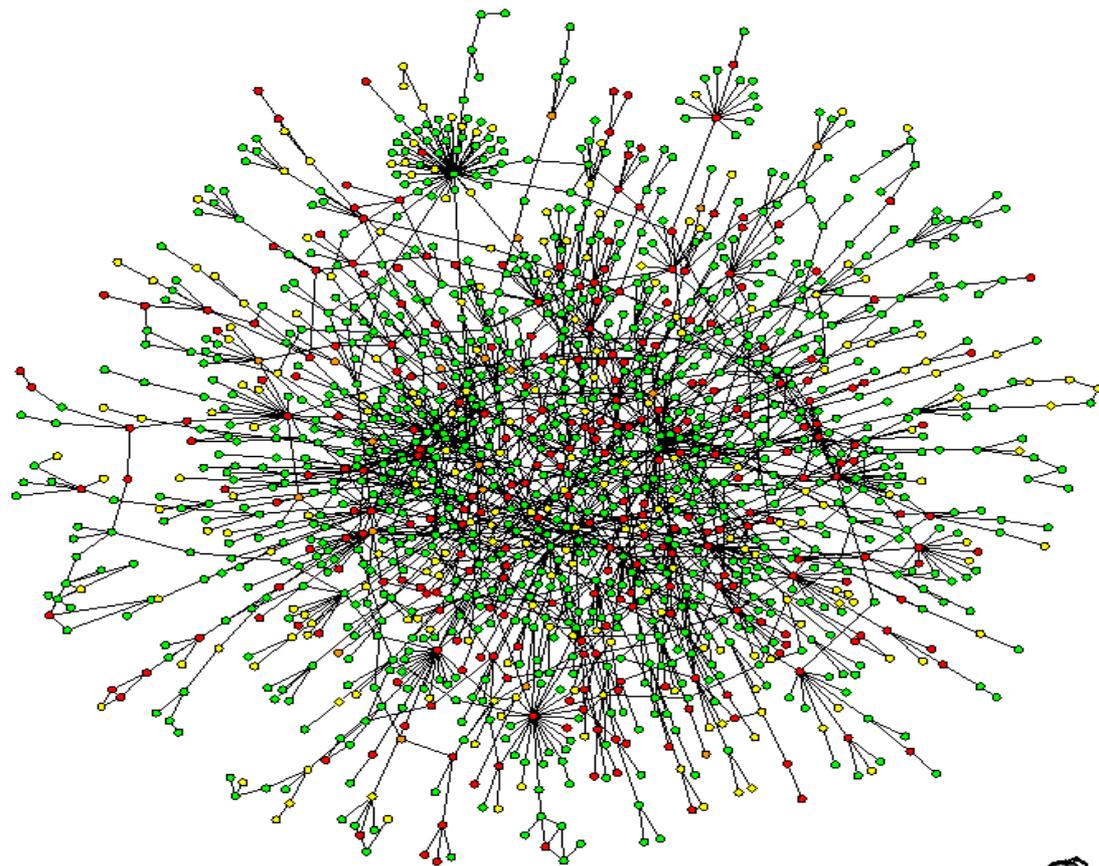
protein-protein
interactions

TOPOLOGY OF THE PROTEIN NETWORK

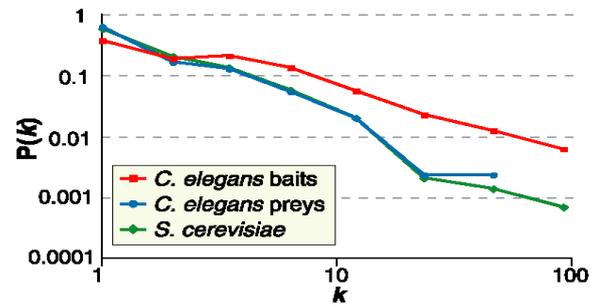
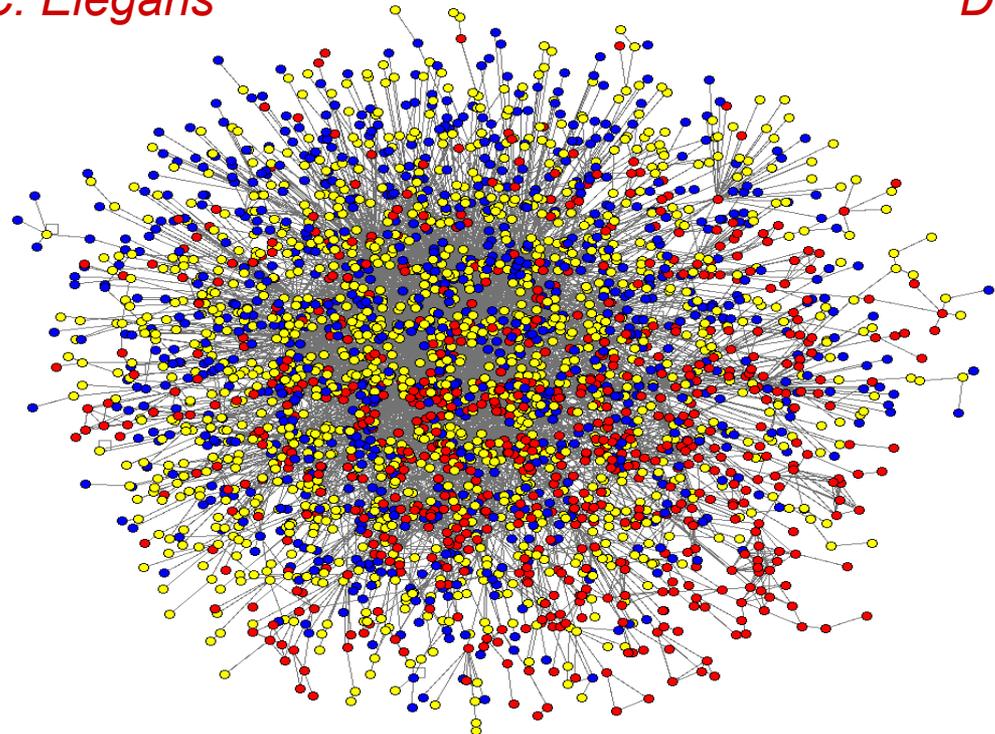
Nodes: proteins
Links: physical interactions-binding



$$P(k) \sim (k + k_0)^{-\gamma} \exp\left(-\frac{k + k_0}{k_\tau}\right)$$

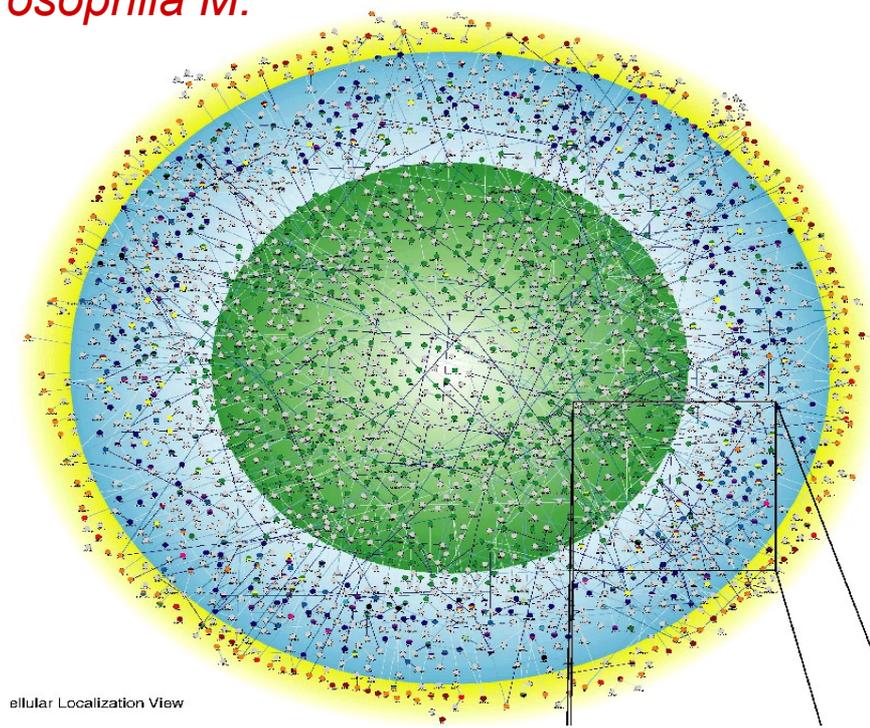


C. Elegans

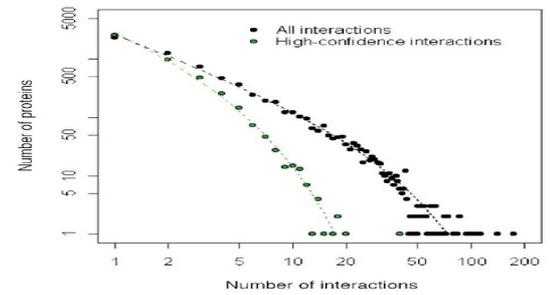


Li et al. Science 2004

Drosophila M.

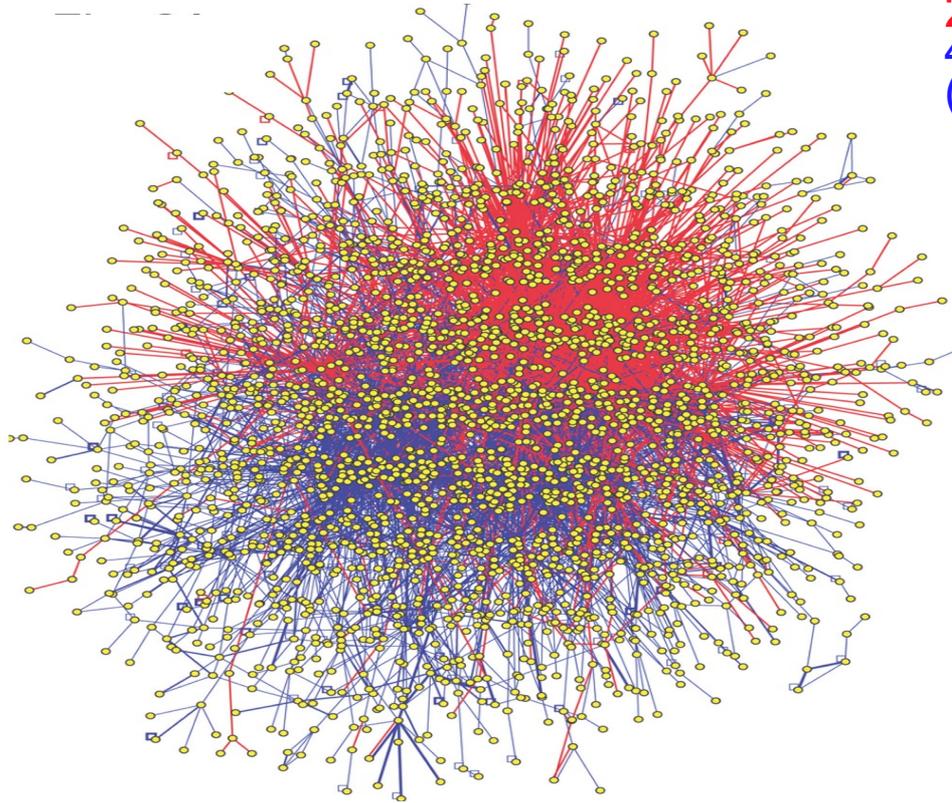


Cellular Localization View

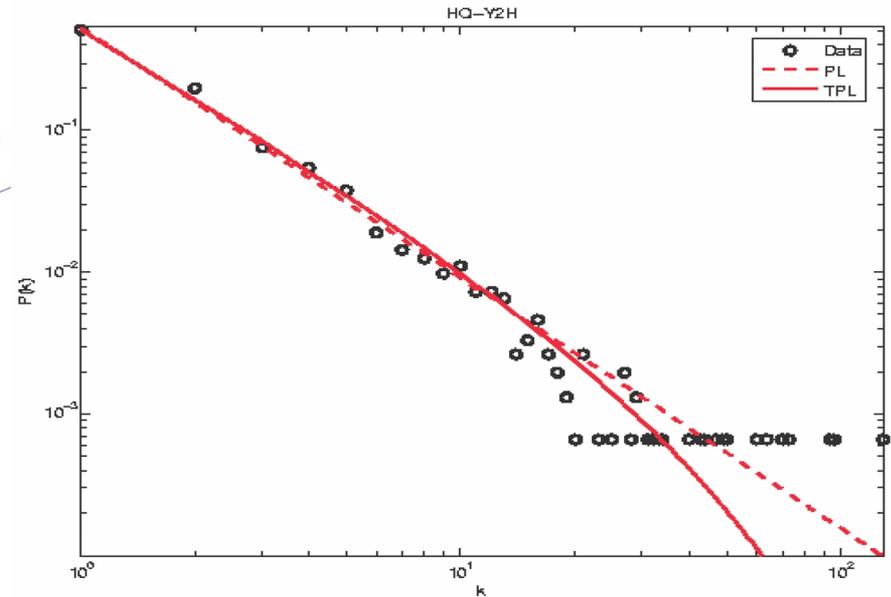


Giot et al. Science 2003

HUMAN INTERACTION NETWORK



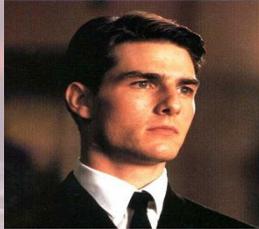
2,800 Y2H interactions
4,100 binary LC interactions
(HPRD, MINT, BIND, DIP, MIPS)



Rual *et al.* Nature 2005; Stelzl *et al.* Cell 2005

ACTOR NETWORK

Nodes: actors -
Links: cast jointly



Days of Thunder (1990)
Far and Away (1992)
Eyes Wide Shut (1999)

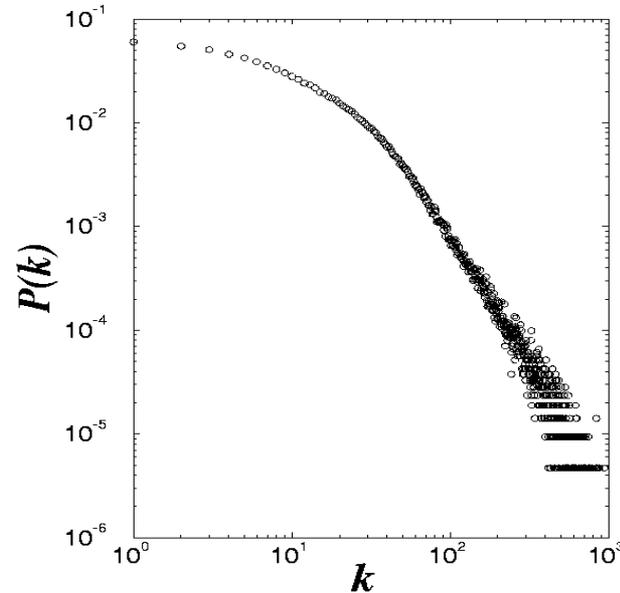


$N = 212,250$ actors

$\langle k \rangle = 28.78$

$P(k) \sim k^{-\gamma}$

$\gamma = 2.3$

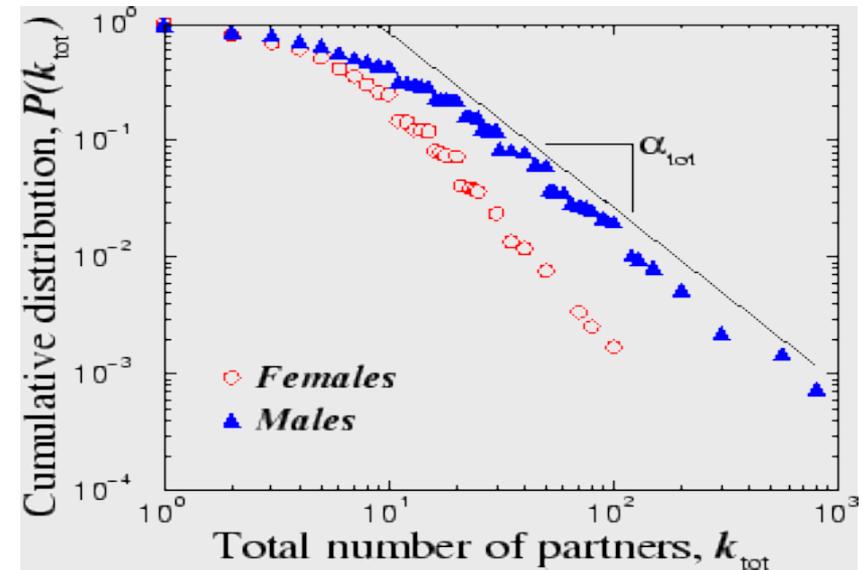


SWEDISH SE-WEB



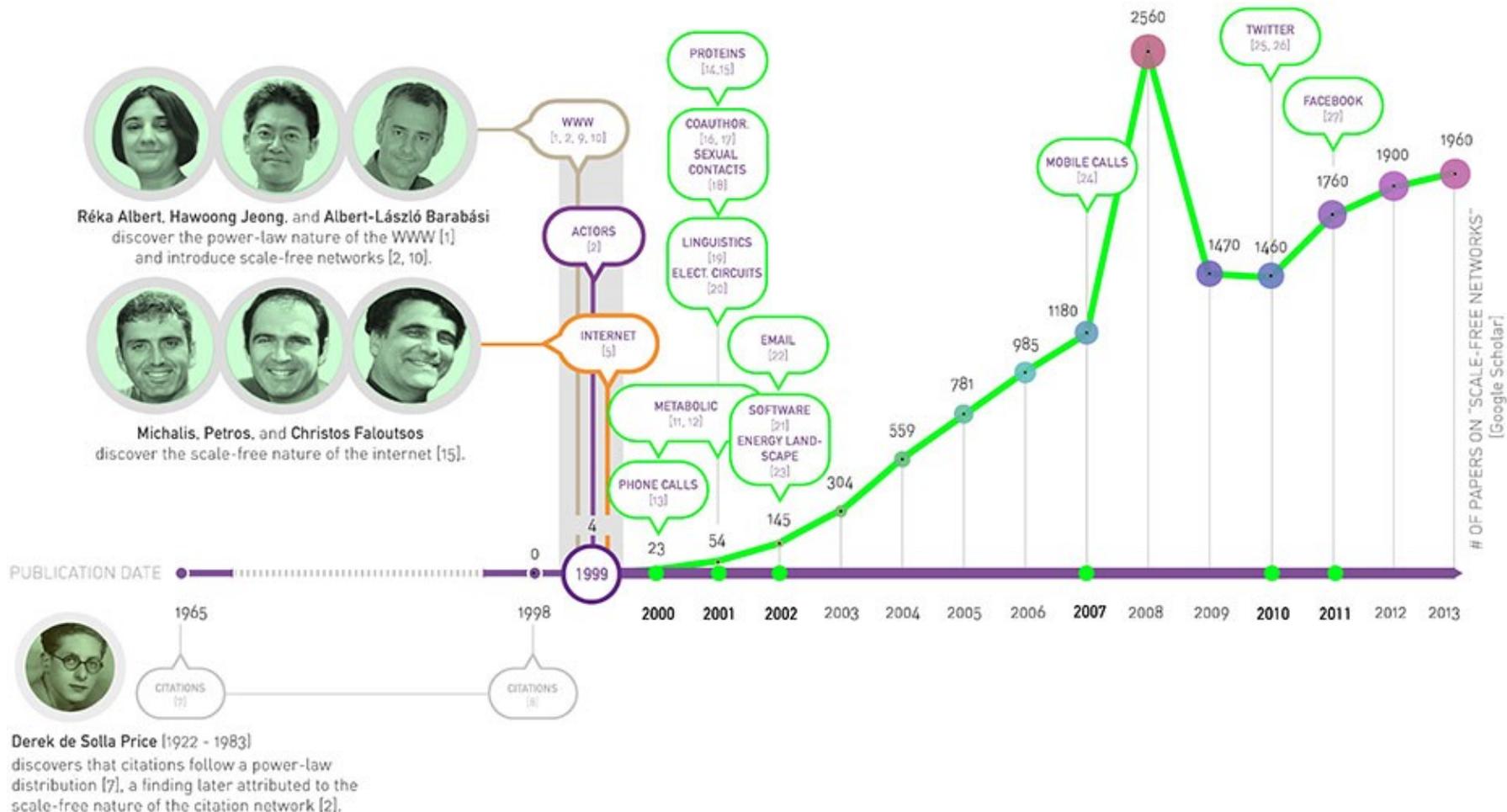
Nodes: people (Females; Males)

Links: sexual relationships



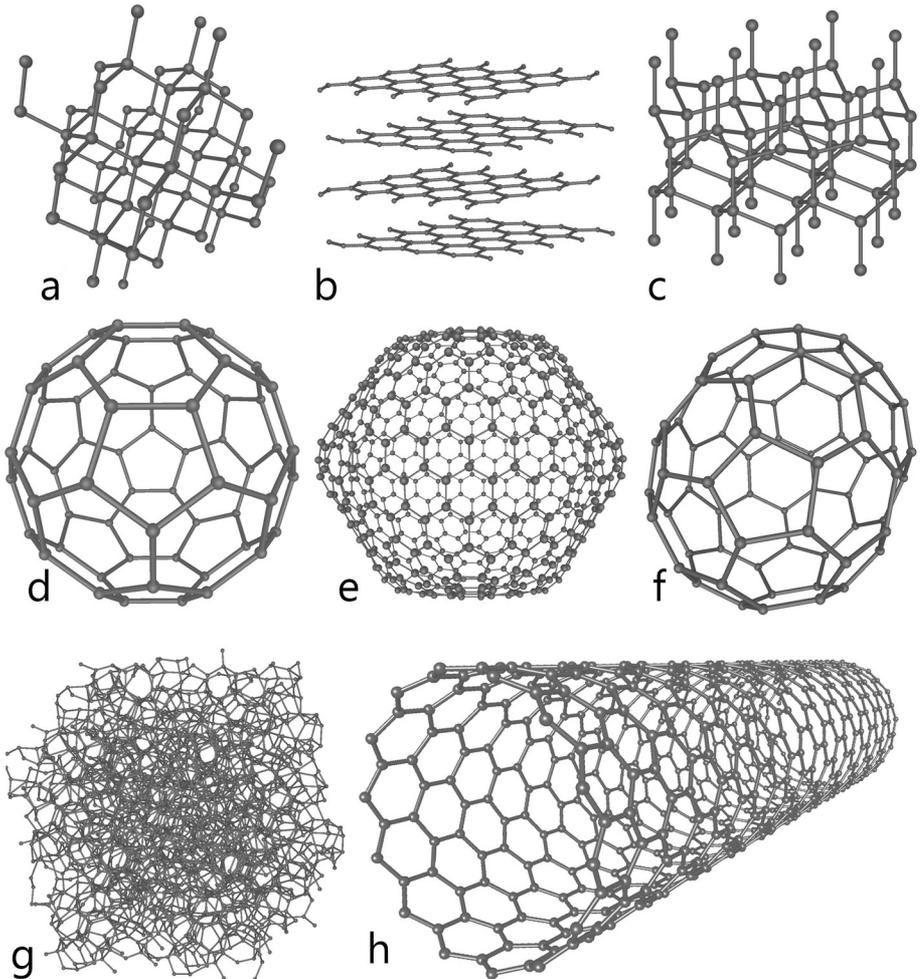
4781 Swedes; 18-74;
59% response rate.

Liljeros et al. Nature 2001



Not all networks are scale-free

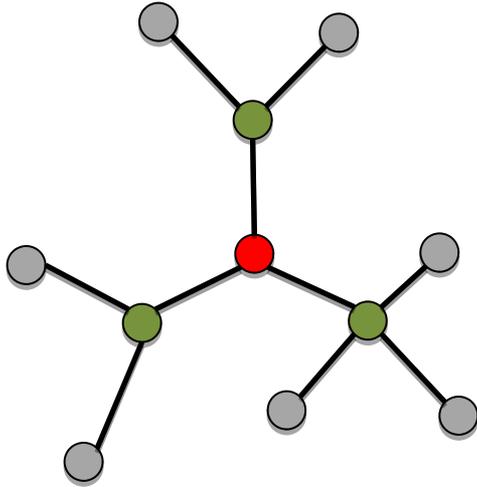
- *Networks appearing in material science, like the network describing the bonds between the atoms in crystalline or amorphous materials, where each node has exactly the same degree.*
- *The neural network of the *C.elegans* worm.*
- *The power grid, consisting of generators and switches connected by transmission lines*



Ultra-small property

DISTANCES IN RANDOM GRAPHS

Random graphs tend to have a tree-like topology with almost constant node degrees.



- nr. of first neighbors:
- nr. of second neighbors:
- nr. of neighbours at distance d :
- estimate maximum distance:

$$N_1 \cong \langle k \rangle$$

$$N_2 \cong \langle k \rangle^2$$

$$N_d \cong \langle k \rangle^d$$

$$1 + \sum_{l=1}^{l_{max}} \langle k \rangle^l = N \Rightarrow l_{max} = \frac{\log N}{\log \langle k \rangle}$$

SMALL WORLD BEHAVIOR IN SCALE-FREE NETWORKS

$$k_{\max} = k_{\min} N^{\frac{1}{\gamma-1}}$$

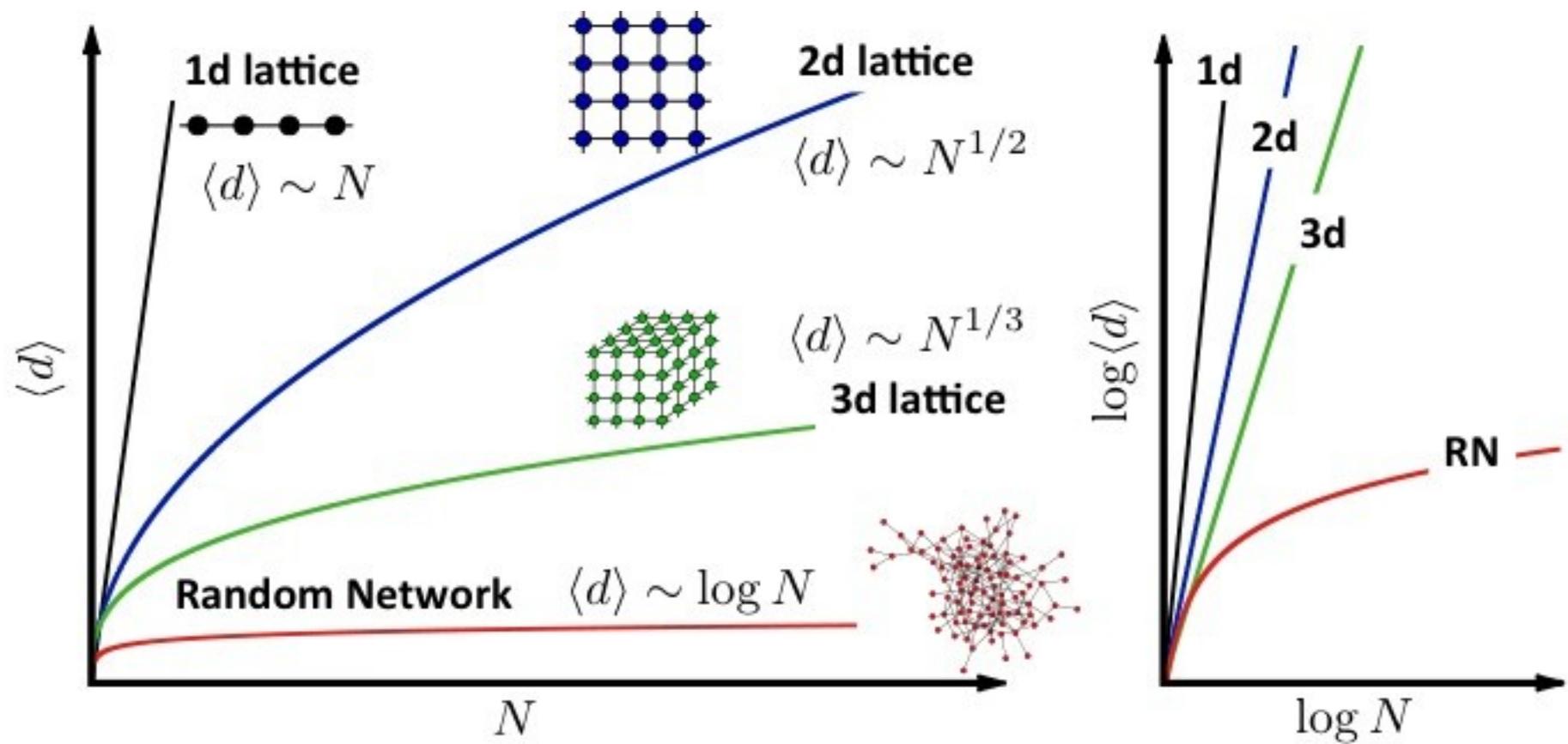
Ultra
Small
World

$\langle l \rangle \sim$

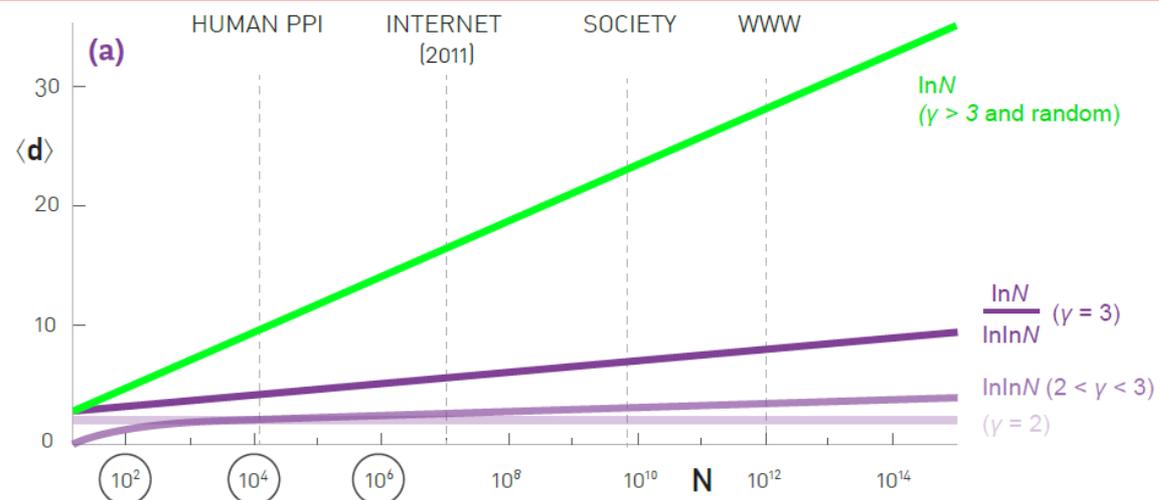
$const.$	$\gamma = 2$	Size of the biggest hub is of order $O(N)$. Most nodes can be connected within two layers of it, thus the average path length will be independent of the system size.
$\frac{\ln \ln N}{\ln(\gamma - 1)}$	$2 < \gamma < 3$	The average path length increases slower than logarithmically. In a random network all nodes have comparable degree, thus most paths will have comparable length. In a scale-free network the vast majority of the path go through the few high degree hubs, reducing the distances between nodes.
$\frac{\ln N}{\ln \ln N}$	$\gamma = 3$	Some key models produce $\gamma=3$, so the result is of particular importance for them. This was first derived by Bollobas and collaborators for the network diameter in the context of a dynamical model, but it holds for the average path length as well.
$\ln N$	$\gamma > 3$	The second moment of the distribution is finite, thus in many ways the network behaves as a random network. Hence the average path length follows the result that we derived for the random network model earlier.

Why are small worlds surprising?

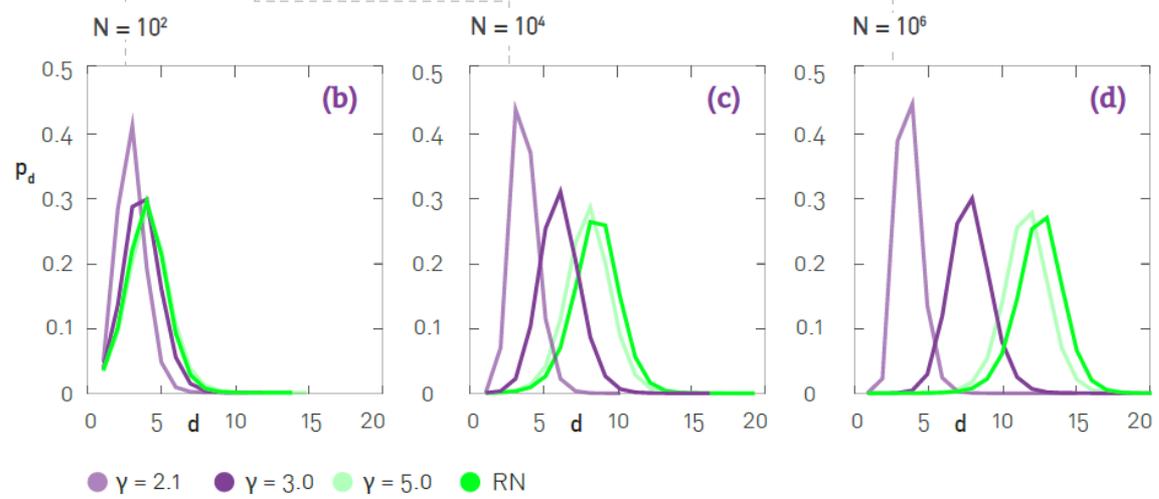
Surprising compared to what?



SMALL WORLD BEHAVIOR IN SCALE-FREE NETWORKS

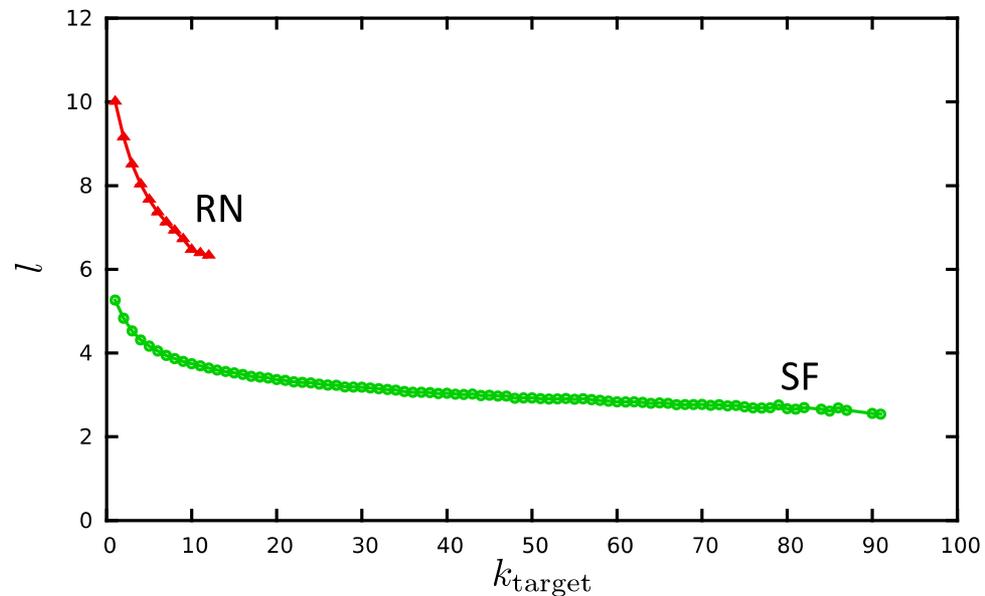


$$\langle d \rangle \sim \begin{cases} \text{const.} & \gamma = 2, \\ \frac{\ln \ln N}{\ln(\gamma - 1)} & 2 < \gamma < 3, \\ \frac{\ln N}{\ln \ln N} & \gamma = 3, \\ \ln N & \gamma > 3. \end{cases}$$



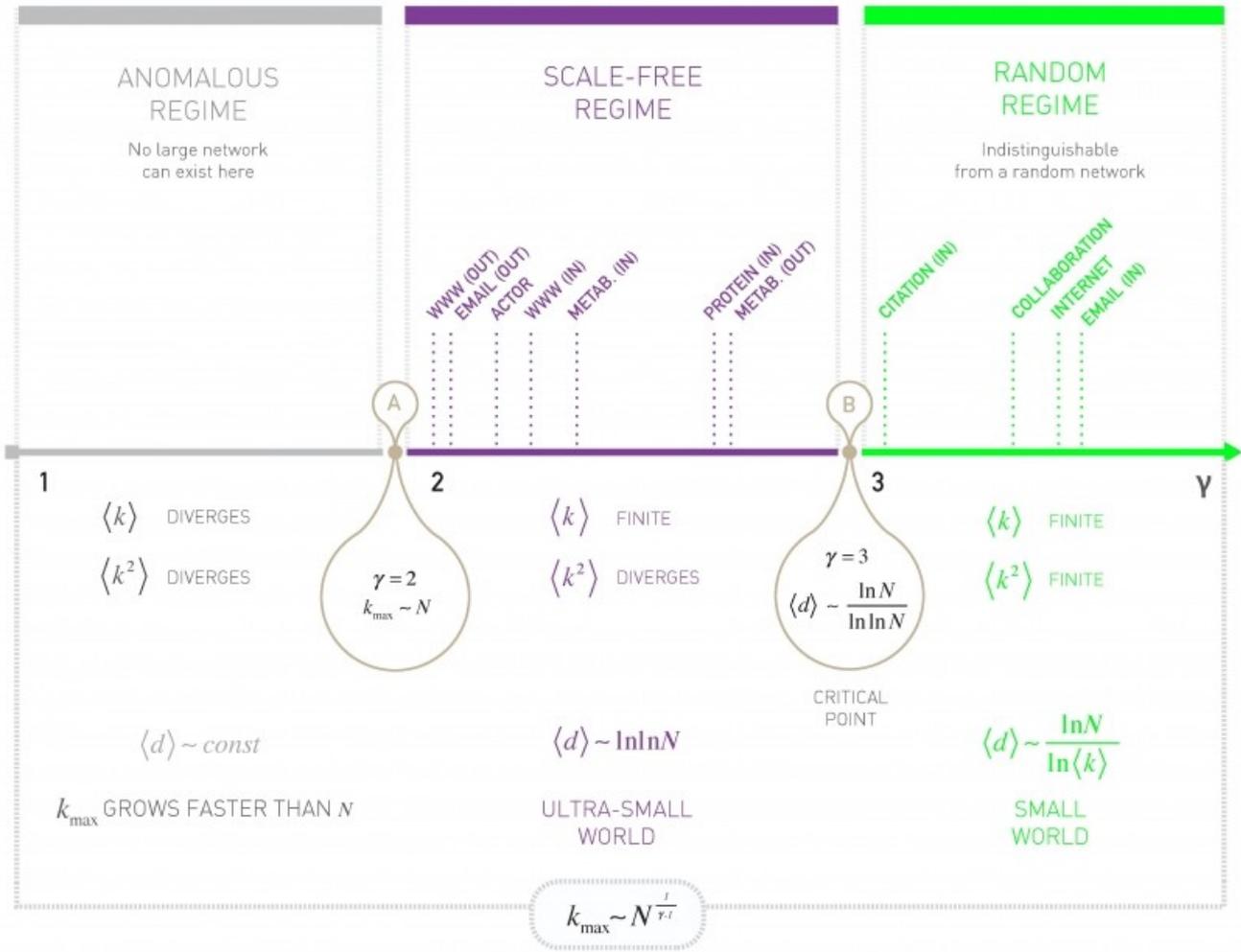
We are always close to the hubs

" it's always easier to find someone who knows a famous or popular figure than some run-the-mill, insignificant person."
(Frigyes Karinthy, 1929)



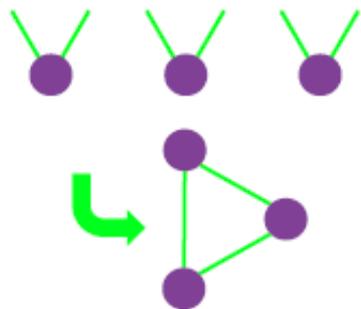
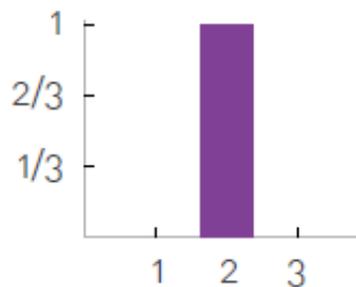
The role of the degree exponent

SUMMARY OF THE BEHAVIOR OF SCALE-FREE NETWORKS

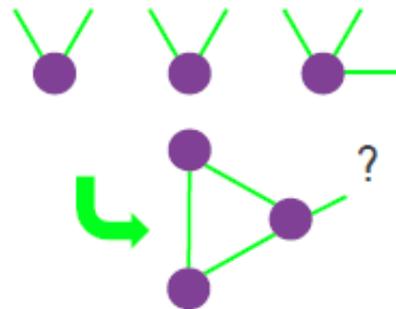
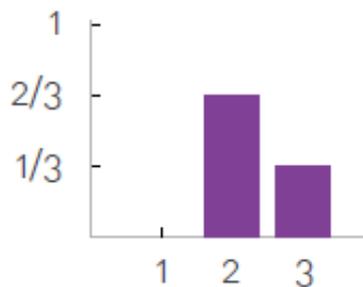


Graphicality: No large networks for $\gamma < 2$

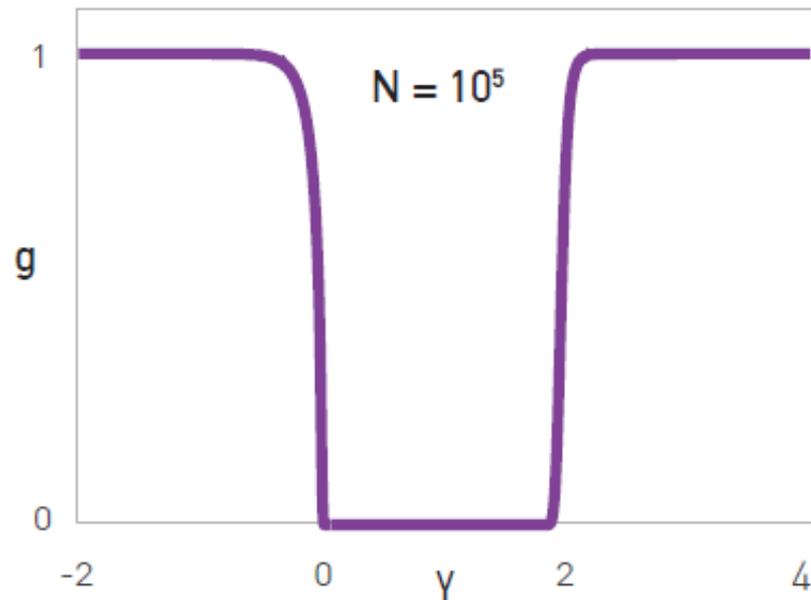
(a) Graphical



(b) Not Graphical



(c)



In scale-free networks: $k_{\max} = k_{\min} N^{\frac{1}{\gamma-1}}$

For $\gamma < 2$: $1/(\gamma-1) > 1$

Why don't we see networks with exponents in the range of $\gamma=4,5,6$, etc?

In order to document scale-free networks, we need 2-3 orders of magnitude scaling.

That is, $K_{max} \sim 10^2 K_{min}$ to $10^3 K_{min}$

However, that constrains on the system size we require to document it.

For example, to measure an exponent $\gamma=5$, we need to maximum degree a system size of the order of

$$K_{max} = K_{min} N^{\frac{1}{\gamma-1}}$$
$$N = \left(\frac{K_{max}}{K_{min}} \right)^{\gamma-1} \approx 10^8$$

Mobile Call
Network

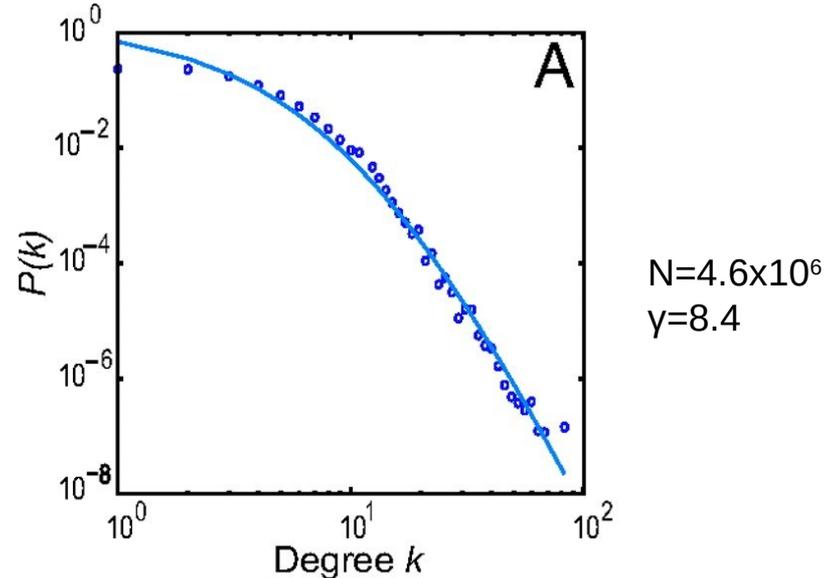
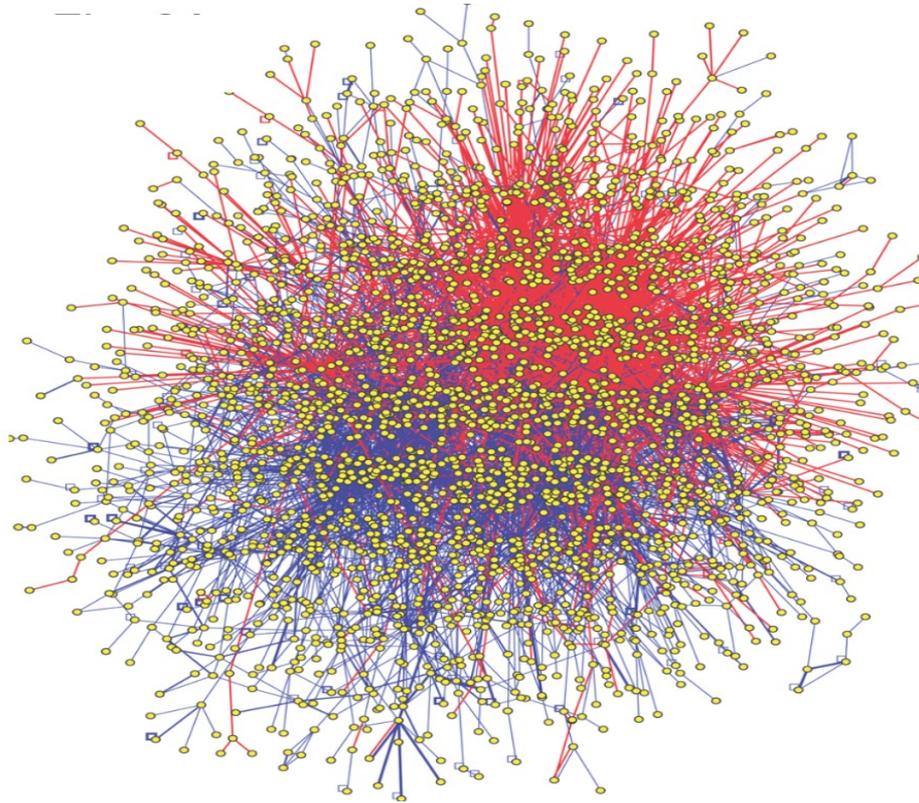


Fig. 1.

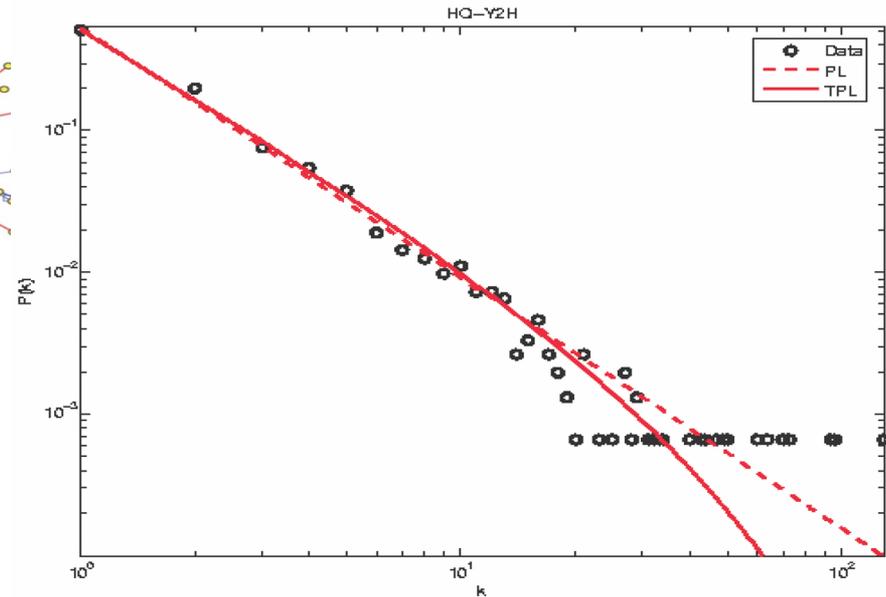
Characterizing the large-scale structure and the tie strengths of the mobile call graph. (A and B) Vertex degree (A) and tie strength distribution (B). Each distribution was fitted with $P(k) = a(k + k_0)^{-\gamma} \exp(-k/k_c)$.

PLOTTING POWER LAWS

HUMAN INTERACTION NETWORK

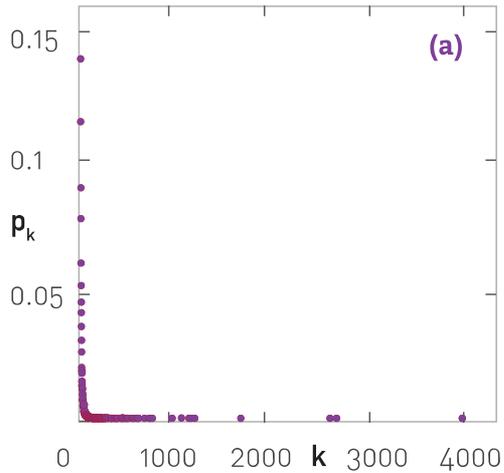


2,800 Y2H interactions
4,100 binary LC interactions
(HPRD, MINT, BIND, DIP, MIPS)

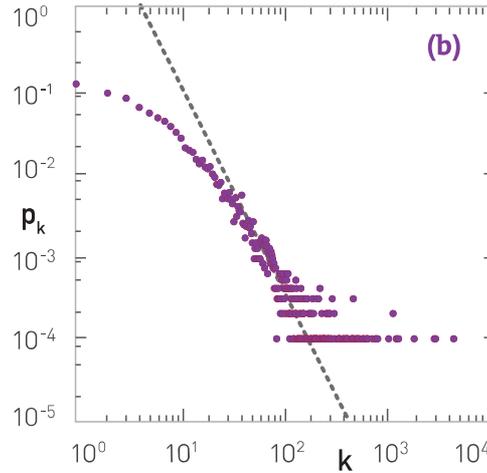


Rual et al. Nature 2005; Stelzl et al. Cell 2005

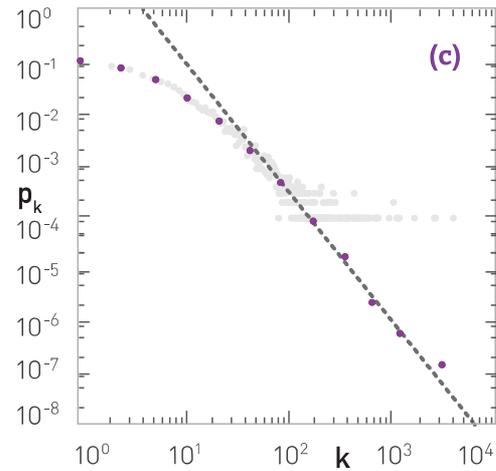
LINEAR SCALE



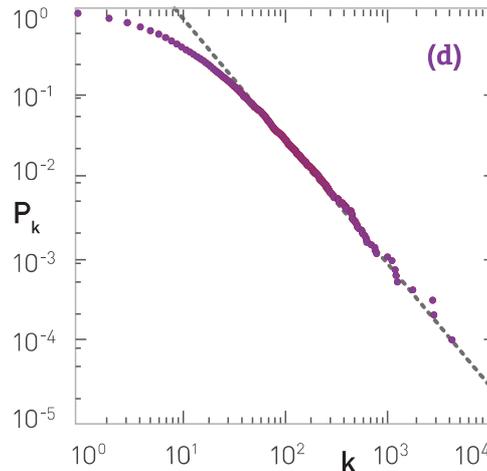
LINEAR BINNING



LOG-BINNING

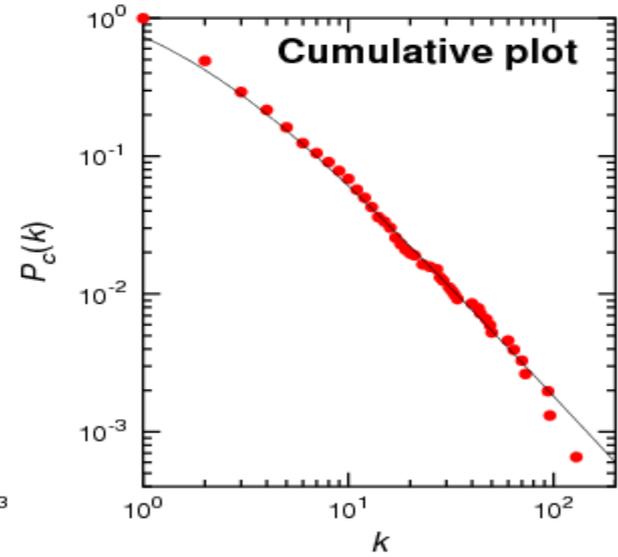
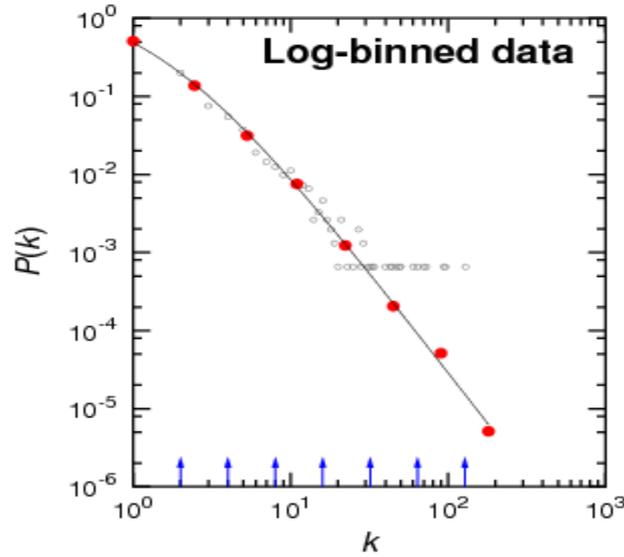
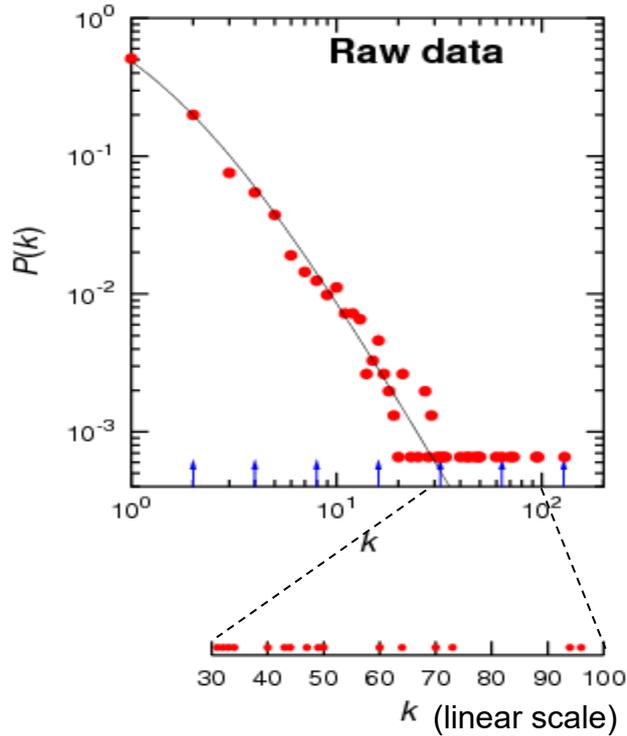


CUMULATIVE



Use a Log-Log Plot
Avoid Linear Binning
Use Logarithmic Binning
Use Cumulative Distribution

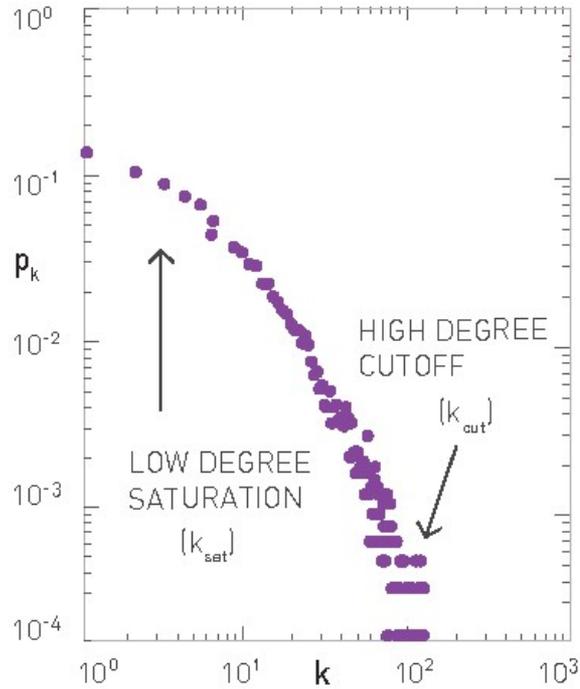
HUMAN INTERACTION DATA BY RUAL ET AL.



$$P(k) \sim (k+k_0)^{-\gamma}$$
$$k_0 = 1.4, \gamma = 2.6.$$

COMMON MISCONCEPTIONS

[Http://www.nd.edu/~networks](http://www.nd.edu/~networks)

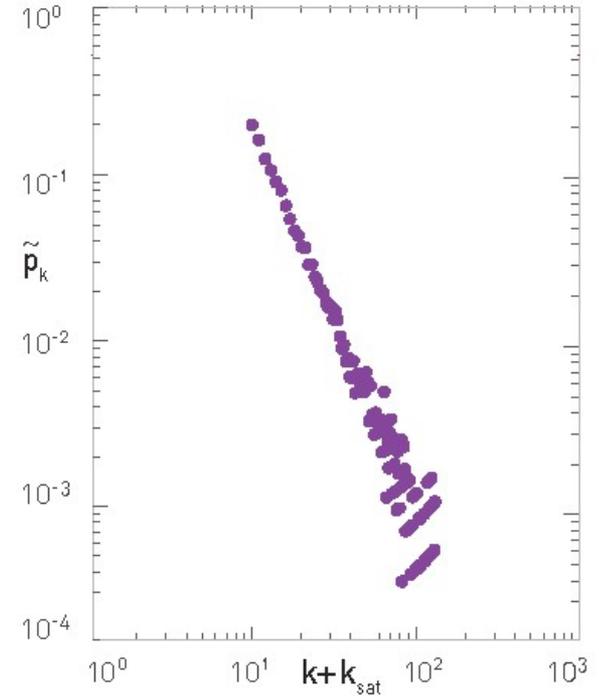


$$p_k = a(k + k_{sat})^{-\gamma} \exp\left(-\frac{k}{k_{cut}}\right)$$

$$\tilde{p}_k = p_k \exp\left(\frac{k}{k_{cut}}\right)$$

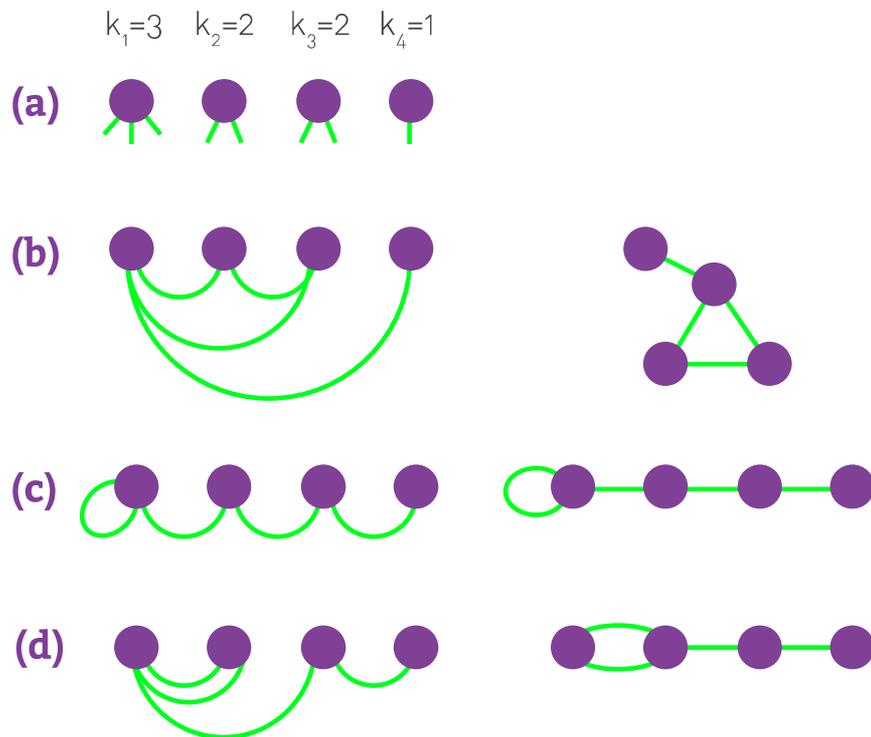
$$\tilde{k} = k + k_{sat}$$

$$\tilde{p}_k \sim \tilde{k}^{-\gamma}$$



Generating networks with a
pre-defined p_k

Configuration model

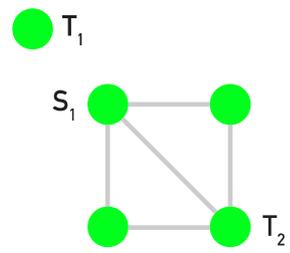


(1) **Degree sequence:** Assign a degree to each node, represented as stubs or half-links. The degree sequence is either generated analytically from a pre-selected distribution (Box 4.5), or it is extracted from the adjacency matrix of a real network. We must start from an even number of stubs, otherwise we will be left with unpaired stubs. (2) **Network assembly:** Randomly select a stub pair and connect them. Then randomly choose another pair from the remaining stubs and connect them. This procedure is repeated until all stubs are paired up. Depending on the order in which the stubs were chosen, we obtain different networks. Some networks include cycles (2a), others self-edges (2b) or multi-edges (2c). Yet, the expected number of self- and multi-edges goes to zero in the limit.

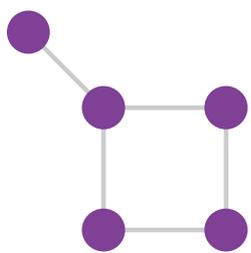
$$p_{ij} = \frac{k_i k_j}{2L - 1}$$

Degree Preserving randomization

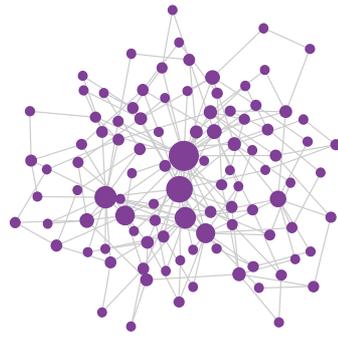
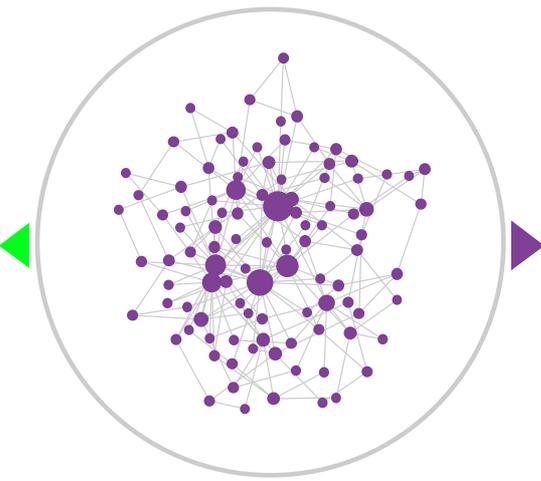
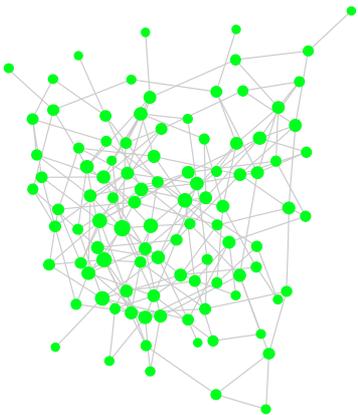
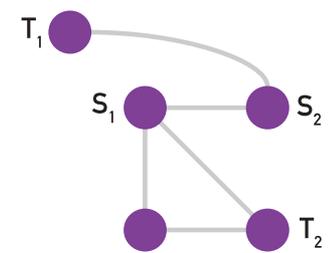
FULL
RANDOMIZATION



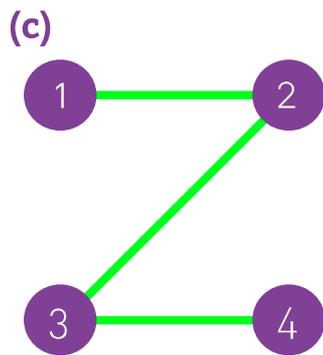
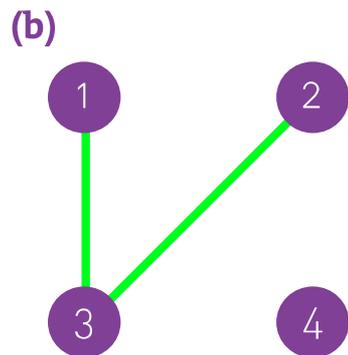
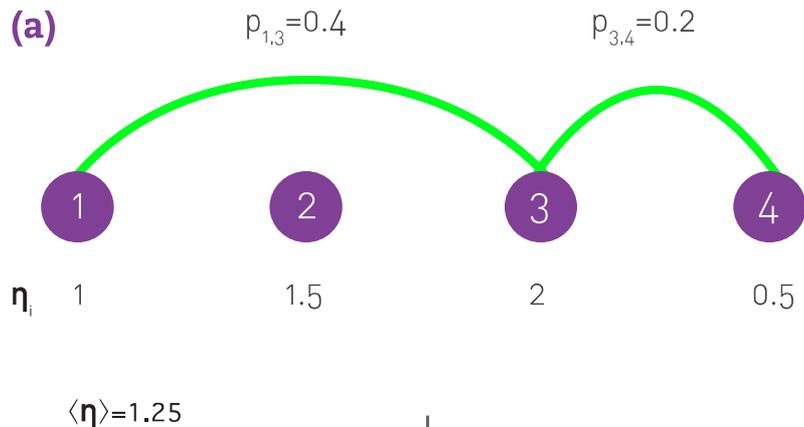
ORIGINAL NETWORK



DEGREE-PRESERVING
RANDOMIZATION



Hidden parameter model



$$p(\eta_i, \eta_j) = \frac{\eta_i \eta_j}{\langle \eta \rangle N}$$

$$p_k = \int \frac{e^{-\eta} \eta^k}{k!} p(\eta) d\eta.$$

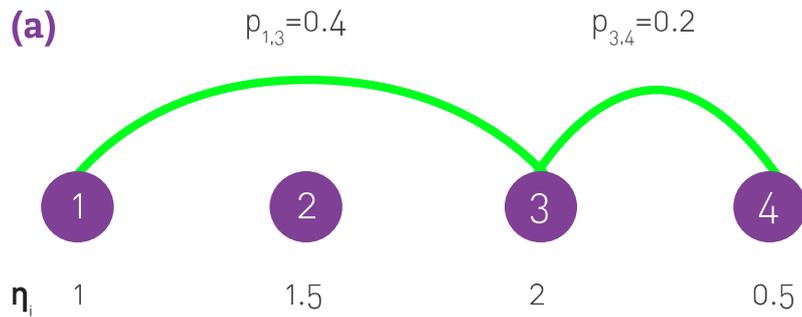
$$\{\eta_1, \eta_2, \dots, \eta_N\}$$

$$p_k = \frac{1}{N} \sum_j \frac{e^{-\eta_j} \eta_j^k}{k!}.$$

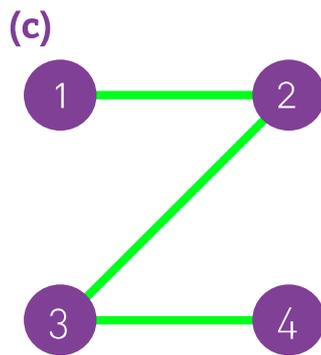
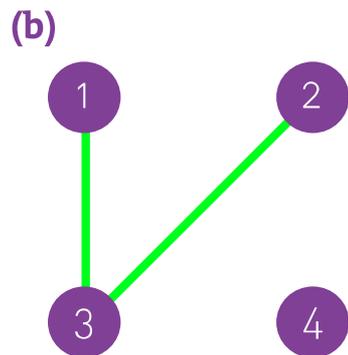
$$\eta_j = \frac{c}{j^\alpha}, i = 1, \dots, N$$

$$p_k \sim k^{-(1+\frac{1}{\alpha})}$$

Hidden parameter model



$\langle \eta \rangle = 1.25$



$$p_k = \int \frac{e^{-\eta} \eta^k}{k!} p(\eta) d\eta.$$

$$\{\eta_1, \eta_2, \dots, \eta_N\} \quad p_k = \frac{1}{N} \sum_j \frac{e^{-\eta_j} \eta_j^k}{k!}.$$

$$\eta_j = \frac{c}{i^\alpha}, i = 1, \dots, N$$

$$p_k \sim k^{-(1+\frac{1}{\alpha})}$$

Start with N isolated nodes and assign to each node a “hidden parameter” η , which can be randomly selected from a $p(\eta)$ distribution. We next connect each node pair with probability

$$p(\eta_i, \eta_j) = \frac{\eta_i \eta_j}{\langle \eta \rangle N}$$

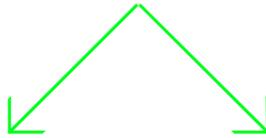
For example, the figure shows the probability to connect nodes (1,3) and (3,4). After connecting the nodes, we end up with

the networks shown in (b) or (c), representing two independent realizations generated by the same hidden parameter sequence (a). The expected number of links in the obtained network is

$$L = \frac{1}{2} \sum_{i,j} \frac{\eta_i \eta_j}{\langle \eta \rangle N} = \frac{1}{2} \langle \eta \rangle N$$

NETWORK OR DEGREE SEQUENCE

k_1, k_2, \dots, k_N



FORBID
MULTI-LINKS

ALLOW
MULTI-LINKS



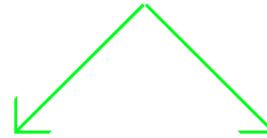
DEGREE-PRESERVING
RANDOMIZATION



CONFIGURATION
MODEL

DEGREE DISTRIBUTION

p_k



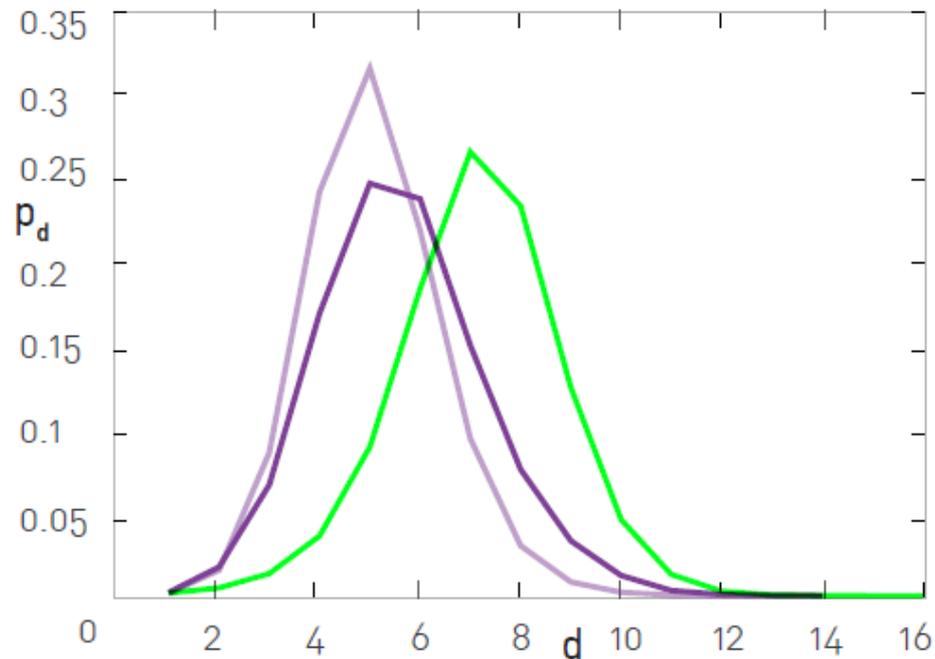
ALLOW
MULTI-LINKS

FORBID
MULTI-LINKS



HIDDEN PARAMETER
MODEL

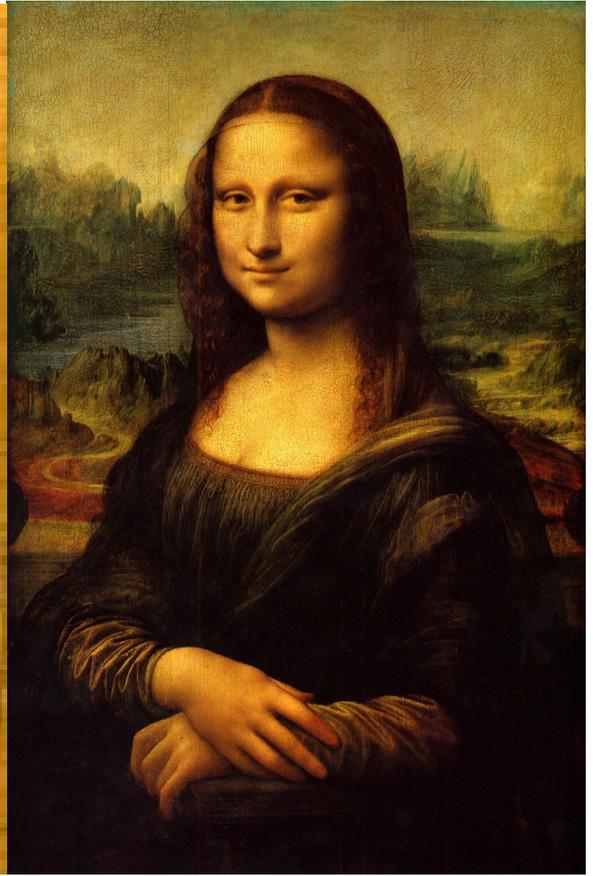
Case Study: PPI Network Distance Distribution



- Original network
- Degree preserving randomization
- Full randomization

We have: $\langle d \rangle = 5.61 \pm 1.64$ (original), $\langle d \rangle = 7.13 \pm 1.62$ (full randomization), $\langle d \rangle = 5.08 \pm 1.34$ (degree-preserving randomization).

Something to keep in mind



summary

Section 9

DEGREE DISTRIBUTION

Discrete form:

$$p_k = \frac{k^{-\gamma}}{\zeta(\gamma)}$$

Continuous form:

$$p(k) = (\gamma - 1) k_{\min}^{\gamma-1} k^{-\gamma}$$

SIZE OF THE LARGEST HUB

$$k_{\max} \sim k_{\min} N^{\frac{1}{\gamma-1}}$$

MOMENTS OF p_k for $N \rightarrow \infty$

$2 < \gamma < 3$: $\langle k \rangle$ finite, $\langle k^2 \rangle$ diverges.

$\gamma > 3$: $\langle k \rangle$ and $\langle k^2 \rangle$ finite.

DISTANCES

$$\langle d \rangle \sim \begin{cases} \text{const.} & \gamma=2, \\ \frac{\ln \ln N}{\ln(\gamma-1)} & 2 < \gamma < 3, \\ \frac{\ln N}{\ln \ln N} & \gamma=3, \\ \ln N & \gamma > 3. \end{cases}$$

Bounded Networks

We call a network *bounded* if its degree distribution decrease exponentially or faster for high k . As a consequence $\langle k^2 \rangle$ is smaller than $\langle k \rangle$, implying that we lack significant degree variations. Examples of p_k in this class include the Poisson, Gaussian, or the simple exponential distribution (Table 4.2). The Erdős-Rényi and the Watts-Strogatz networks are the best known network models belonging to this class. Bounded networks lack outliers, consequently most nodes have comparable degrees. Real networks in this class include highway networks and the power grid.

Unbounded Networks

We call a network *unbounded* if its degree distribution has a fat tail in the high- k region. As a consequence $\langle k^2 \rangle$ is much larger than $\langle k \rangle$, resulting in considerable degree variations. Scale-free networks with a power-law degree distribution (4.1) offer the best known example of networks belonging to this class. Outliers, or exceptionally high-degree nodes, are not only allowed but are expected in these networks. Networks in this class include the WWW, the Internet, the protein interaction networks, and most social and online networks.

CLASS INFORMATION