

Spectra of Complex Networks

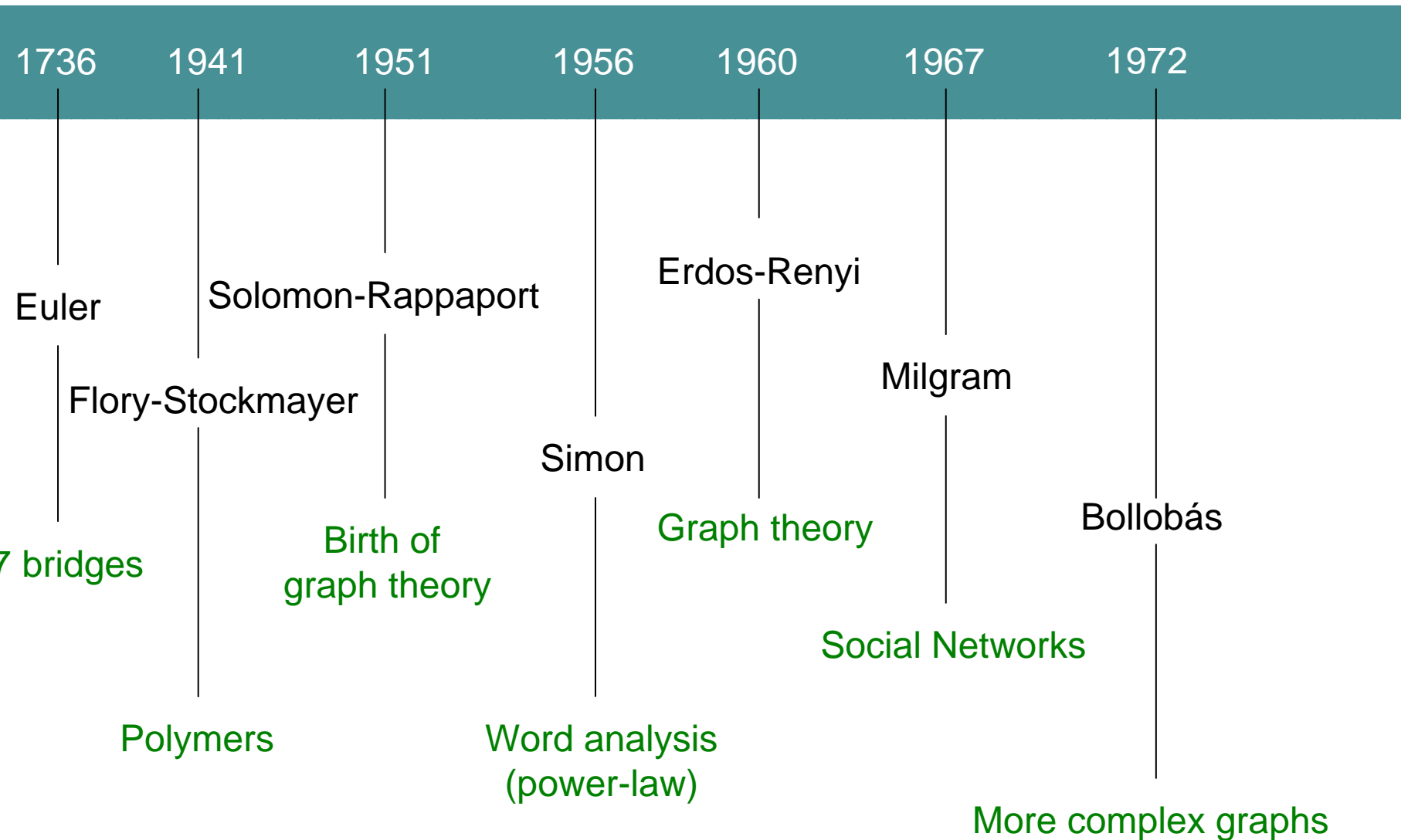
José F. F. Mendes
University of Aveiro



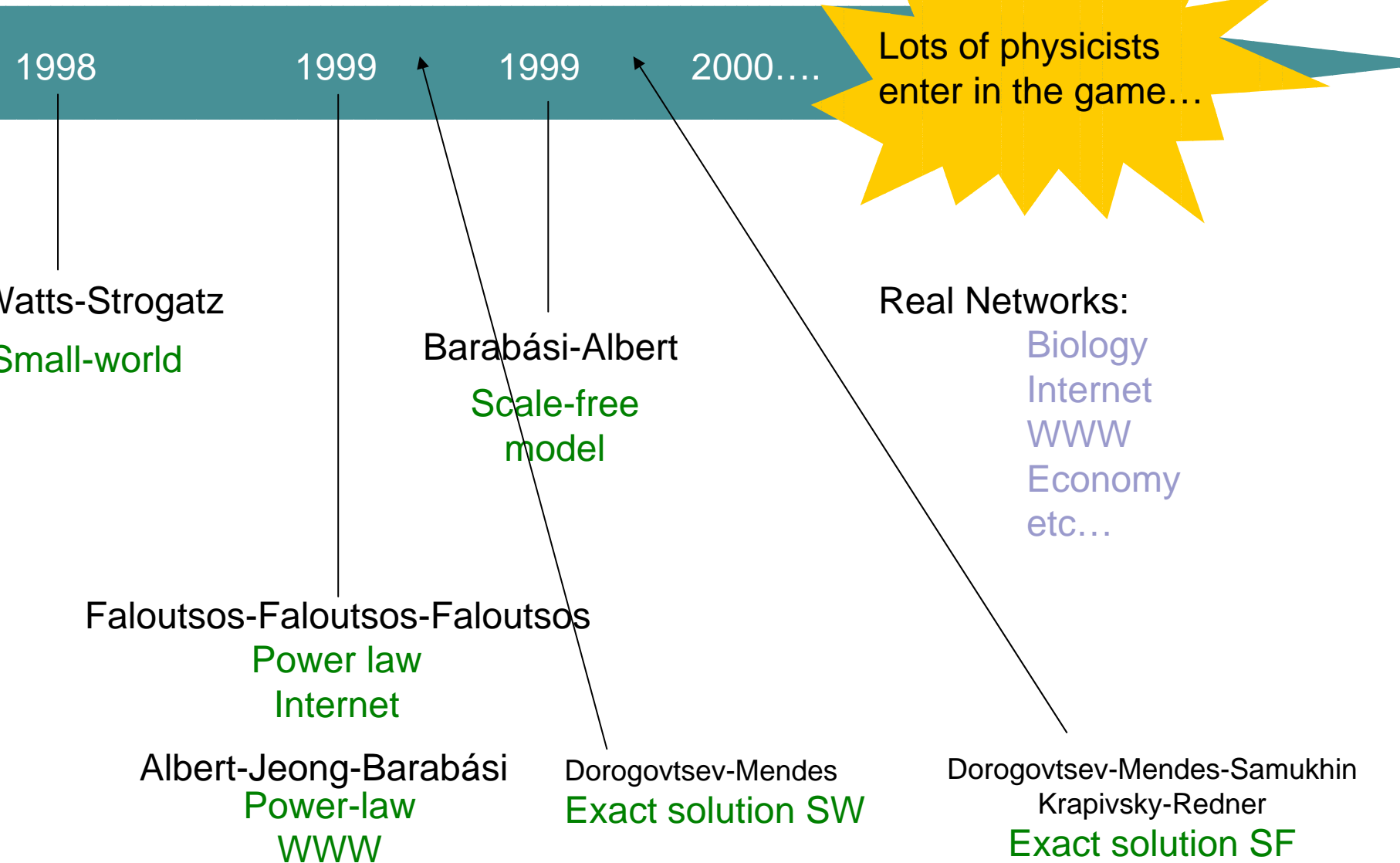
Talk Outline

- Short introduction to networks
 - Time line
 - Some concepts
- Spectra of several networks
- General theory
- Application to Internet
- Conclusions

Time Line on Networks



Time Line on Networks



Network complexity

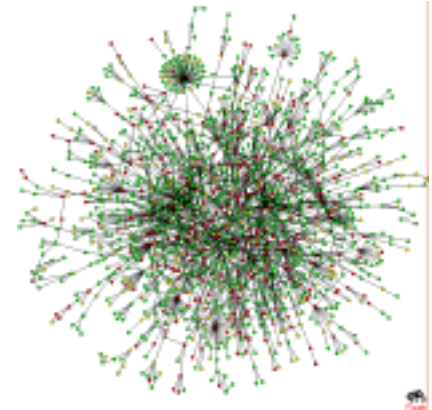
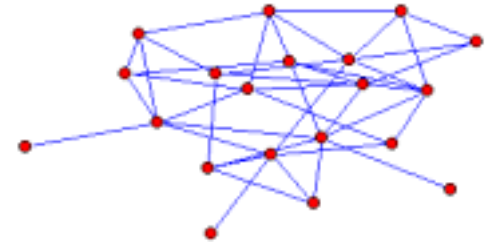
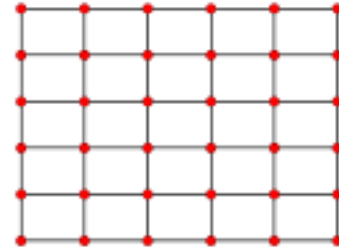
- Structure: *different types of topology*
- Network evolution: *grow of the # links and # nodes*
- Links diversity: *links can have direction, weight, etc*
- Node diversity: *different types of nodes*
- Dynamical complexity: *to each node we can assign a set of dynamical rules (spins, agents, etc)*

Some topological properties

- Degree & degree distribution
- Clustering
- Correlations
- Shortest paths
- Betweenness
- Spectrum (*we will focus attention on it!*)

What should we expect?

- In regular lattices all nodes are identical (same degree)
- In random networks the majority of nodes have approximately the same degree ($k_i \sim \langle k \rangle$)
- Real-world networks: the distribution has a power tail



$$P(k) \approx k^{-\gamma} \quad \text{"scale-free" networks}$$

Classical Random Graph (CRG)

- Maximal random networks under the constrain that the mean degree is $\langle k \rangle$.
- **Erdos-Renyi** model (1959)
 - Statistical ensemble of graphs with N vertices and L edges, where each member has equal probability of realization ($\langle k \rangle = 2L/N$).
- **Gilbert model** (1959)
 - Each pair of N vertices is connected with probability p

In the thermodynamic limit both models are equivalent:

$$\langle k \rangle = p(N-1)$$

The degree distribution of these CRG is **Poisson like**.

What types of networks can we have?

■ Equilibrium

□ N, L fixed; $\langle k \rangle = 2L/N = \text{const.}$

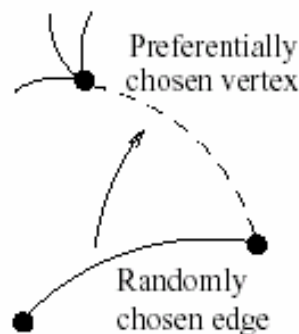
■ Non-equilibrium (growing)

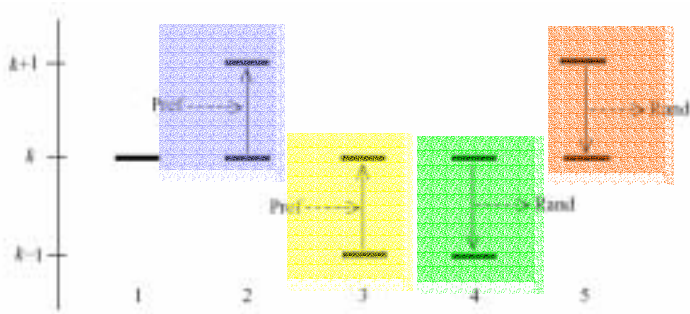
□ Linear: $L \sim N \sim t$; $\langle k \rangle \sim \text{const.}$

□ Non linear: $N \sim t, L \sim t^{a+1} \Rightarrow \langle k \rangle \sim t^a$

How we built and equilibrium network?

- The construction of **Erdos-Renyi** is restricted, it only produce Poissons!
- We can use different ensembles (microcanonical, canonical, ...)
- Can equilibrium networks have a fat tailed distribution?
 - In principle yes!
 - Canonical procedure:
 - (**set**) Set of all graphs with L edges.
 - (**rules**) At each step of evolution, one of the ends of a randomly chosen edge is rewired to a preferentially chosen vertex of degree k . The rate of this process is $f(k)$.





$$\langle N(k, t+1) \rangle = \langle N(k, t) \rangle - \frac{f(k)}{N \langle f(k) \rangle} \langle N(k, t) \rangle + \frac{f(k-1)}{N \langle f(k) \rangle} \langle N(k-1, t) \rangle - \frac{k}{Nk} \langle N(k, t) \rangle + \frac{k+1}{Nk} \langle N(k+1, t) \rangle.$$

$$N \frac{\partial P(k, t)}{\partial t} = \frac{1}{\langle f(k) \rangle} [-f(k)P(k, t) + f(k-1)P(k-1, t)] + \frac{1}{k} [-kP(k, t) + (k+1)P(k+1, t)].$$

Stationary solution:

$$\frac{f(k)}{\langle f(k) \rangle} P(k) - \frac{k+1}{k} P(k+1) = \text{const} = 0$$

We set const=0, given $kP(k) \rightarrow 0$, then:

$$f(k) = \frac{(k+1)P(k+1)}{P(k)} \frac{\langle f(k) \rangle}{k}$$

Fat-tailed: $f(k) \bar{k} / \langle f(k) \rangle = k + o(k)$

A fat-tailed degree distribution can be realized in an equilibrium network only at a single value (critical) of the average degree, $\langle k \rangle_c$ given by the condition:

$$\langle k \rangle = \langle f(k) \rangle$$

If we give, $P(k) \sim k^{-\gamma}$, what will be $f(k)$?

$$f(k) \cong k + 1 - \gamma + O(k^{-1})$$

Uncorrelated networks

- In the case of *CRG* correlations are absent:
 - The degree of connected vertices are uncorrelated, and *loops* are not essential in the large network limit.
 - The fact that *loops* are not essential in the thermodynamic limit implies that any finite neighborhood of a vertex has a *tree-like structure*.

What are complex networks?

- Are nets with a more complex structure than *CRG*'s.
 - Degree distribution
 - Correlations
 - Real nets are complex networks, with fat-tailed degree distribution, usually with strong correlations and loops.

Degree-degree correlations

- In the case of uncorrelated, one end of an edge is attached to a vertex of degree k with probability $kP(k)/\langle k \rangle$.
- If correlations exist, the joint distribution $P(k, k')$ differs from the uncorrelated case:

$$P(k, k') = \frac{kP(k)k'P(k')}{\langle k \rangle^2}$$

- For the citation graph

for $k \gg k' \gg 1$ we have $P(k, k') \sim k^{-(\gamma-1)} k'^{-2}$

Reasons for the fat-tailed distributions

- Self-organization
- Optimization processes involving many agents
- Multiplicative stochastic processes
- Interconnection of geographically close vertices
- Secondary effects...

Preferential linking

- The most popular mechanism of self-organization is *preferential attachment*.
 - Nodes with high degree attract new connections with higher probability
 - Probability to become attached to a node of degree k , is proportional to some function of k , $f(k)$.
 - Scale-free degree distributions appear when:

$$f(k) = \frac{k + A}{\langle k \rangle + A}$$

- The exponent is between 2 and infinity.
- Models based on this concept were presented by:
 - G. Yule (1925)
 - H.E. Simon (1955)
 - D.J. de Price (1976)
 - A.-L. Barabási and R. Albert (1999)
 - A new vertex connects to already existing one with probability proportional to the degree of such vertex.

Evidence *preferential linking*...

Maps taken at different times ($\Delta t = 6$ months)

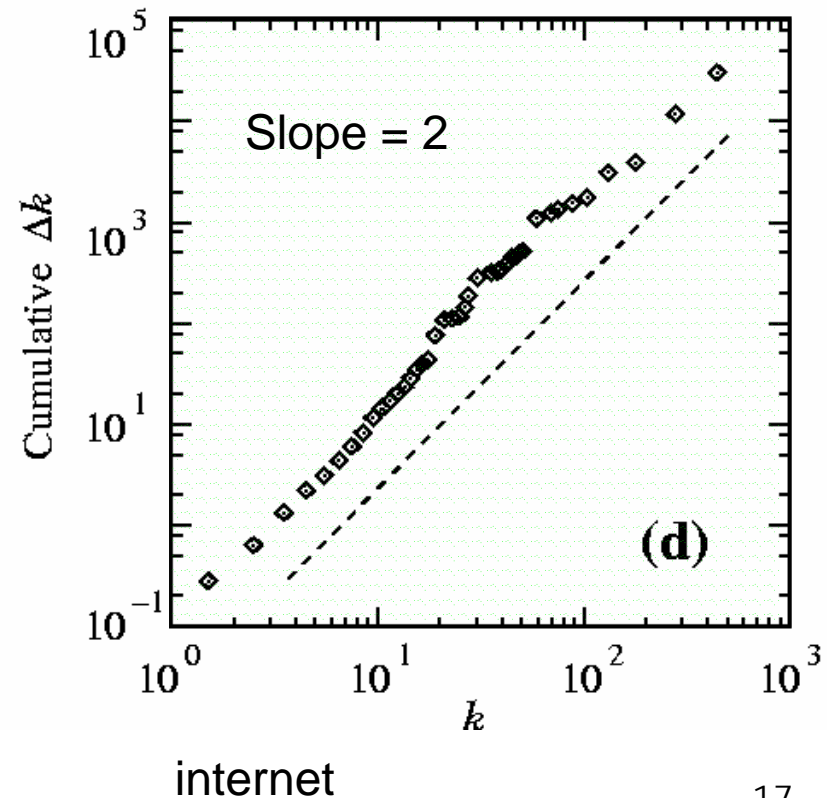
Measure $\Delta k(k)$, change of the # of links for a vertex with k edges

(S.-H. Yook et al.)

$$\Delta k(k) \sim k$$

Other types of linking $\Pi(k_i) \sim k_i^\alpha$

does not produce power laws
(Krapivsky & Redner, 2000)



BA model (Barabási&Albert, Science 286, 509(1999))

Rules:

- Network growth
 - Network evolves in size over time.
- Preferential attachment
 - Probability that a newly added node will attach to node, i

$$\Pi(k_i) = \frac{k_i}{\sum_j k_j}$$

- Degree distribution

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

- Exact solution (DMS, PRL 85, 4633 (2000))

$$P(k) = \frac{(1+a)\Gamma((m+1)a+1)\Gamma(q+ma)}{\Gamma(ma)\Gamma(k+2(m+1)a)} \sim k^{-(2+a)}$$

Condensation of edges

- Only in growing networks (non-equilibrium) the mechanism of preferential linking gives rise to scale-free nets.
- In equilibrium nets (fixed N) only above a critical value of mean degree the preferential linking produce fat-tailed degree distributions.
- Condensation appears, i.e. a big fraction of edges get connected to a vanishingly small fraction of nodes (or even to a single vertex).
- The degree distribution of the rest of vertices is fat-tailed.

Clustering coefficient

- Local clustering (# loops of length 3): $C_i = \frac{n_i}{k_i(k_i-1)/2}$
- Degree dependent local clustering, $C(k)$: average of C_i over nodes of degree k .
 - Probability that two nearest neighbors of a vertex has degree k .

- Mean clustering: $\langle C \rangle \equiv \langle C_i \rangle = \sum_k P(k)C(k)$

- Clustering coefficient: $C \equiv \frac{\langle n_i \rangle}{\langle k_i(k_i-1)/2 \rangle} = \frac{\sum_k P(k)\langle n(k) \rangle}{\left(\langle k^2 \rangle - \langle k \rangle^2 \right) / 2}$

Note: $\langle C \rangle \neq C$ if the local clustering is degree-dependent.

For the CRG: $C(k) = C = \langle C \rangle \sim \langle k \rangle / N$.

Small-world effect

- Is the mean length of the shortest path between two vertices.

- For the *CRG* model:
$$l = \frac{\ln N}{\ln \langle k \rangle}$$

- For a d -dimensional lattice:
$$l \sim N^{1/d}$$

- When the growth of $l(N)$ is slower than any positive power law of N , is called *small-world effect*.

Ultra small-world effect

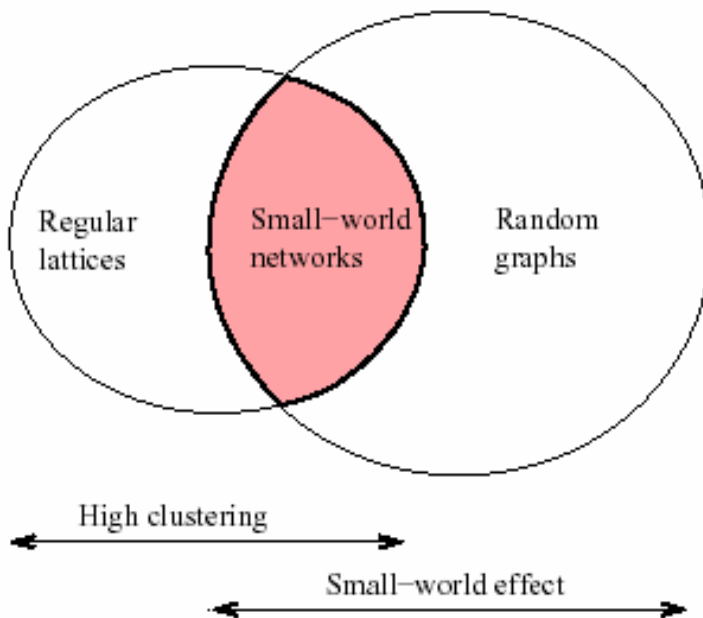
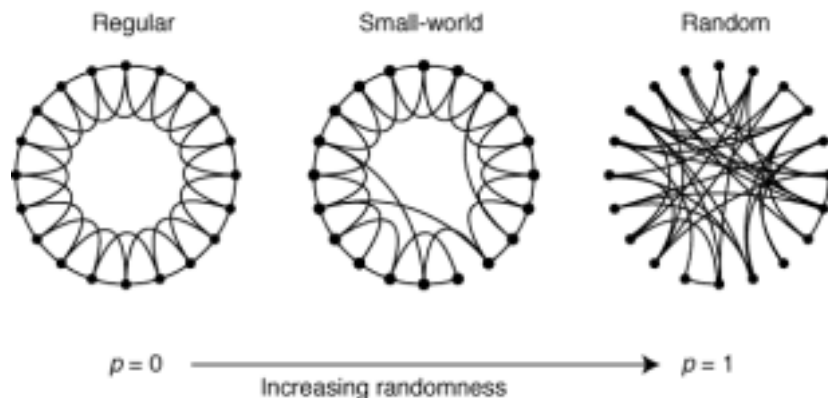
- In a correlated network the mean degree of a *nn* of a vertex is $\langle k^2 \rangle / \langle k \rangle$ which is greater than the mean degree of a vertex.
- This implies a change on the formula for the small-world

$$l \approx \frac{\ln N}{\ln \left[\left(\frac{\langle k^2 \rangle}{\langle k \rangle} \right) - 1 \right]}$$

- If the second moment of the degree distribution diverges (infinite network), the average number of *nn* of a vertex approach infinity. Previous formula is not valid.
- In this case $l(N)$ grows with N slower than $\ln N$, its called “*ultra small-world*” effect.

What happens in real networks?

- The clustering coefficient is much larger than it is in an equivalent random network



Watts & Strogatz,
Nature **393**, 440 (1998)

Betweenness (correlated with $P(k)$)

- Let $B(i,j)$ be the total number of shortest paths between vertices i and j .
- And, $B(i,j;m)$ the set of them that pass through vertex m (set of matrices, one for each vertex).
- The betweenness of vertex m , is:

$$b(m) = \sum_{i \neq j} \frac{B(i, j; m)}{B(i, j)} \quad 0 \leq B_{ij}^k \leq 1$$

- This is the probability that a shortest path between a pair of vertices passes through vertex m .
- Vertices with high betweenness play an important role.
- Real cases $\sim k^{-2}$!

Cut-off of degree distribution

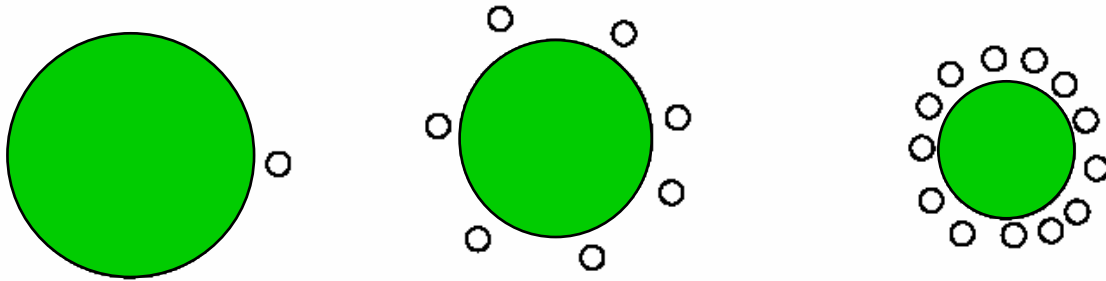
- In finite nets, vertices with infinitely large degree are absent.
- No “perfect” scale-free degree distributions.
- In finite nets, it obstructs the observation of fat-tailed distributions.
- In a scale-free network of size N ,

$$k_{cut} \sim N^{1/(\gamma-1)}$$

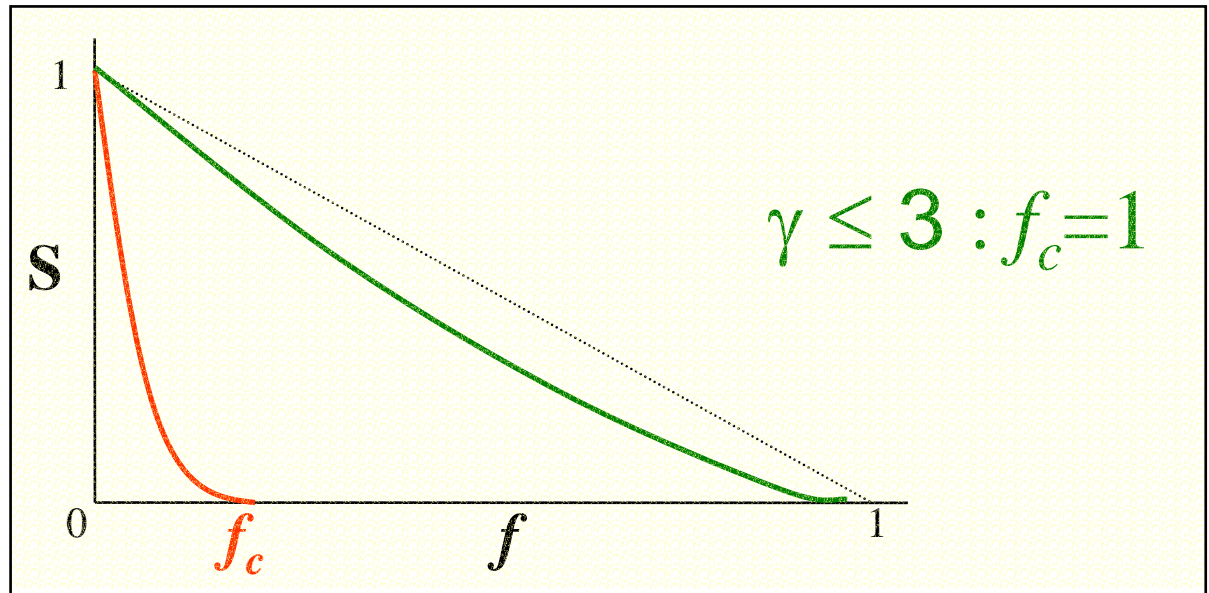
Ultra-resilience

- If the second moment of the degree distribution diverges (this happens when $\langle k^n \rangle \equiv \sum_k k^n P(k) \rightarrow \infty$ for $n \geq \gamma - 1$) the average degree of the nn of a vertex also diverges.
 - This means that a vertex in the infinite network, in average, has an infinite number of second nn 's.
 - Equivalent to the existence of a giant connected component on the net.
- Remove a finite fraction of vertices (random failure), the average number of second nn 's still infinity (does not eliminate the giant component).
- The same is not true in the case of intentional attach (remove vertices with high degree).

Robustness of scale-free networks



Failures



Attacks



Critical behavior of cooperative models on nets

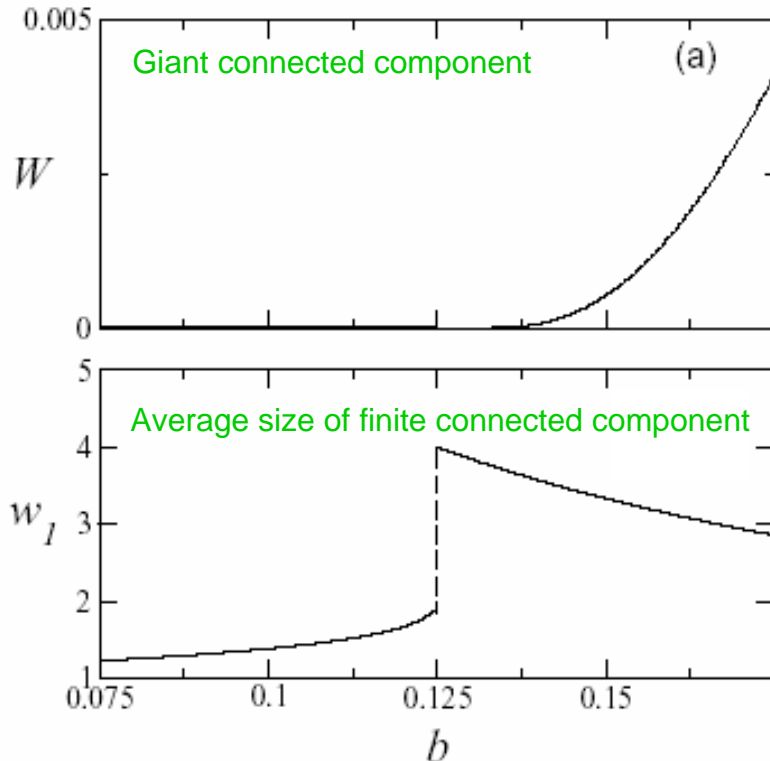
- **Networks are infinite dimension objects**
 - Critical fluctuations in cooperative models are absent
 - Critical behavior is described by mean field theories
- **In the case of equilibrium nets with degree distribution with a well defined scale, standard mean-field theory (with standard exponents) is valid.**
- **If the degree distribution is fat-tailed, critical behavior is non-standard.**
 - Unusual critical exponents
 - Order of the phase transition is high or even infinite
 - No critical fluctuations
 - Mean-field still works, but is non-standard, because the presence of highly connected vertices
 - This is valid for various cooperative phenomena: percolation, magnetic phase transitions, synchronization, etc and in various networks: correlated and uncorrelated, small-worlds, etc.

Ising model on a scale-free net

	M	$\delta C(T < T_c)$	χ	T_c
$\gamma > 5,$ $\langle k^4 \rangle < \infty$	$\propto \sqrt{T_c - T}$	jump at T_c decreases as $\langle k^4 \rangle$ grows	$\propto T_c - T ^{-1}$	$2J / \ln \frac{\langle k^2 \rangle}{\langle k^2 \rangle - 2k}$
$\gamma = 5,$ $\langle k^4 \rangle = \infty,$ $\langle k^2 \rangle < \infty$	$\propto \sqrt{(T_c - T) / \ln(T_c - T)^{-1}}$	$\propto 1 / \ln(T_c - T)^{-1}$		
$3 < \gamma < 5,$ $\langle k^4 \rangle = \infty,$ $\langle k^2 \rangle < \infty$	$\propto (T_c - T)^{1/(\gamma-3)}$	$\propto (T_c - T)^{(5-\gamma)/(\gamma-3)}$		
$\gamma = 3,$ $\langle k^2 \rangle = \infty$	$\propto e^{-2T/\bar{k}}$	$\propto T^2 e^{-4T/\bar{k}}$	J/T	$\propto \bar{k} \ln N$
$2 < \gamma < 3,$ $\langle k^2 \rangle = \infty$	$\propto T^{-1/(3-\gamma)}$	$\propto T^{-(\gamma-1)/(3-\gamma)}$		$\propto \bar{k} N^{(3-\gamma)/(\gamma-1)}$

Percolation transition

- Exception maybe the case of non-equilibrium networks where a “non-mean-field” phase transition appears of the type *Berezinskii-Kosterlitz-Thouless singularity*.



Size of the giant connected component versus the ratio of creation of new edges.

All derivatives of $W(b)$ are zero at critical point (*infinite order phase transition*).

$$W(b) = 0.590 \dots \exp\left(-\frac{\pi}{2\sqrt{2}} \frac{1}{\sqrt{b - b_c}}\right)$$

Adjacency matrix. What can we get from it?

$$\text{Tr}(\mathbf{A}) = 0$$

$$\text{Tr}(\mathbf{A}^2) = 2m \quad (m = \# \text{ edges})$$

$$\text{Tr}(\mathbf{A}^3) = 6t \quad (t = \# \text{ triangles})$$

- if $\text{tr}(\mathbf{A}^3) = 0$ means the graph has no cycles (null clustering)

$(\mathbf{A}^n)_{ik} = \#$ of paths of length n between i and k

- If the adjacency matrix is symmetric and real => eigenvalues are real and the largest is not degenerate
- **Largest eigenvalue:** related with the maximum degree on the net (k_{cut})
- **Second largest:** related to the diameter of the graph

$$D(G) \leq \frac{\log(N - 1)}{\log(1/\lambda_2)}$$

Adjacency Matrix

- If the adjacency matrix ($N \times N$) is random (random entries), $N \rightarrow \infty$, it satisfies the Wigner theorem, and the density of states converges to the semi-circular law

$$\rho(\lambda) = \begin{cases} (2\pi)^{-1} \sqrt{4 - \lambda^2}, & \text{if } |\lambda| < 2\sigma; \\ 0, & \text{otherwise.} \end{cases}$$

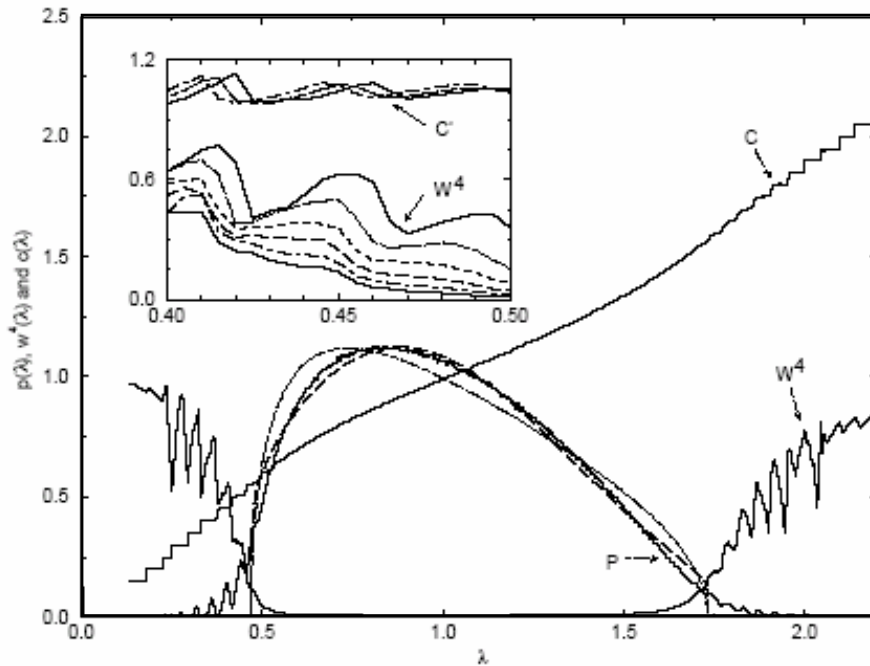
E.P. Wigner, Ann. Math. 62, 548 (55)

Ann. Math. 65, 203 (57)

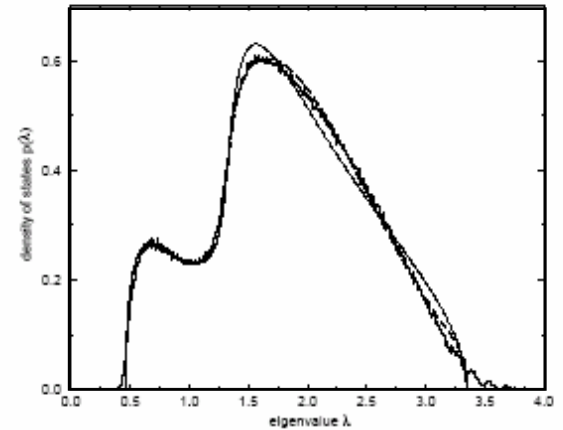
Ann. Math. 67, 325 (58)

Spectra: small-world

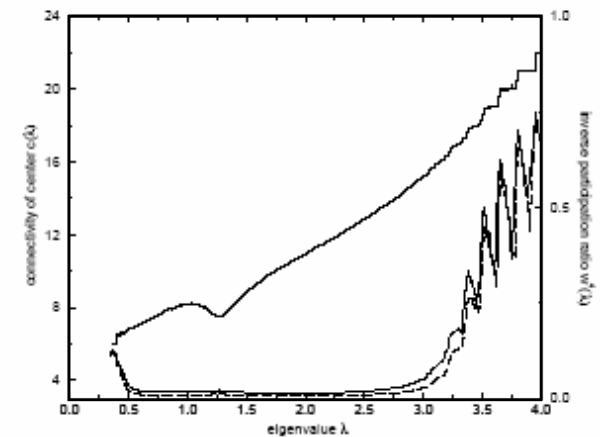
G. Biroli, R. Monasson, *J. Phys. A: Math. Gen.* **32**, L255 (1999);
 R. Monasson, *Eur. Phys. J. B* **12**, 555 (1999).



Density of states $p(\lambda)$, inverse participation ratio $w_4(\lambda)$ and connectivity of the centers $c(\lambda)$ (divided by q) averaged over 2000 samples for $q = 20$, $N = 800$.



Small-world network $K = 3$, $q = 5$.
 Density of states from numerics, EMA and SDA approximation.



Inverse participation ratio for $N = 256$ and $N = 512$ averaged over 1000 samples.

Spectra: sparse random matrix

Rodgers & Bray, PRB [37](#), 3557 (88)

Bond occupation probability = p / N ($N = \#$ nodes)

(p is like the mean number of non zero elements per row)

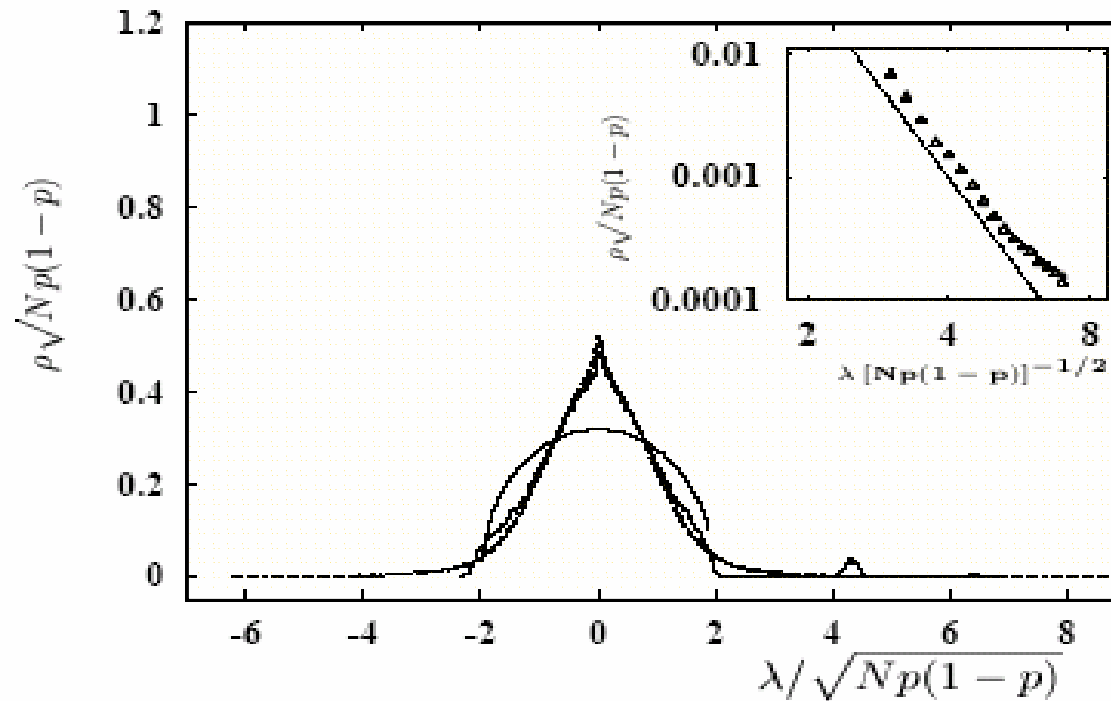
$$\rho(\lambda) = \frac{2}{\pi\lambda_c} (\lambda_c^2 - \lambda)^{1/2} \left\{ 1 + \frac{1}{p} \left(1 - \frac{4\lambda^2}{\lambda_c^2} \right) + \dots \right\}$$

tail:

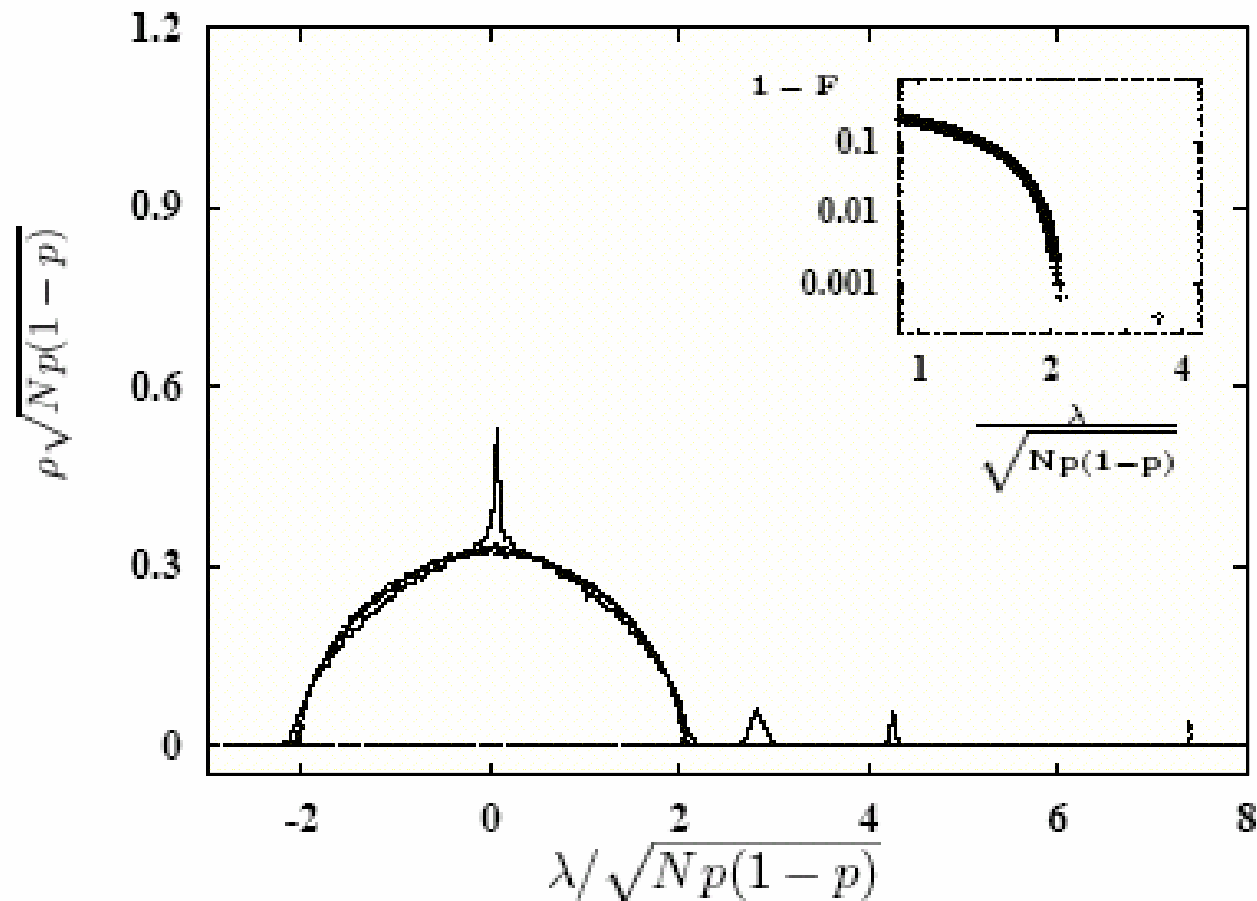
Semi-circular law

$$\rho(\lambda) \cong e^{-\lambda^2 \ln(\lambda^2 / ep)}; \lambda^2 \gg \lambda_c^2$$

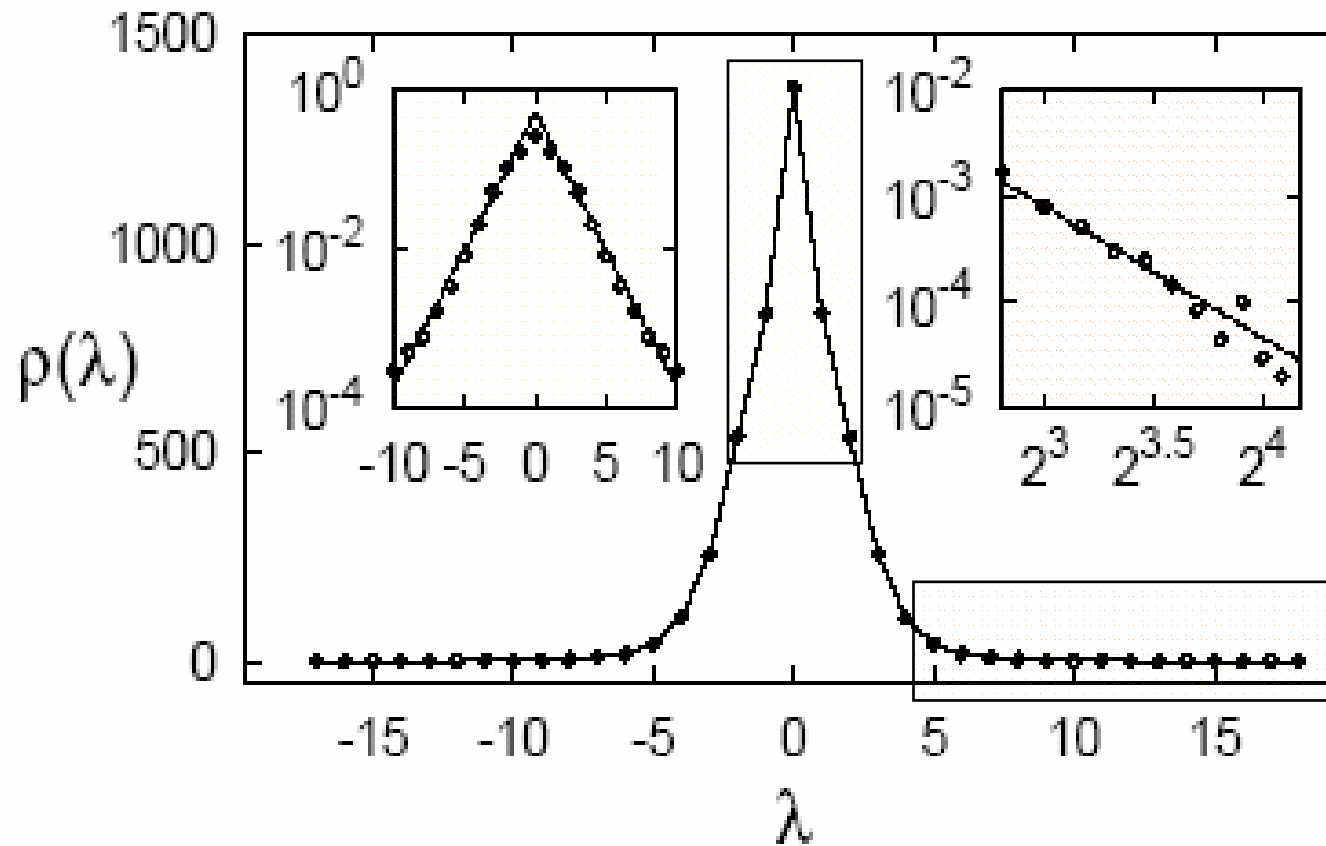
Spectra: scale-free network



Spectra: random graph



Spectra: scale-free network



We propose:

Study the spectra of random *Bethe* lattices as a standard spectra for complex networks

■ Why?

- they mimic very well the main topological properties of complex networks
 - their tree-like structure is described completely by the degree distribution and degree correlations.
 - there are exact methods to study the spectra of random walks on tree-like graphs.
 - the clustering coefficient is equal to zero, contrarily to real nets.

General theory...

Adjacency matrix; $\mathbf{A} = a_{wv}$, $N \times N$ and symmetric.

Method: RW's on a tree like graph

$$\rho_v(n) = \begin{array}{c} \text{Diagram 1: loop of length } n \\ \text{Diagram 2: two loops of lengths } n_1, n_2 \\ \text{Diagram 3: three loops of lengths } n_1, n_2, n_3 \\ \dots \end{array} + \dots$$

$$= q_n + q_{n_1} q_{n_2} \delta_{n_1+n_2, n} + q_{n_1} q_{n_2} q_{n_3} \delta_{n_1+n_2+n_3, n} + \dots$$

$$R(z) = \frac{1}{N} \sum_{v=1}^N \sum_{n=0}^{\infty} \rho_v(n) z^n$$

Generating function of the number of walks, $\rho_v(n)$, of length n starting in v and end in v .

$$q_v(n) = \begin{array}{c} \text{Diagram 1: loop of length } n \\ \text{Diagram 2: two loops of lengths } n_1, n_2 \\ \dots \end{array} + \dots$$

If $q_v(n)$, is the number of walks of length n starting in v and end in v for the first time.

$$Q_v(z) = \sum_{n=0}^{\infty} q_v(n) z^n$$

The previous relations are related by:

$$R(z) = \frac{1}{N} \sum_{v=1}^N \frac{1}{1 - Q_v(z)}$$

$t_{w,v}^{(m)}(n) \equiv$ Number of paths of length n starting in w and ending in v for the first time

Defining the respective **generating function**: $T_{w,v}^{(m)} = \sum_{n=0}^{\infty} t_{w,v}^{(m)}(n) z^n$

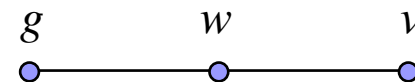
$$q_v(n) = t_{wv}(n-1); \quad t(0) = 0; \quad q_0 = q_1 = 0$$

On can prove:

$$Q_v(z) = z \sum_w T_{wv}^{(1)}(z),$$

$$T_{wv}^{(m)}(z) = T_{wg_1}^{(1)}(z) T_{g_1g_2}^{(1)}(z) \dots T_{g_{m-1}v}^{(1)}(z)$$

where: $w \rightarrow g_1 \rightarrow g_2 \rightarrow \dots \rightarrow g_{m-1} \rightarrow v$



$$T_{wv}^{(1)}(z) = z + z \sum_g T_{gv}^{(2)}(z)$$

$$= z + z \sum_g T_{gw}^{(1)}(z) T_{wv}^{(1)}(z)$$

The node g is the neighbor of w and a second neighbor of the node v .

Solving the previous recurrence equation, we can find $T_{wv}^{(1)}(z)$ and $Q_v(z)$

Let's change $z \rightarrow z^{-1}$, we obtain:
$$\tilde{T}_{wv}^{(1)}(z) = \frac{1}{z - \sum_g \tilde{T}_{gw}^{(1)}(z)}$$

$$B(z) \equiv z^{-1}R(z^{-1}) \quad z = \lambda + i\varepsilon \quad (\varepsilon > 0)$$

$$\rho(\lambda) = -\frac{1}{\pi} \text{Im} \langle B(\lambda + i\varepsilon) \rangle$$

This equations are valid both for correlated and uncorrelated tree-like graphs.

Example: k-regular graph

$\tilde{T}_{wv}^{(1)}(z) \equiv T(z)$ and $Q_v(z) \equiv Q(z)$ then $zT(z) - (k-1)T^2(z) = 1$, solving this equation :

$$\rho(\lambda) = \frac{k}{2\pi} \frac{\sqrt{4(k-1) - \lambda^2}}{k^2 - \lambda^2}$$

Continuous spectra of extended states with eigenvalues: $|\lambda| < 2\sqrt{k-1}$

Spectra of uncorrelated graph

Distribution function of $\tilde{T}_{wv}^{(1)}(z)$: $F_\lambda(x) = \left\langle \exp(-ix\tilde{T}_{wv}^{(1)}(\lambda + i\varepsilon)) \right\rangle$

The average is over the ensemble of uncorrelated graphs with given $P(k)$. The statistical independence of the $k-1$ random parameters

$$\tilde{T}_{wv}^{(1)}(\lambda + i\varepsilon) \equiv T_i \quad \text{with } i = 1, 2, \dots, k-1, \quad k = k_w$$

$$F_\lambda(x) = \left\langle \exp(-ix\tilde{T}_{wv}^{(1)}(\lambda + i\varepsilon)) \right\rangle = \left\langle \exp\left(-\frac{ix}{\lambda + i\varepsilon - \sum_{i=1}^{k-1} T_i}\right) \right\rangle = 1 - \sqrt{x} \int_0^\infty \frac{dy}{\sqrt{y}} J_1(2\sqrt{xy}) e^{i\lambda y} \Phi_1(F_\lambda(y))$$

$$\rho(\lambda) = -\frac{1}{\pi} \operatorname{Re} \int_0^\infty e^{i\lambda y} \Phi(F_\lambda(y)) dy$$

$$\Phi_1(x) \equiv \sum_{k=1}^{\infty} kP(k)x^{k-1} / \langle k \rangle$$

$$\Phi(x) \equiv \sum_{k=1}^{\infty} P(k)x^k$$

If we can solve the previous auto-consistent equation, we get the density of states, but ...

We need some approximation!

Effective medium approximation (*EMA*)

Neglect fluctuations of T around $\langle T \rangle$.

If we use: $F_\lambda(x) \cong e^{-ixT(\lambda)}$ we get:

$$T(\lambda) = \frac{1}{\langle k \rangle} \sum_k \frac{kP(k)}{\lambda + i\varepsilon - (k-1)T(\lambda)}$$

and

$$\rho(\lambda) = -\frac{1}{\pi} \sum_k \frac{kP(k) \operatorname{Im}T(\lambda)}{(\lambda - k \operatorname{Re}T(\lambda))^2 + k^2 \operatorname{Im}T(\lambda)^2}$$

Tail behavior:

$$(|\lambda| \gg 1)$$

$$T(\lambda) \cong \frac{1}{\lambda} - i\pi \frac{|\lambda|^3 P(k)}{\langle k \rangle}$$

$$\rho(\lambda) \cong 2|\lambda|P(\lambda^2)$$

For scale-free net...

$$P(k) = P_0 k^{-\gamma}$$

$$\rho(\lambda) = 2P_0 |\lambda|^{-(2\gamma-1)} \cong \lambda^{-\delta}$$

$$\Rightarrow \delta = 2\gamma - 1 \quad (\text{exact result})$$

- A classical random graph has the Poisson degree distribution

$$P(k) = e^{-\langle k \rangle} \langle k \rangle^k / k!$$

- The tail is given by:

$$\rho(\lambda) \sim \lambda^{-2(\lambda^2 + \alpha)} \exp[(1 + \ln \langle k \rangle) \lambda^2]$$

Adjacency matrix

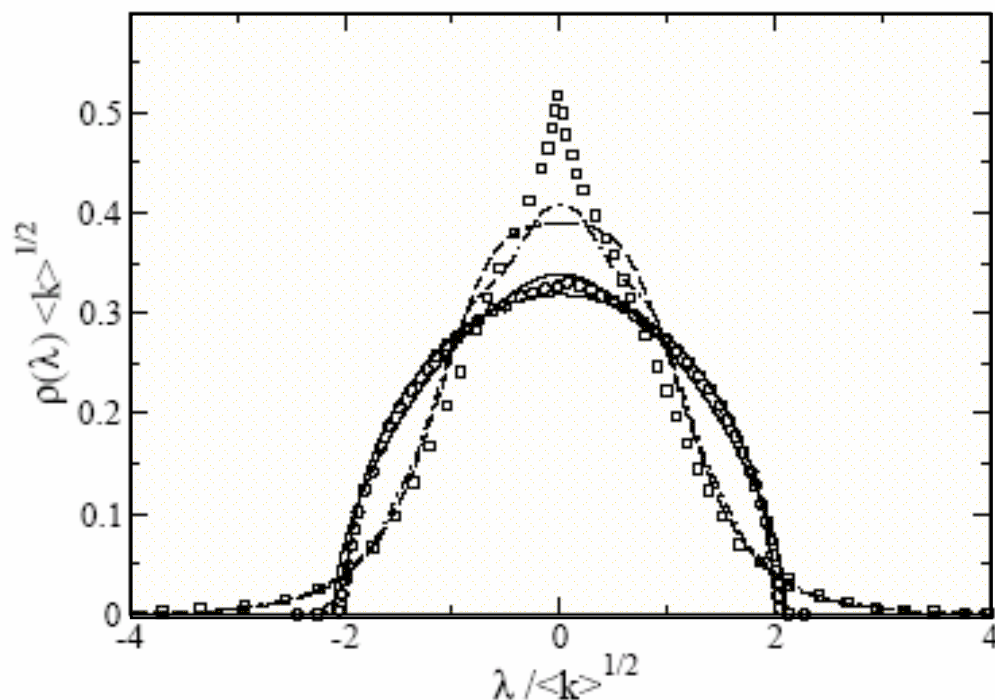


FIG. 1. Density of eigenvalues of the adjacency matrices of two networks. (i) The classical random graph (the Erdős-Rényi model) with the average degree $\langle k \rangle = 10$: the effective medium (EM) approach (the solid line) and numerical calculations for the graphs of 20 000 vertices [13] (the open circles).

Simulations:

I. Farkas et al., PRE 64, 026704 (0

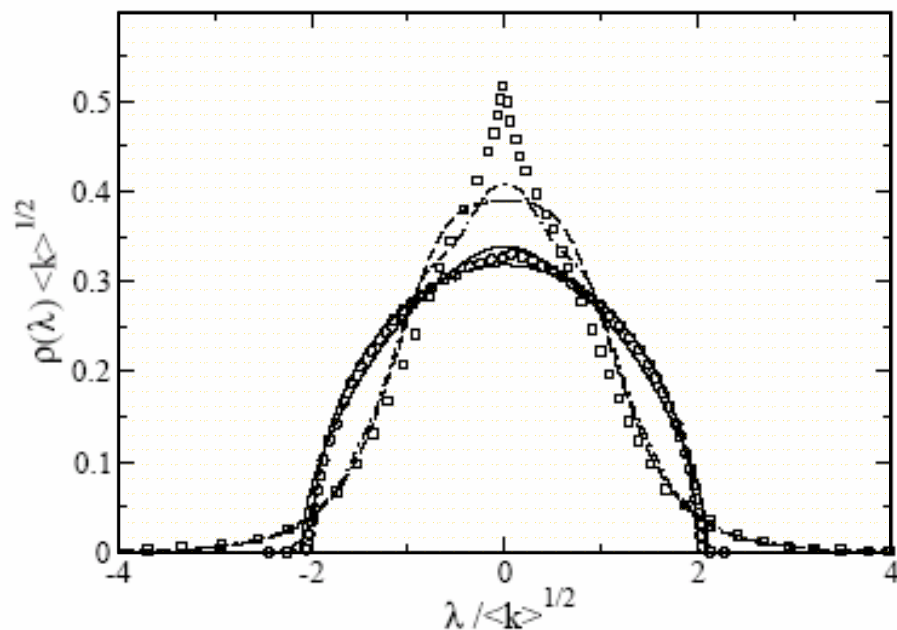
$$N \rightarrow \infty, pN = \text{const.}$$

$$N = 20000, L = 100000$$

$$\Rightarrow \langle k \rangle = \frac{2L}{N} = 10$$

Scale-free network

The spectra differs strongly from the semi-circular law



The BA model has:

- Tree like structure
- No correlations
- Negligibly small clustering

**Random uncorrelated
Bethe lattice mimic well
this net!**

Improve the EM approximation:

$$F_{\lambda}(x) = \left[1 + a(\lambda)x^2 \right] e^{-ixT(\lambda)}$$

Power-law tail

Density of eigenvalues for $\lambda \gg 1 \rightarrow \rho(\lambda) \propto \lambda^{-\delta}$ ($k_\lambda = \lambda^2$)

Our prediction agrees with simulation results by Farkas *et al.* and Goh *et al.*

Internet (AS level) $\gamma \cong 2.1$

$$\lambda_i \propto i^\varepsilon \quad (i = \text{order of eigenvalue})$$

Multi data set $\rightarrow \varepsilon \approx -0.447$

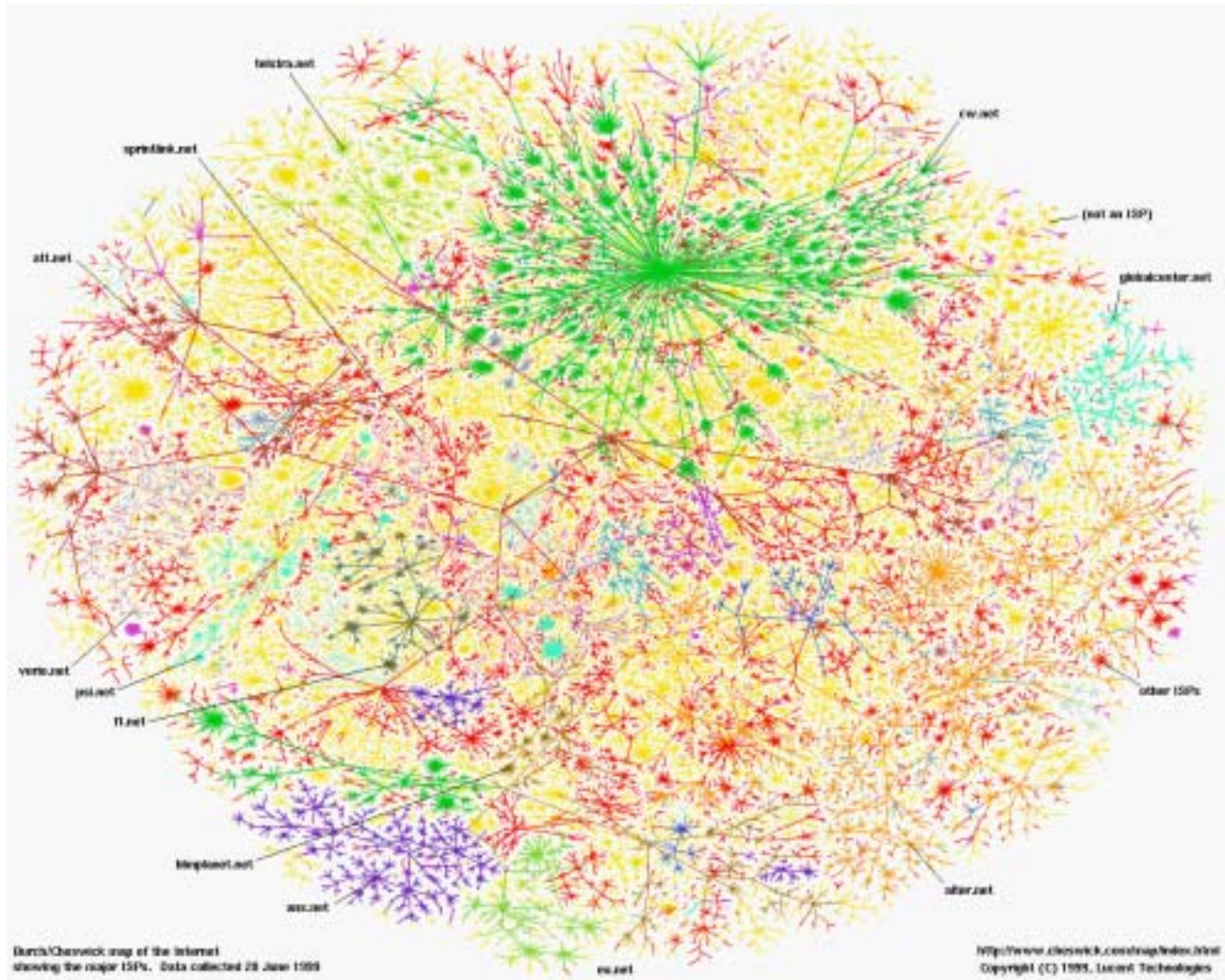
Oregon data set $\rightarrow \varepsilon \approx -0.477$

$$\rho(\lambda) = -\text{Im} \sum_i \frac{1}{\lambda - \lambda_i + i\varepsilon} = \sum_i \delta(\lambda - \lambda_i) \propto \lambda^{-1 + \frac{1}{\varepsilon}}$$

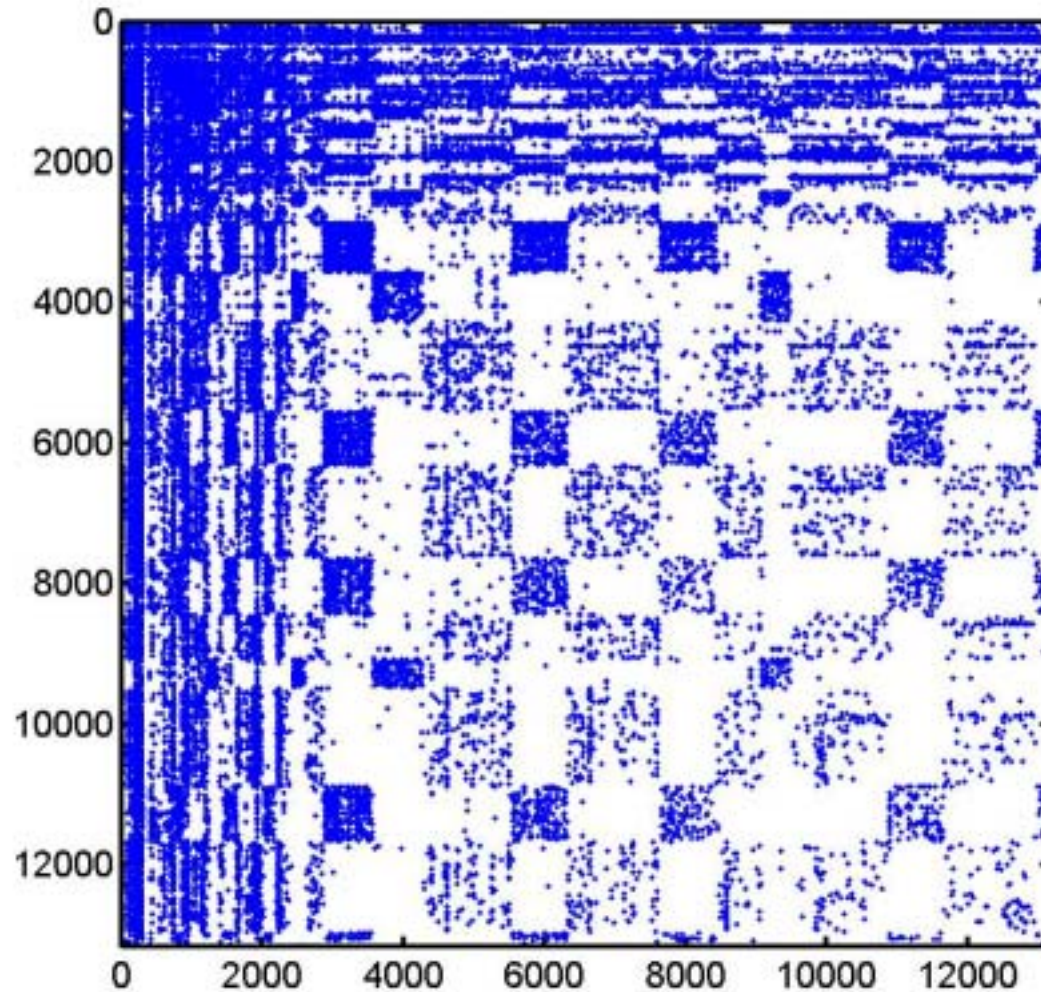
$$1 - \frac{1}{\varepsilon} \approx \begin{cases} 3.2 & \text{(Multi)} \\ 3.1 & \text{(Oregon)} \end{cases}$$

From our result: $\delta = 2\gamma - 1 \cong 3.2$

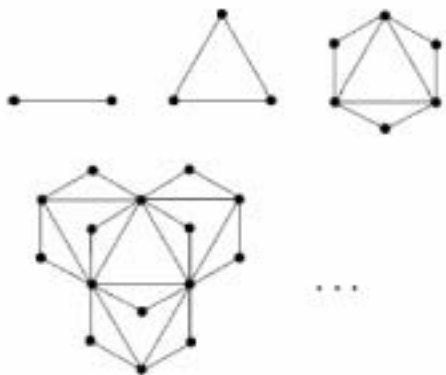
Internet (map): Lumeta



Respective adjacency matrix...



Pseudo fractal graph (hierarchical network)

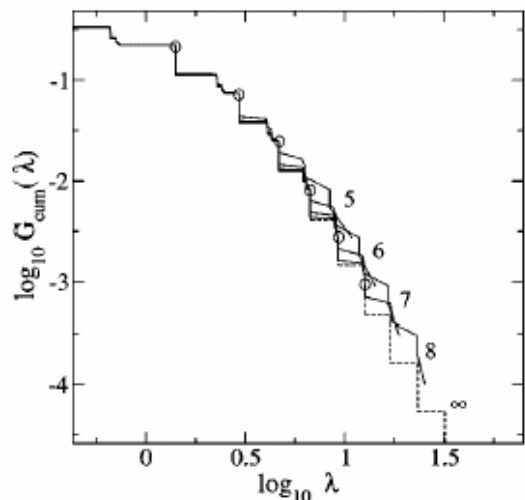


Adjacency matrix



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

$$\gamma = 1 + \frac{\ln 3}{\ln 2} \approx 2.58$$



$$G_{cum}(\lambda) \approx \lambda^{-(\delta-1)}$$

$\delta = 4.575 \pm 0.015 \approx 4.6$ (by numerical diagonalization)

Ansatz: $\delta = 2 + \gamma$

Using $\delta = 2\gamma - 1$ we get ≈ 4.2

Why this disagreement?

$C=0.8$ (large!)

$$C(k) = k^{-1}$$

there are long range correlations

Log-log plot of the **cumulative distribution** of eigenvalues of the adjacency matrix, G_{cum} . The curves show the spectra for $t = 5, 6, 7, 8$.

Weakly connected nodes

- What is the effect of nodes with degree $1 \leq k \leq 5$ on the spectra of a graph with degree distribution $P(k) = P_0 k^{-\gamma}$?

For $k_0 \geq 5$, the “form” is the same as BA model.

For $k_0 \leq 4$, two peaks ($\lambda \neq 0$) appear.

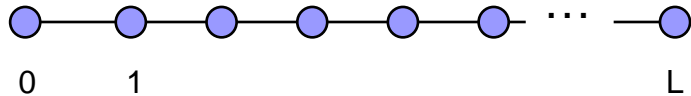
- What is the origin of the peaks?

$\langle k \rangle$ close to k_0

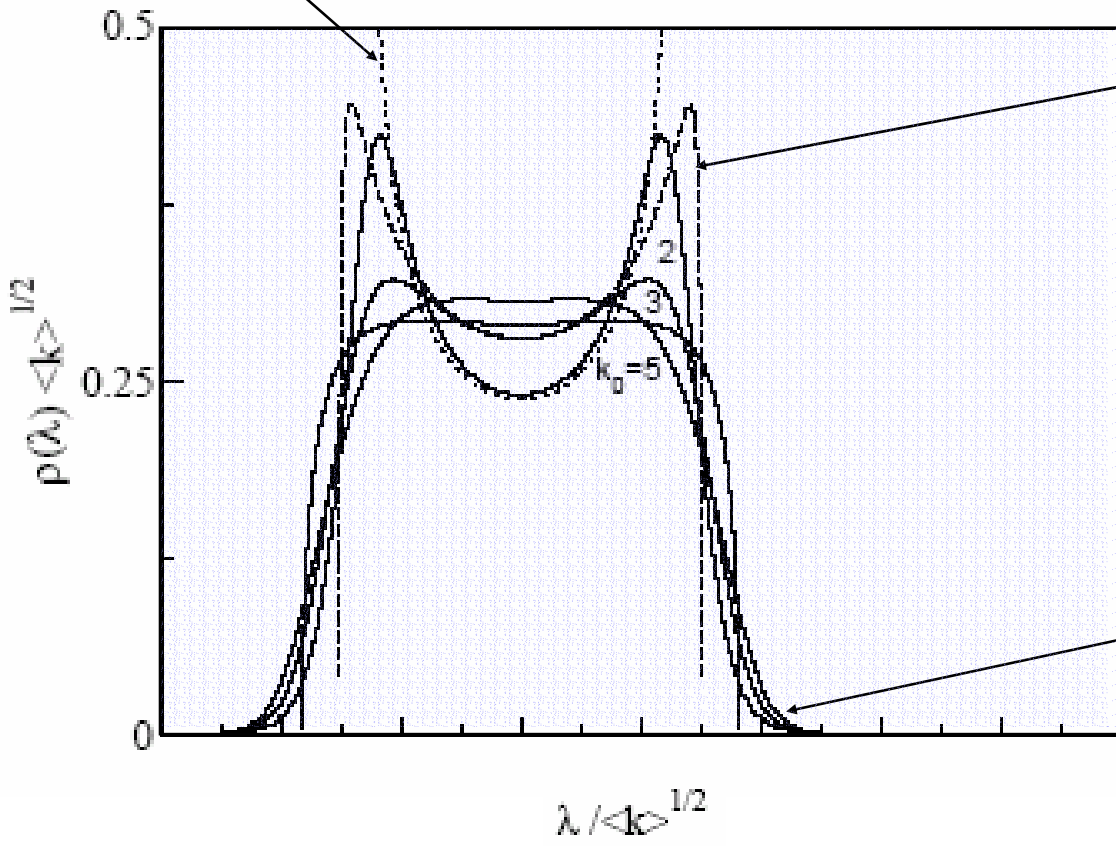
At $k_0 = 3$, $\langle k \rangle \sim 3.49 \Rightarrow$ probability to find nodes with 3 links is larger than for nodes with $k \geq 4$

Large parts of the net have local $k=3$ -regular structure

Linear chain:



$$\rho(\lambda) = (4 - \lambda^2)^{-1/2}; \quad \rho(\lambda)_{|\lambda \rightarrow \pm 2} \rightarrow \infty$$



k=3-regular lattice

$$\rho(\lambda) = \frac{k}{2\pi} \frac{[4(k-1) - \lambda^2]^{1/2}}{k^2 - \lambda^2}$$

for: $|\lambda| < 2(k-1)^{1/2}$

$$\rho(\lambda) \sim \lambda^{-\delta}; \quad \delta = 2\gamma -$$

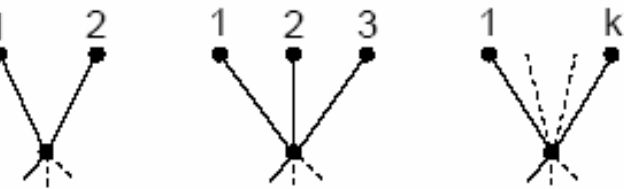
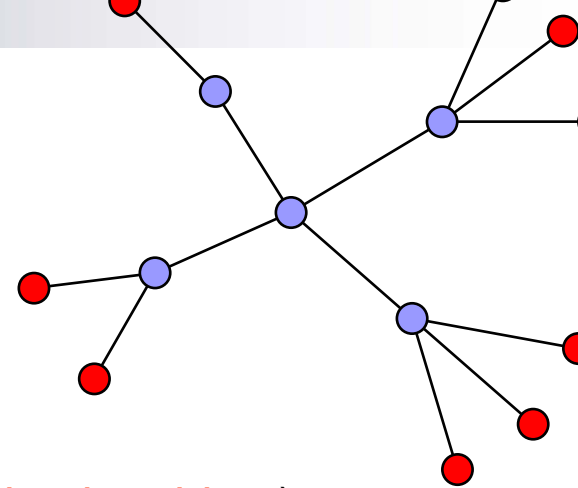
Dead end nodes

(they produce a peak at $\lambda = 0$)

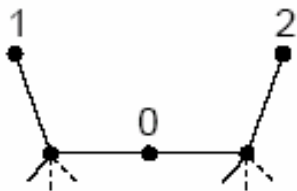
This effect is also present in classical random graphs.

The peak at $\lambda = 0$ is related with localized states (**unsolved problem**)

D. Vukadinović, P. Huang, and T. Erlebach, Lect. Notes Comput. Sci. 2346, 83 (2002).

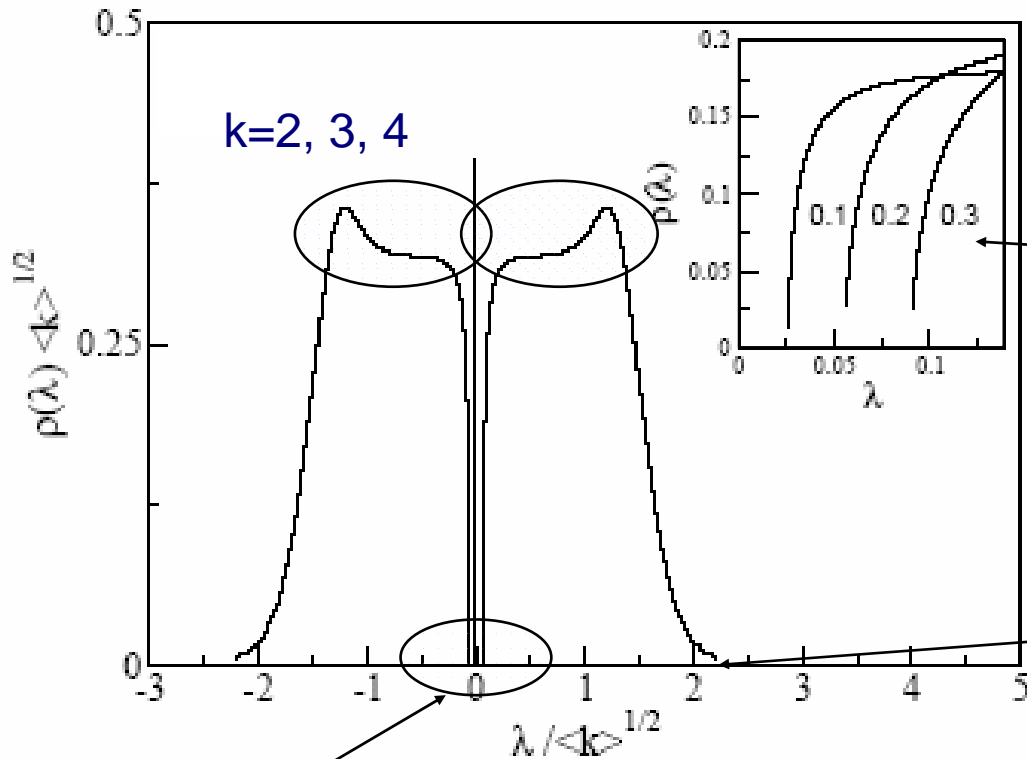


These vertices produce eigenstates with eigenvalue $\lambda = 0$



eigenvector is localized at vertices 0, 1 and 2

$$\gamma = 5; P(1) = 0.3$$



Effect of $P(1)$

Tail as before:
 $\rho(\lambda) \sim \lambda^{-\delta}$

Emergence of a dip (EMA)

Accuracy of the EM approximation

$$M_n \equiv \langle T^n \rangle = \frac{1}{(n-1)! i^n} \int_0^\infty dy y^{n-1} e^{iy\lambda} \Phi_1(F_\lambda(y))$$

Define: $q_n \equiv M_n/T^n(\tilde{\lambda})$

The function $F(x) = e^{-ixT(\lambda)}$ would be an exact solution if $q_n = 1$ for all $n > 1$. Note that at $n = 1$ we have $q_1 = 1$, this equality is the basic equation in the framework of the EM approximation.

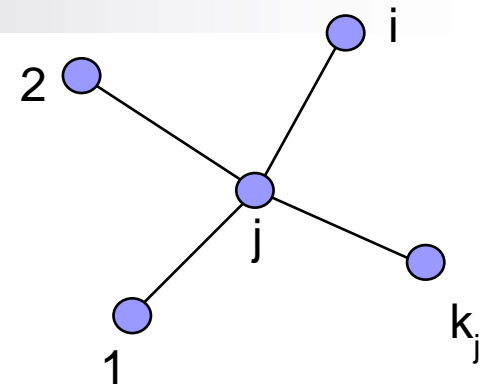
For $P(k) = P_0 k^{-\gamma}$ and $\lambda \gg 1$ in the leading order of $1/\lambda$:

$$\begin{aligned} q_n &\cong 1 - Ank_0\lambda^{-2} && \text{at } \gamma > 3, \\ &\cong 1 - Ank_0\lambda^{-2} \ln \lambda && \text{at } \gamma = 3, \\ &\cong 1 - Ank_0^{\gamma-2}\lambda^{-2(\gamma-2)} && \text{at } 2 < \gamma < 3, \end{aligned}$$

For $k_0^{1/2} \ll \lambda \ll k_0^{1/2} N^{1/(2(\gamma-1))}$ the EM is asymptotically exact!

The problem is for $\lambda \approx k_0^{1/2}$!

Diffusion



Transition matrix:

$$P_{ij} \equiv \text{prob.}(j \rightarrow i) \quad \left(\sum_{i=1}^{k_j} P_{ij} = 1 \right) \quad P_{ij} = \frac{a_{ij}}{k_j}; \quad a_{ij} \text{ is the adjacency matrix}$$
$$g_i(t); \quad g_0(t=0) = 1$$

The temporal evolution of the probability of occupation of node i ($g_i(t)$)

$$\frac{\partial g_i(t)}{\partial t} = \sum_l P_{il} g_l(t) - g_i(t) \sum_k P_{ki} = -\sum_l (\delta_{il} - P_{ij}) g_l(t)$$

The Laplacian:

$$L_{ij} \equiv \delta_{il} - P_{ij}$$

Spectrum of transition matrix

Probability to go from a node v to a $n.n.$ $= 1/k_v$

Transition matrix: $P(w,v) = a_{wv} / k_v$

Laplacian of the graph:

$$L_{v,w} = \begin{cases} 1 & \text{if } v = w \\ -a_{v,w} / \sqrt{k_v k_w} & \text{otherwise} \end{cases} \quad \hat{P} = \hat{D}^{1/2} (1 - \hat{L}) \hat{D}^{-1/2}$$

Let $\rho(\lambda)$ the density of eigenvalues of P , and $1 = \lambda_1 > \lambda_2 > \dots > \lambda_N$

Diameter of the graph is related with the second eigenvalue: $D(G) \leq \frac{\log(N-1)}{\log(1/\lambda_2)}$

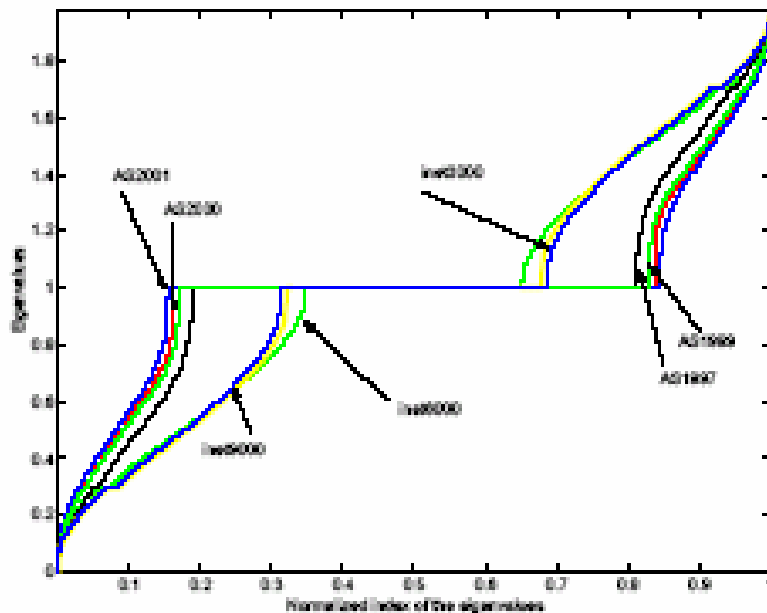
To find the spectra for $\lambda \leq \lambda_2$

$$T(\lambda) = \frac{1}{\langle k \rangle} \sum_k \frac{kP(k)}{k\lambda + i\varepsilon - (k-1)T(\lambda)} \quad \rho(\lambda) = -\frac{1}{\pi} \text{Im} \frac{1}{\lambda - T(\lambda)}$$

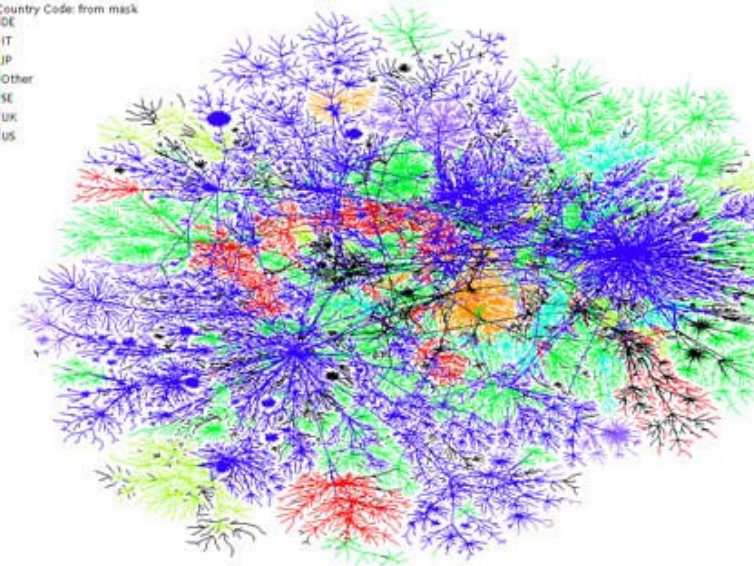
For a k -regular graph

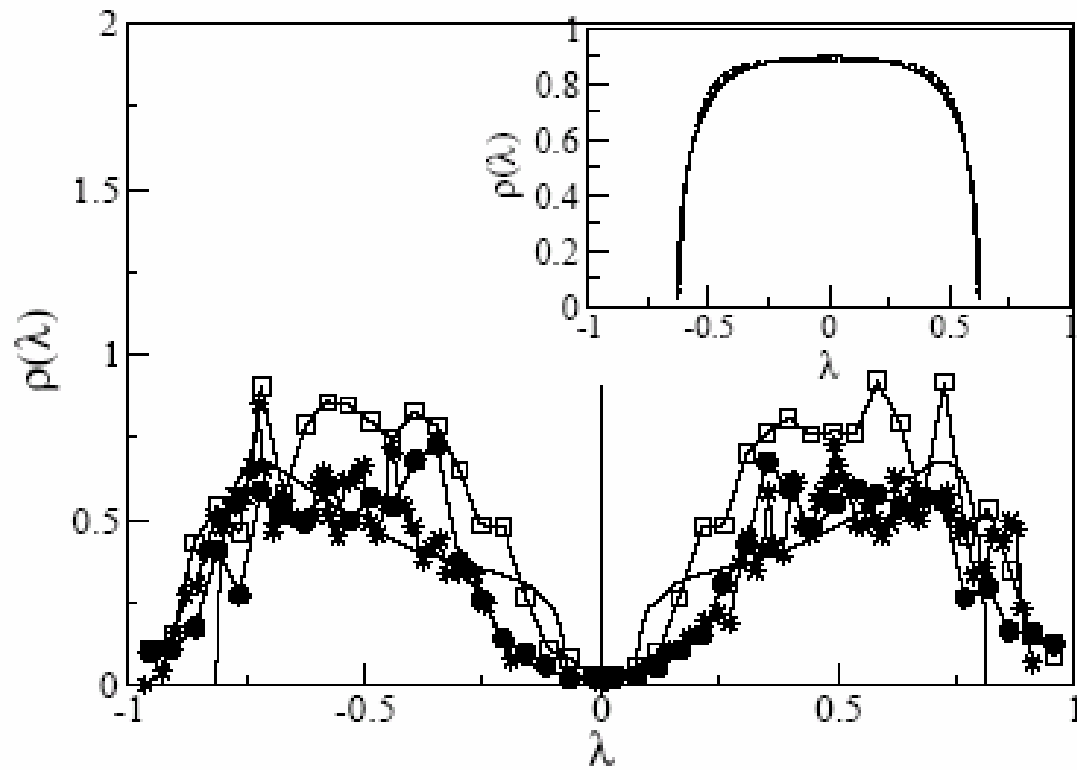
$$\lambda_2 = 2\sqrt{k-1}/k, \quad \text{and} \quad \rho(\lambda) = \frac{k}{2\pi} \frac{\sqrt{4(k-1)/k^2 - \lambda^2}}{1 - \lambda^2}$$

$$\mathcal{L}(G)(u, v) = \begin{cases} 1 & \text{if } u = v \text{ and } d_v \neq 0, \\ -\frac{1}{\sqrt{d_u d_v}} & \text{if } u \text{ and } v \text{ are adjacent,} \\ 0 & \text{otherwise.} \end{cases}$$



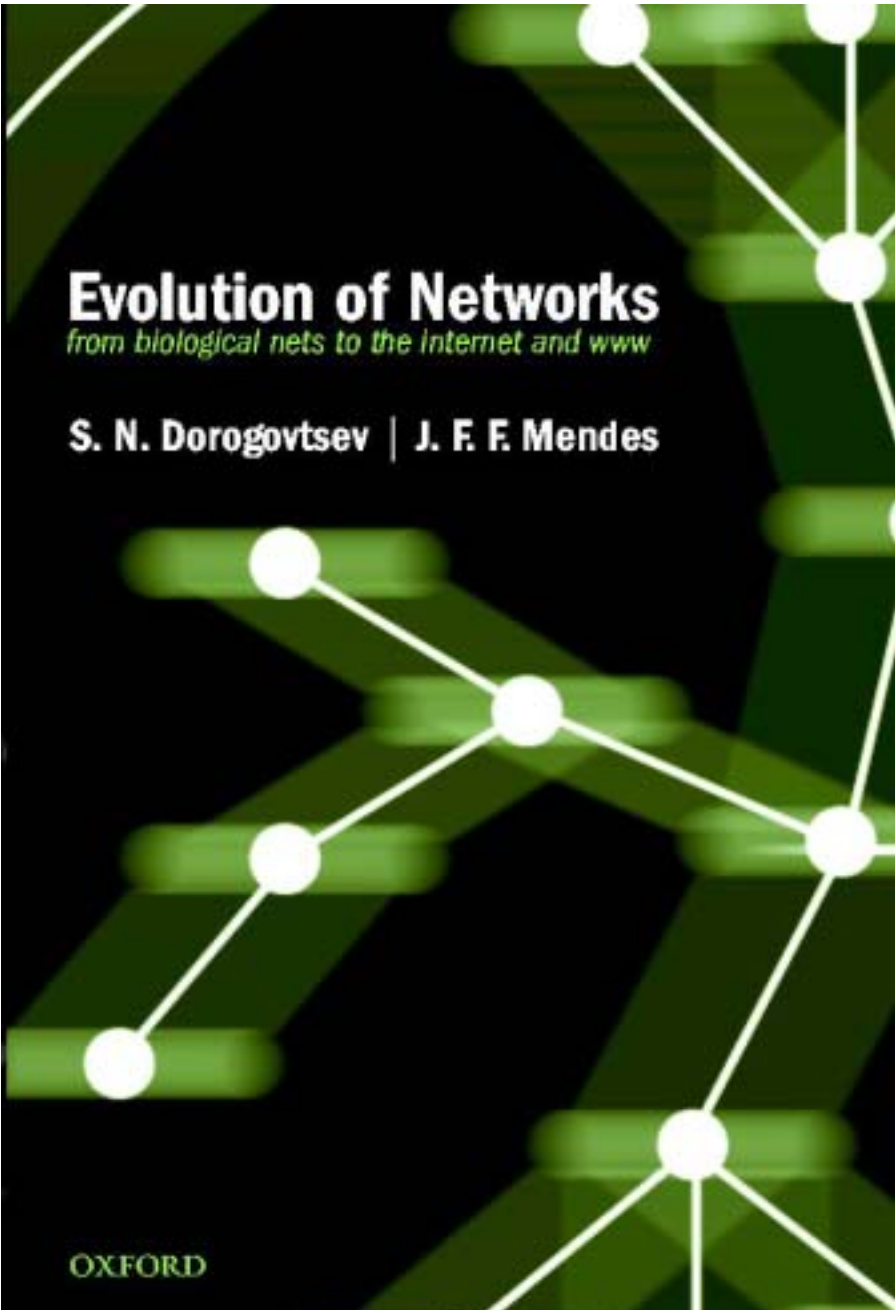
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Conclusions

- We derived exact equations that describe the spectra of random tree-like graph (correlated & uncorrelated)
- We proposed a simple approximation (effective medium approx.)
- We confirm that the spectra of *SF* & *CRG* do not follow the semi-circular law
- $\rho(\lambda) \propto |\lambda|^{-\delta}$ with $\delta = 2\gamma - 1$
- Large eigenvalues are produced by the highly connected nodes ($k = \lambda^2$)
- Dead end nodes play a special role, they produce localized eigenstates with $\lambda = 0$ and a dip around the central peak.
- EM approximation gives good results for: $k_0 \leq \lambda^2 \leq k_{cut}$
- Results for the Internet are in good agreement with theory for random like-tree, because although the $c = 0.2$, the local clustering coefficient decreases rapidly with the increasing of the degree of a node.



Evolution of Networks

from biological nets to the Internet and www

S. N. Dorogovtsev | J. F. F. Mendes

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