

Robustness of Complex Networks

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Network Architecture and Services (NAS)

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Outline

Introduction

Graph metrics

Spectrum

Network models

Attacks & failures

Framework for robustness



Birth of graph theory: the Königsberg bridge problem (Euler, 1736)

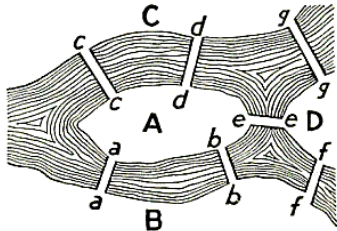
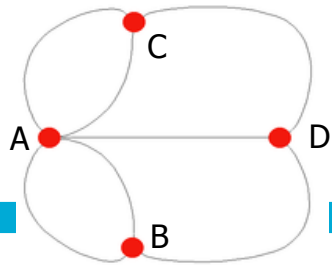


FIGURE 98. Geographic Map: The Königsberg Bridges.



Can one walk across the seven bridges and never traverse the same bridge twice?

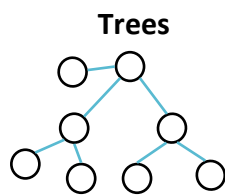
Leonhard Euler



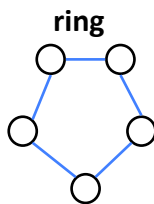
Eulerian walk: zero or two nodes with odd degree 

What is a network?

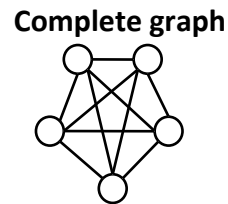
A graph $G(N, L)$ specifies how items, called nodes, are interconnected or related to other nodes by links.



$$L = N - 1$$

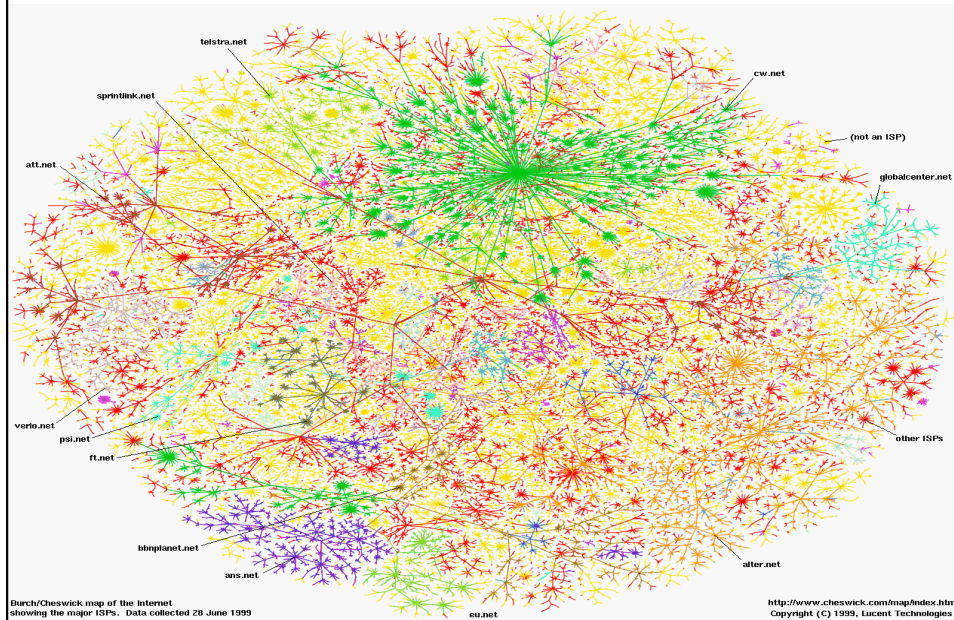


$$L = N$$



$$L = N(N-1)/2$$

Fractal Nature of the Internet



Our Brain network

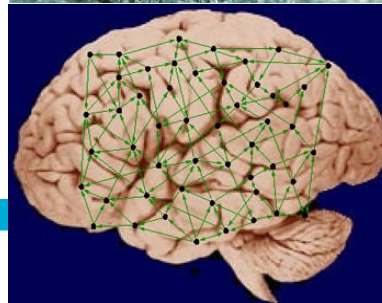
The average human cerebral cortex contains

$N = 10^{11}$ neurons

$L = 10^{14}$ connections

500,000 km of wiring

moon-earth: 384 405 km



Network Science

- Are there properties common to all complex networks?
- if so, why?
- Can we formulate a general theory of the structure (topology), evolution and dynamics of complex networks?
- How do complex networks give rise to “adaptive”, “living”, “intelligent” behavior?
- How can we learn from nature to design robust, efficient, self-adaptive “man-made” networks ?

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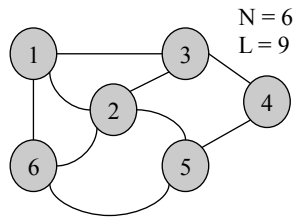
Attacks & failures

Framework for robustness



graph metric: degree

degree d_j of node j : number of neighbors of j



$$\begin{aligned} d_1 &= 3 \\ d_2 &= 4 \\ d_3 &= 3 \\ d_4 &= 2 \\ d_5 &= 3 \\ d_6 &= 3 \end{aligned}$$

$$d_1 + d_2 + d_3 + d_4 + d_5 + d_6 = 18$$

$$\sum_{j=1}^N d_j = 2L$$



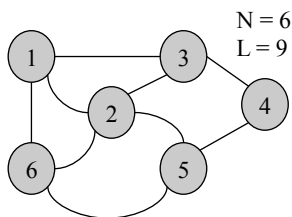
average degree in G equals

$$E[D] = \frac{1}{N} \sum_{j=1}^N d_j = \frac{2L}{N}$$

$$\text{bounds : } 2 - \frac{2}{N} \leq E[D] \leq N - 1$$



Adjacency matrix A



$$A_{N \times N} = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 1 & 0 \end{bmatrix}$$

For an undirected graph: $A = A^T$ is symmetric

Number of neighbors of node i is the degree: $d_i = \sum_{k=1}^N a_{ik}$



Ajacency matrix A

Degree vector d: $Au = d$ and $u = (1,1,\dots,1)$

Walk of length k from node i to j: succession of k links(arcs)
 $(n_0 \rightarrow n_1)(n_1 \rightarrow n_2)\dots(n_{k-1} \rightarrow n_k)$ where $n_0 = i$ and $n_k = j$

Path: a walk in which all nodes/vertices are different

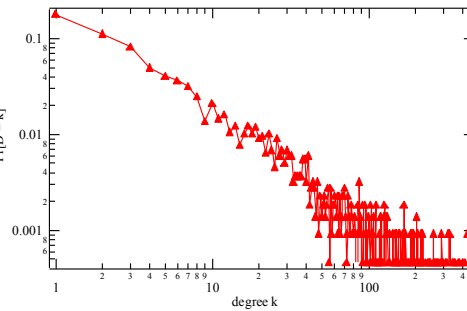
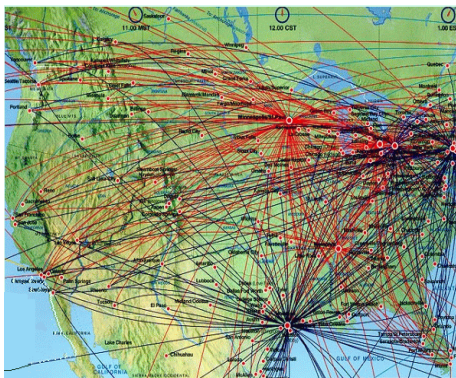
Number of k-hop walks between node i and j : $(A^k)_{ij}$

Open: Number of k-hop paths between node i and j
in terms of adjacency elements

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graph metric: degree

Airline transportation network



$$\Pr[D_{\text{Air}} = k] \sim k^{-1.21}$$

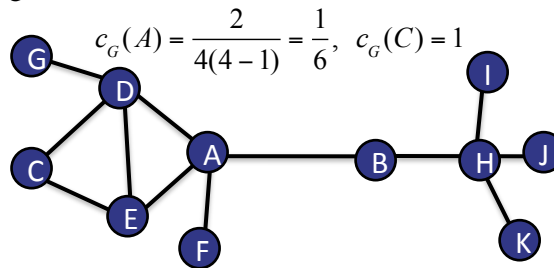
Internet: $\Pr[D_{\text{Internet}} = k] \sim k^{-\tau}$, $\tau \in (2.2, 2.5)$

Graph Metric: Clustering coefficient

The clustering coefficient of node v is $c_G(v) = \frac{2y}{d_v(d_v - 1)}$

where y is the number of links between neighbors.

If $d_v = 1$, $c_G(v) = 0$.

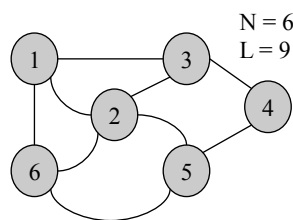


The clustering coefficient of a graph G : $c_G = \frac{1}{N} \sum_{v=1}^N c_G(v)$



Graph Metric: Hopcount

hopcount H : number of links in a shortest path in G



$$H_{14} = 2$$

diameter of G : hopcount of the longest shortest path in G

average hopcount $E[H]$ reflects “efficiency” of transport in G

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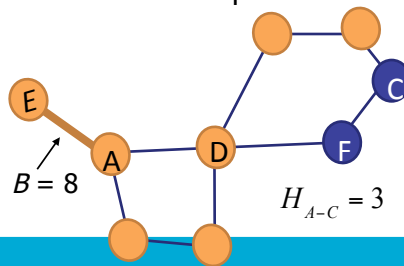


Graph Metric: Betweenness

The betweenness B_l of a link l is the number of shortest paths between all possible node pairs in G that traverse the link.

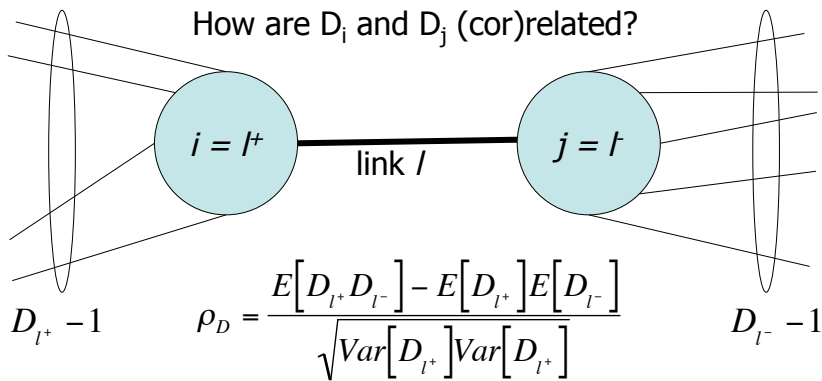
$$H_G = \sum_{i=1}^N \sum_{j=i+1}^N H_{i-j} = \sum_{l=1}^L B_l \quad \text{and} \quad E[B] = \frac{\binom{N}{2}}{L} E[H_N] \geq E[H_N]$$

H_{i-j} is the hopcount of the shortest path between i and j .



Assortativity

How are D_i and D_j (cor)related?



A network is (degree) *assortative* if $\rho_D > 0$

A network is (degree) *disassortative* if $\rho_D < 0$

(dis)assortativity

Reformulation of Newman's definition into algebraic graph theory

$$\rho_D = \frac{E[D_{l^+} D_{l^-}] - E[D_{l^+}] E[D_{l^-}]}{\sqrt{\text{Var}[D_{l^+}] \text{Var}[D_{l^-}]}} = \frac{N_1 N_3 - N_2^2}{N_1 \sum_{j=1}^N d_j^3 - N_2^2}$$

where $N_k = u^T A^k u$ is the total number of walks with k hops:

$$N_0 = \sum_{j=1}^N d_j^0 = N \quad N_1 = \sum_{j=1}^N d_j^1 = 2L \quad N_2 = \sum_{j=1}^N d_j^2 = d^T d$$

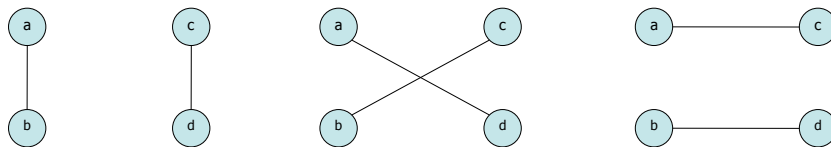
$$N_k \leq \sum_{j=1}^N d_j^k$$

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P. Van Mieghem, H. Wang, X. Ge, S. Tang and F. A. Kuipers, 2010, "Influence of Assortativity and Degree-preserving Rewiring on the Spectra of Networks", The European Physical Journal B, vol. 76, No. 4, pp. 643-652



Degree-preserving rewiring



$$\rho_D = 1 - \frac{\sum_{i \sim j} (d_i - d_j)^2}{\sum_{j=1}^N d_j^3 - \frac{1}{2L} \left(\sum_{j=1}^N d_j^2 \right)^2}$$

only two terms change

degree-preserving rewiring algorithm

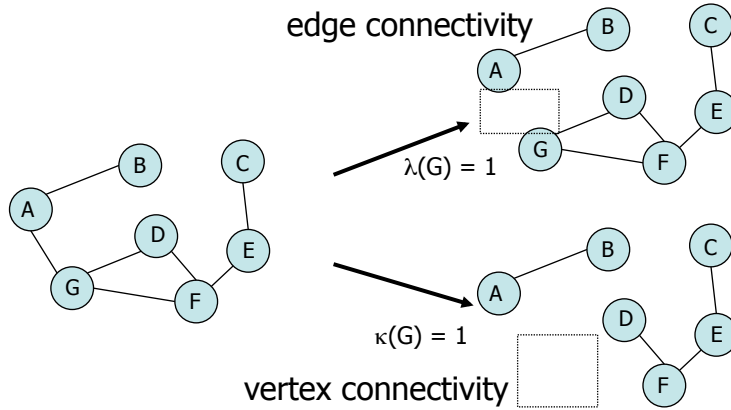
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How many graphs do there exist with given N and d ?

Open question (see B. McKay)

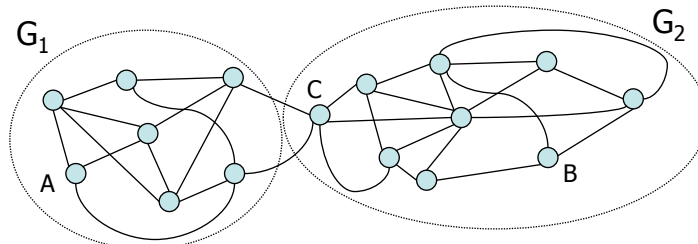


Connectivity of a Graph



$\lambda(G)$ (or $\kappa(G)$) : the minimum number of links (nodes) whose removal disconnects G

Menger's Theorem



$$\begin{aligned} d_a &= 4 \\ d_{\min}(G) &= 3 \\ \lambda(G) &= 2 \\ \kappa(G) &= 1 \end{aligned}$$

Important inequality: $\kappa(G) \leq \lambda(G) \leq d_{\min}(G) \leq \frac{2L}{N}$

Menger's Theorem:

The maximum number of link(node)-disjoint paths between A and B is equal to the minimum number of links(nodes) separating A and B.

There are at least $\lambda(G)$ link-disjoint and at least $\kappa(G)$ node-disjoint paths between any pair of nodes in G

List of topological metrics (undirected, unweighted graphs)

- hopcount
- closeness
- eccentricity
- diameter
- radius
- girth
- expansion
- distortion
- degree
- entropy
- joint degree
- assortativity
- modularity
- coreness
- clique number
- clustering coefficient
- rich club coefficient
- size giant component
- (node/link) connectivity
- coloring
- effective graph resistance
- *and many more*

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Eigenvalues and eigenvectors

$$Ax = \lambda x$$

$$A \begin{bmatrix} x_1 & x_2 & \cdots & x_N \end{bmatrix} = \begin{bmatrix} x_1 & x_2 & \cdots & x_N \end{bmatrix} \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_N \end{bmatrix}$$

$$AX = X\Lambda \longrightarrow A = X\Lambda X^{-1}$$

$$A = A^T = X\Lambda X^T = \sum_{k=1}^N \lambda_k x_k x_k^T$$

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Basic theorem for symmetric matrices

Any **real symmetric matrix** S can be written as $S = X \Lambda X^T$, where X is the orthogonal matrix with real eigenvectors in the columns and $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_N)$, where λ_j is the j -th real eigenvalue.

The real eigenvalues can be ordered as

$$\lambda_N \leq \lambda_{N-1} \leq \cdots \leq \lambda_2 \leq \lambda_1$$

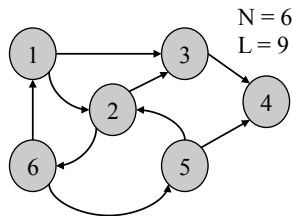
The eigenvalues are the zeros of the characteristic polynomial

$$\det(A - \lambda I) = 0$$

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Algebraic graph theory

Any graph G with N nodes and L links can be represented by an adjacency matrix A and an incidence matrix B , and a Laplacian Q



$N = 6$
 $L = 9$

$$A_{N \times N} = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 1 & 0 \end{bmatrix} = A^T$$

$$B_{N \times L} = \begin{bmatrix} 1 & 1 & -1 & \dots & 0 \\ -1 & 0 & 0 & & 0 \\ 0 & -1 & 0 & & 0 \\ 0 & 0 & 0 & & 0 \\ 0 & 0 & 0 & -1 & \\ 0 & 0 & 1 & & 1 \end{bmatrix}$$

$$Q = BB^T = \Delta - A$$

$$\Delta = \text{diag}(d_1 \quad d_2 \quad \dots \quad d_N)$$

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Basic properties of graph spectra

Spectrum of A : 1) all eigenvalues lie in the interval $(-d_{\max}, d_{\max}]$

$$2) \sum_{j=1}^N \lambda_j = 0 \quad \sum_{j=1}^N \lambda_j^2 = 2L \quad \sum_{j=1}^N \lambda_j^k = \text{Trace}(A^k) = \sum_{j=1}^N (A^k)_{jj}$$

3) Perron-Frobenius Theorem: λ_1 non-negative and components eigenvector are non-negative. (irreducible = connected: positive)

Spectrum of Q : 1) any eigenvalue μ_k is non-negative and the smallest $\mu_N = 0$

$$2) \text{ complexity (number of spanning trees) is } \xi(G) = \frac{1}{N} \prod_{k=1}^{N-1} \mu_k$$

3) the second smallest eigenvalue,

algebraic connectivity $a(G) = \mu_{N-1}$,
is related to how strongly a graph is connected

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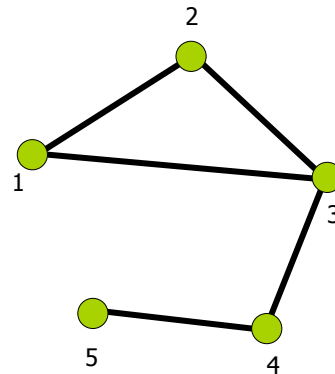
There exists a wealth of properties of graph spectra: see e.g.

P. Van Mieghem, *Graph Spectra of Complex Networks*, Cambridge University Press, 2011

Refreshing your knowledge (1/2)

- Adjacency matrix

$$A = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$



- λ_1 = spectral radius = largest eigenvalue of A

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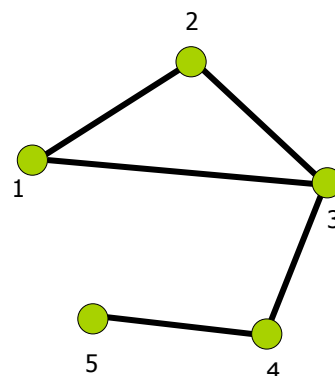
Refreshing your knowledge (2/2)

- Laplacian matrix

$$Q = \Delta - A$$

$$\Delta = \text{diag}(d_1 \ d_2 \ \dots \ d_N)$$

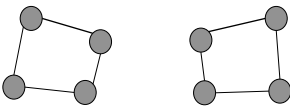
$$Q = \begin{pmatrix} 2 & -1 & -1 & 0 & 0 \\ -1 & 2 & -1 & 0 & 0 \\ -1 & -1 & 3 & -1 & 0 \\ 0 & 0 & -1 & 2 & -1 \\ 0 & 0 & 0 & -1 & 1 \end{pmatrix}$$

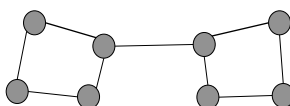


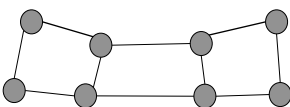
- $a(G)$ = algebraic connectivity = second smallest eigenvalue of Q

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Connectivity of graphs

G_1  $a(G_1) = 0$

G_2  $a(G_2) = 0.29$

G_3  $a(G_3) = 0.59$

Difficulty to disconnect



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Largest eigenvalue of a symmetric matrix

if $Ax = \lambda x$ then $A^k x = \lambda^k x$ for nonnegative integers k

Power method: $A^k w = \alpha_1 \lambda_1^k x_1 \left(1 + O\left(\left| \frac{\lambda_2}{\lambda_1} \right|^k \right) \right)$

Gerschgorin's theorem: $\lambda_1 \leq d_{\max}$

Rayleigh principle: $\lambda_1 \geq \frac{w^T A w}{w^T w}$ with equality only if $w = x_1$

There are many variations possible on the Rayleigh principle:

- 1) find suitable vector w
- 2) apply to powers of A recalling that $N_k = u^T A^k u$ is the total number of walks with k hops

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Bounds largest eigenvalue adjacency matrix

Classical bounds: $d_{\max} \geq \lambda_1(A) \geq \frac{2L}{N} = E[D]$

Walks based: $\lambda_1(A) \geq \left(\frac{N_{2k}}{N}\right)^{1/(2k)} \geq \left(\frac{N_k}{N}\right)^{1/k}$

$k = 2: \lambda_1(A) \geq \left(\frac{d^T d}{N}\right)^{1/2} = \frac{2L}{N} \sqrt{1 + \frac{\text{Var}[D]}{(E[D])^2}}$

$k = 3: \lambda_1(A) \geq \frac{N_3}{N} = \frac{1}{N} \left(\rho_D \left(\sum_{j=1}^N d_j^3 - \frac{N_2^2}{N_1} \right) + \frac{N_2^2}{N_1} \right)$

Optimized: $\lambda_1(A) \geq \frac{NN_3 - N_1N_2 + \sqrt{(NN_3)^2 - 6NN_1N_2N_3 + \text{others}}}{2(NN_2 - N_1^2)}$

P. Van Mieghem, Graph Spectra for Complex Networks, Cambridge University Press, 2011



Optimization

- Remove m nodes in G such that each removal decreases $\lambda_1(A)$ maximally.
- Remove l links in G such that each link removal decreases $\lambda_1(A)$ maximally.
 - What are the optimal strategies?
- Unfortunately, these problems are NP-complete...

The Interlacing Theorem

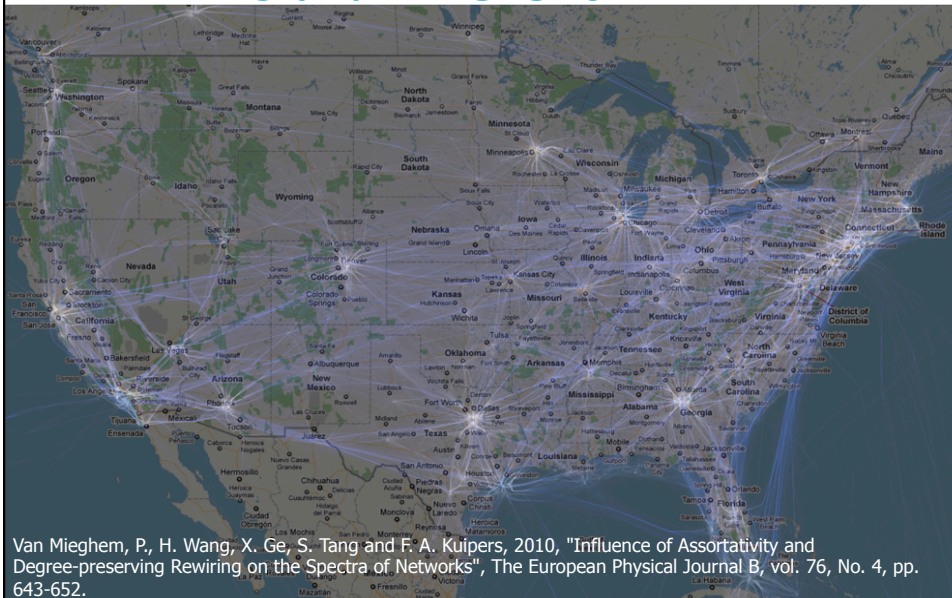
For a real symmetric $n \times n$ matrix A and any principal $m \times m$ submatrix B of A obtained by deleting $n-m$ same rows and columns in A , the eigenvalues of B interlace with those of A as

$$\lambda_{n-m+i}(A) \leq \lambda_i(B) \leq \lambda_i(A) \text{ for any } 1 \leq i \leq m$$

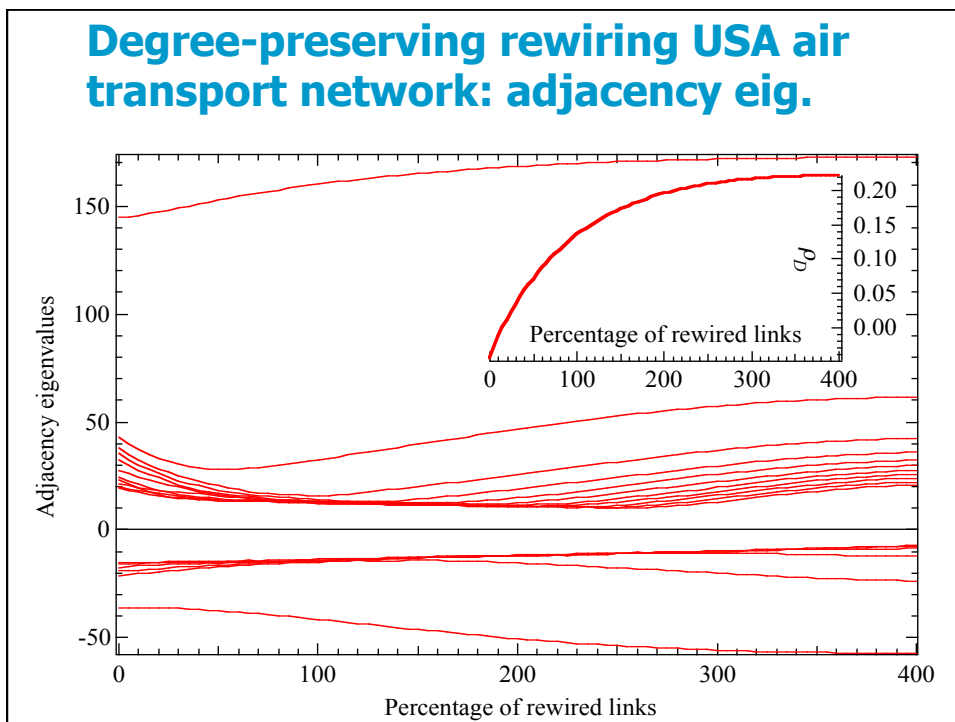
P. Van Mieghem, D. Stevanovic, F. A. Kuipers, C. Li, R. van de Bovenkamp, D. Liu and H. Wang, 2011, "Decreasing the spectral radius of a graph by link removals", Physical Review E, Vol. 84, No. 1, July, p. 016101



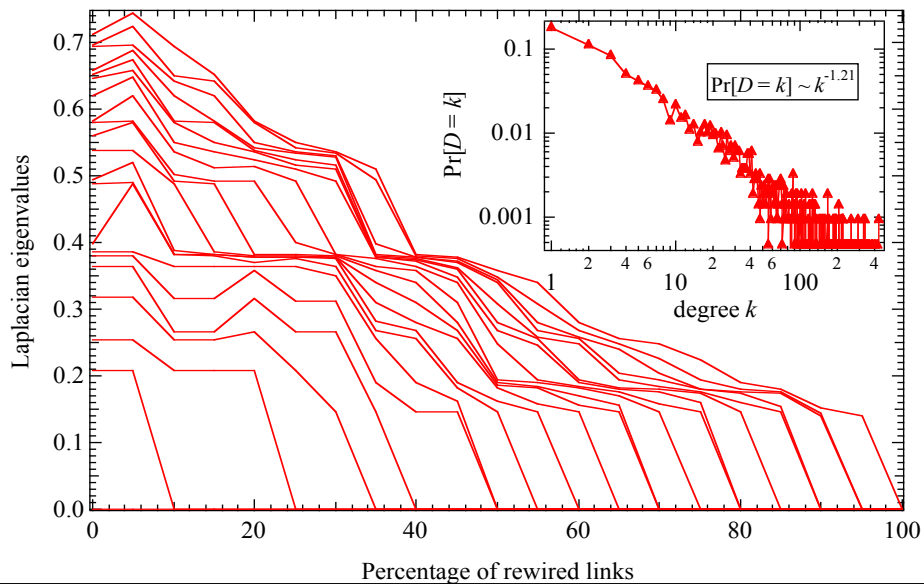
USA air transportation network $N = 2179$ and $L = 31326$



Degree-preserving rewiring USA air transport network: adjacency eig.



Degree-preserving rewiring USA air transport network: Laplacian eig.



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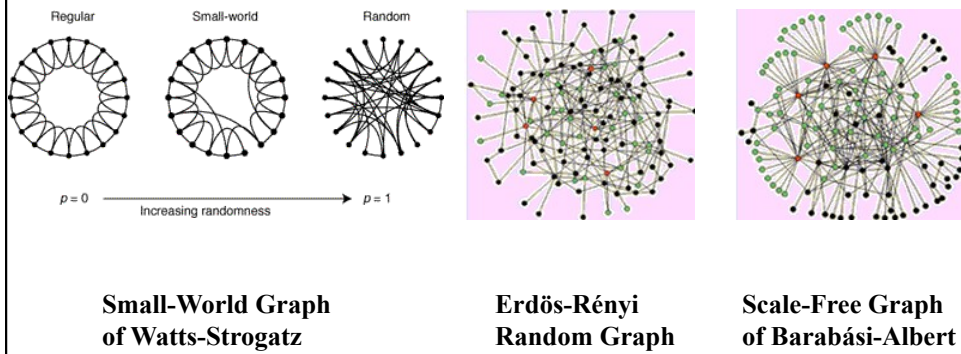
Network models

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Complex network models



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Network Model: Erdős-Rényi random graph

It is a class of graphs with N nodes and each node pair is connected independently with probability p .

$$E[L] = \frac{N(N-1)}{2} p$$

The average clustering coefficient follows

$$E[c_{G_p(N)}] = p$$



Network Model: Erdős-Rényi random graph

Degree distribution: Binomial distribution

$$\Pr[D_{rg} = k] = \binom{N-1}{k} p^k (1-p)^{N-1-k}$$

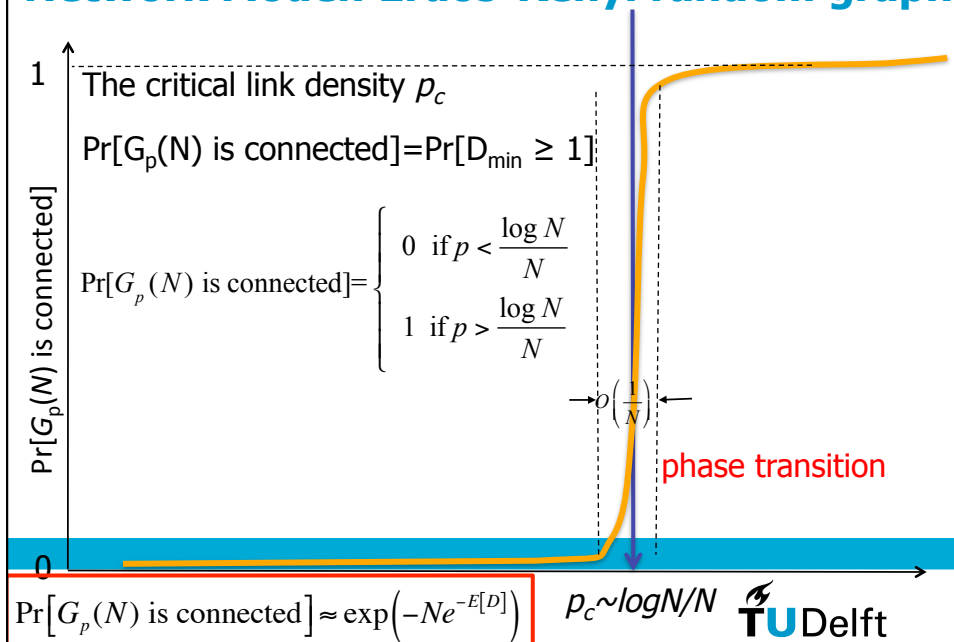
For large N and $p = \lambda/N$ approaches a Poisson distribution

$$\Pr[D_{rg} = k] \approx \frac{(pN)^k}{k!} e^{-Np}$$

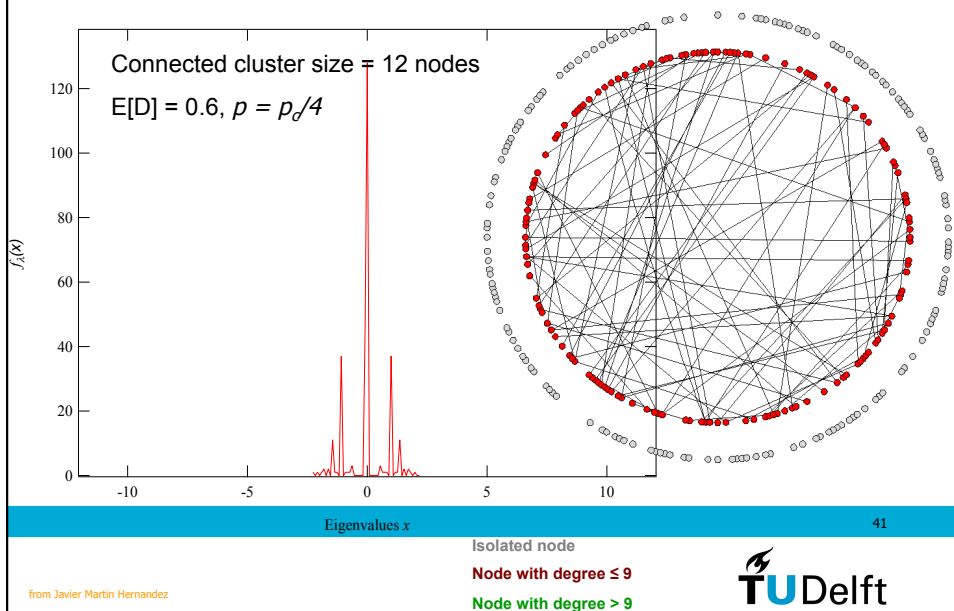
Simplest proof via pgf:

$$E[z^{D_{rg}}] = (1-p+pz)^{N-1} = \left(1 + \frac{\lambda(z-1)}{N}\right)^{N-1} \rightarrow e^{\lambda(z-1)}$$

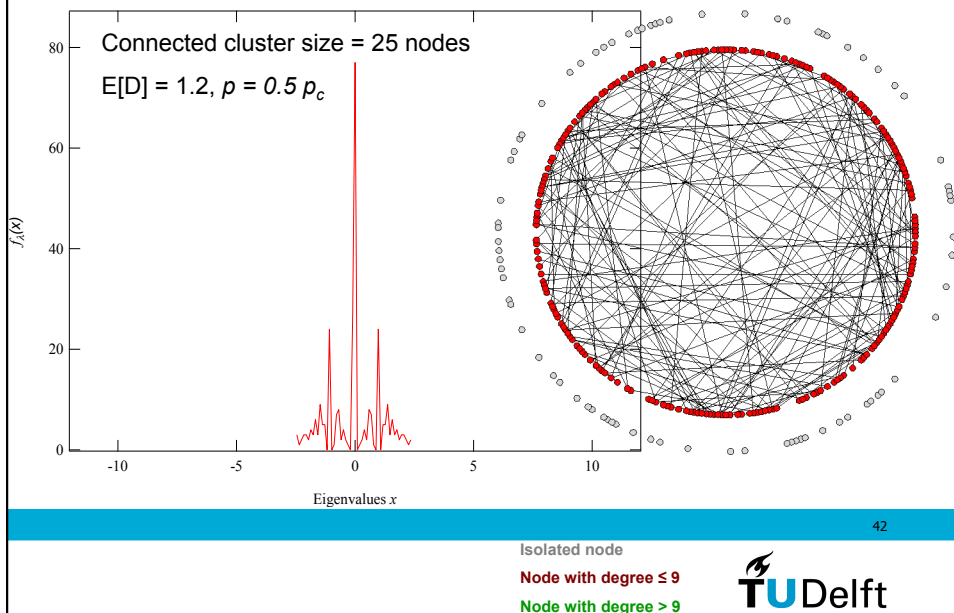
Network Model: Erdős-Rényi random graph



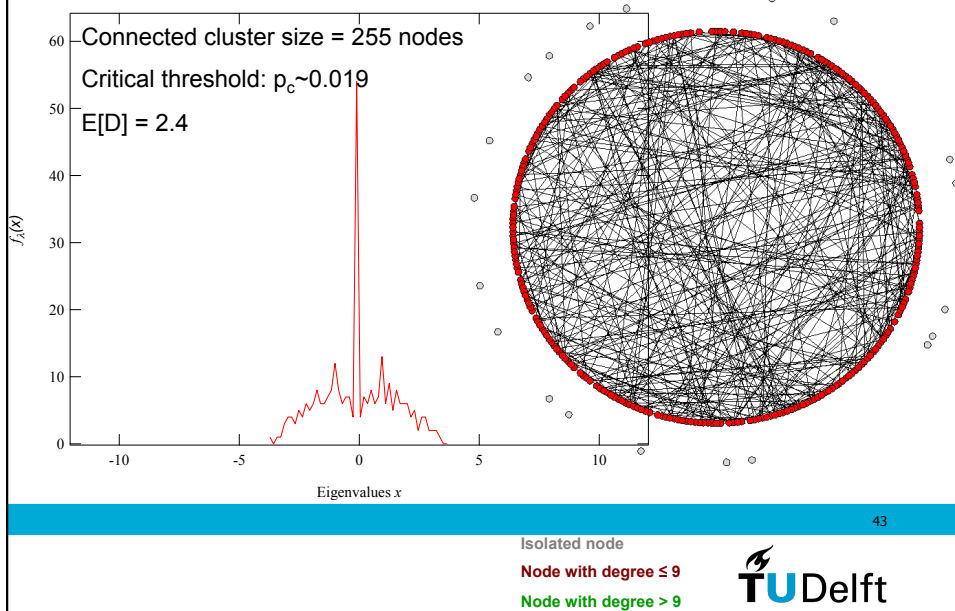
Random Graph $G_{0.002}(300)$



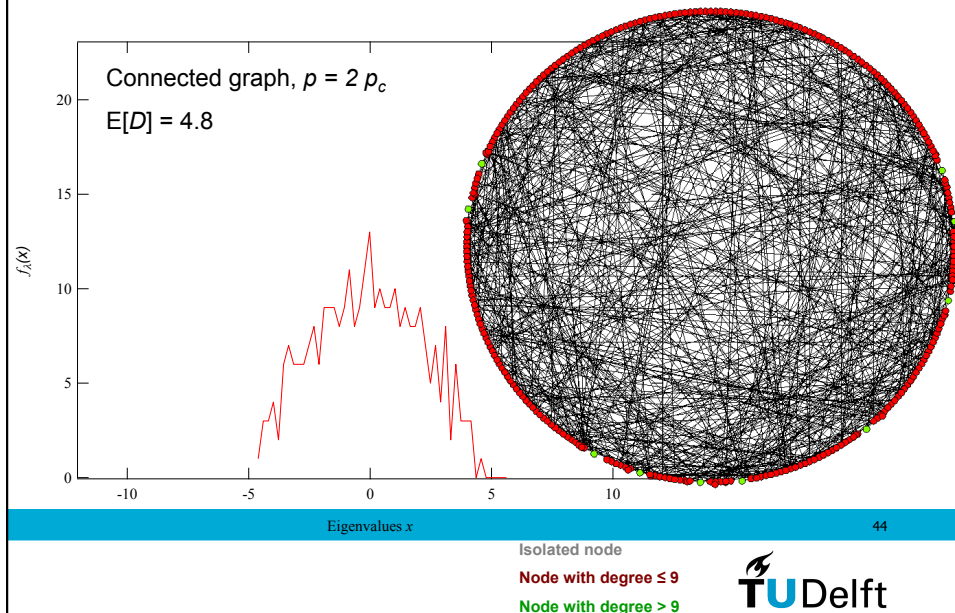
Random Graph $G_{0.004}(300)$



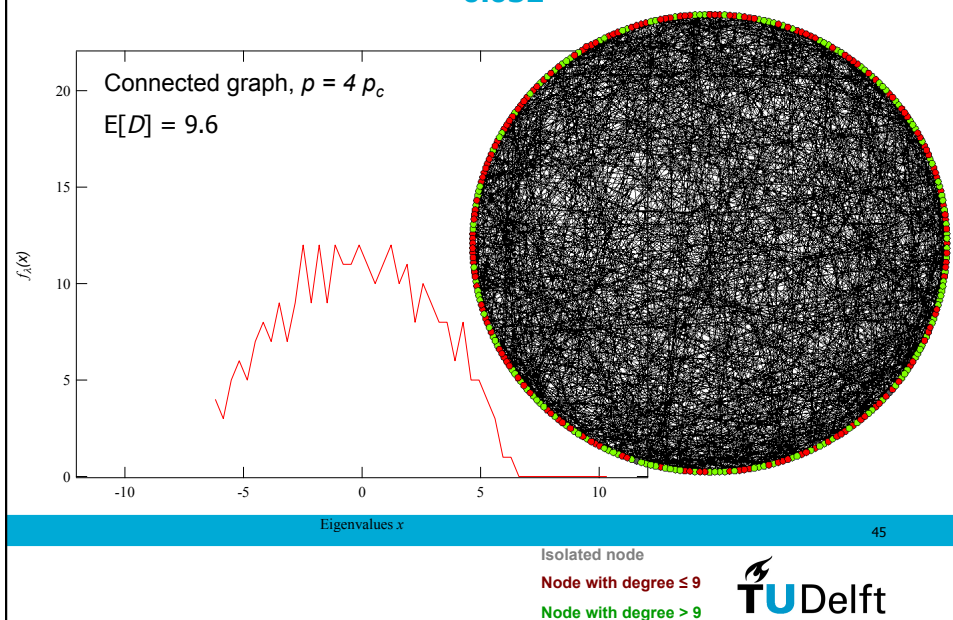
Random Graph $G_{0.008}(300)$



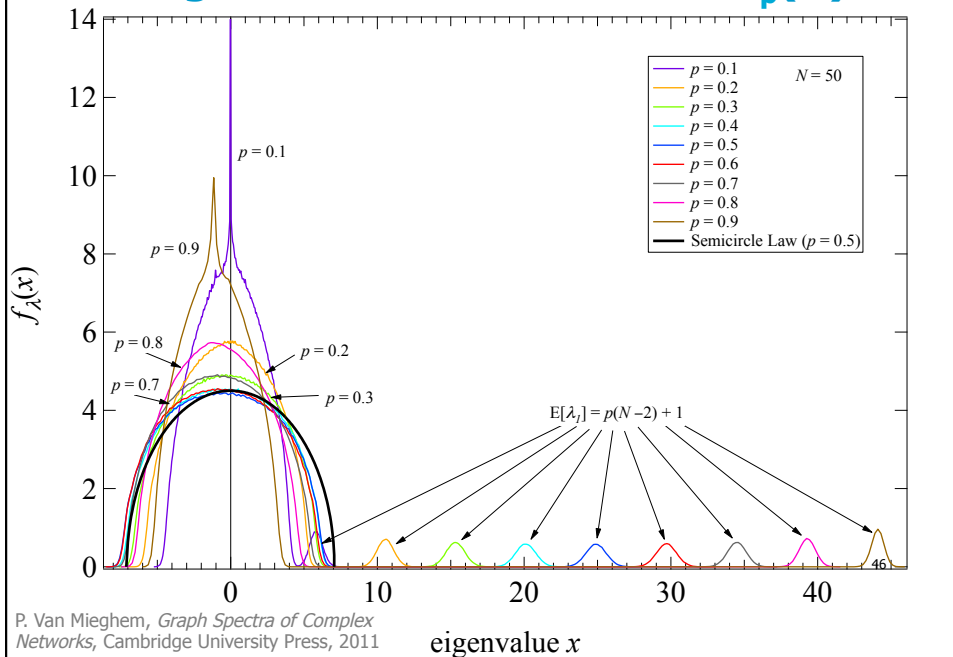
Random Graph $G_{0.016}(300)$



Random Graph $G_{0.032}(300)$



Wigner's semicircle law for $G_p(N)$



Network Model: Small-world graph

Collective dynamics of 'small-world' networks letters to nature

Duncan J. Watts* & Steven H. Strogatz

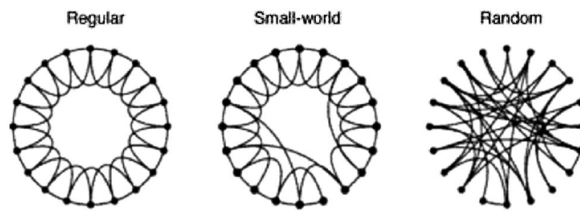
Department of Theoretical and Applied Mechanics, Kimball Hall,
Cornell University, Ithaca, New York 14853, USA

Table 1 Empirical examples of small-world networks

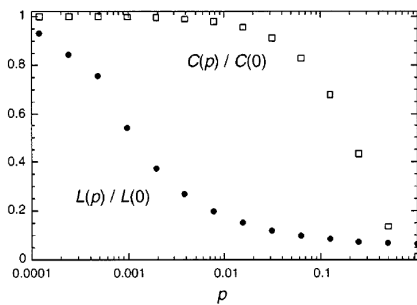
	L_{actual}	L_{random}	C_{actual}	C_{random}
Film actors	3.65	2.99	0.79	0.00027
Power grid	18.7	12.4	0.080	0.005
<i>C. elegans</i>	2.65	2.25	0.28	0.05

TU Delft

Network Model: Small-world graph

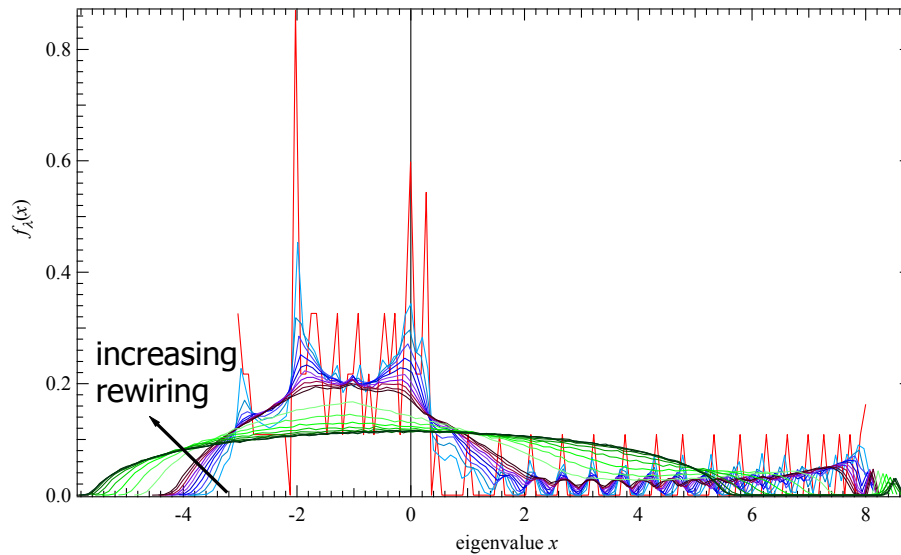


$p = 0$ ———> $p = 1$
Increasing randomness



TU Delft

Spectrum small world graph

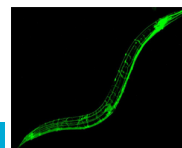
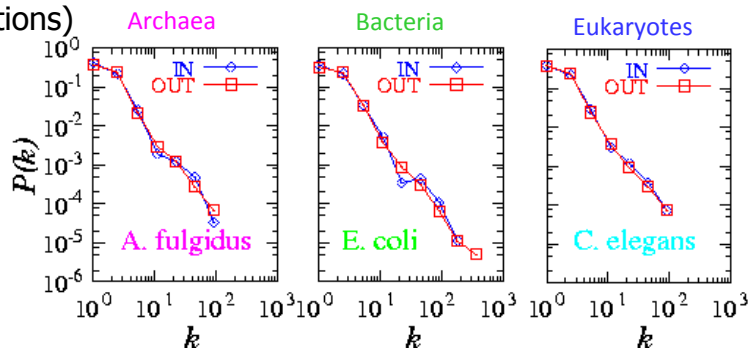


P. Van Mieghem, *Graph Spectra of Complex Networks*, Cambridge University Press, 2011



Network Model: BA power law graph

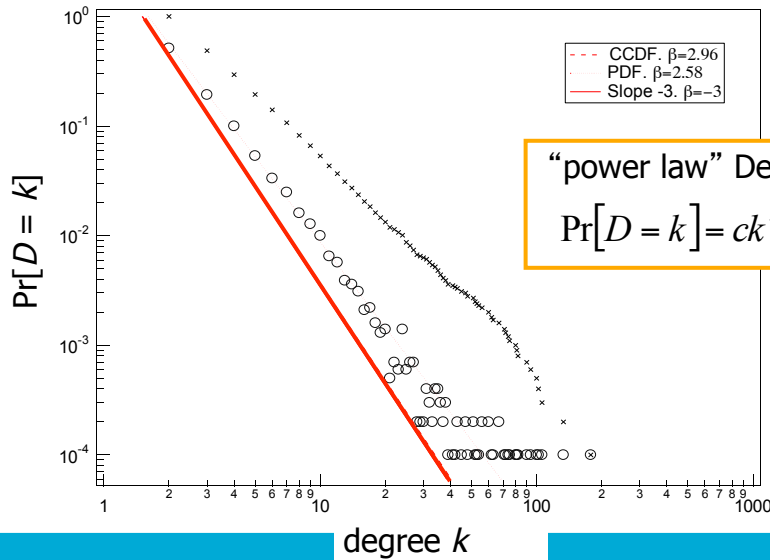
Metabolic network: nodes(chemicals) and links(bio-chemical reactions)



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



“Power laws” in complex networks



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Power law graphs

Measurements of the degree of nodes in (subgraphs of) the Internet topology indicate that

$$\Pr[D = k] \approx ck^{-\tau}$$

A power law degree distribution is also called scale-free:

$$\Pr[D = ak] = ca^{-\tau}k^{-\tau} = a^{-\tau} \Pr[D = k]$$

Any number a just multiplies the probability density; there is no characteristic length

Moreover, $E[D] = \frac{\zeta(\tau-1)}{\zeta(\tau)}$ provided $\tau > 2$, where $\zeta(\tau) = \frac{1}{\tau-1} + \gamma + O(\tau-1)$

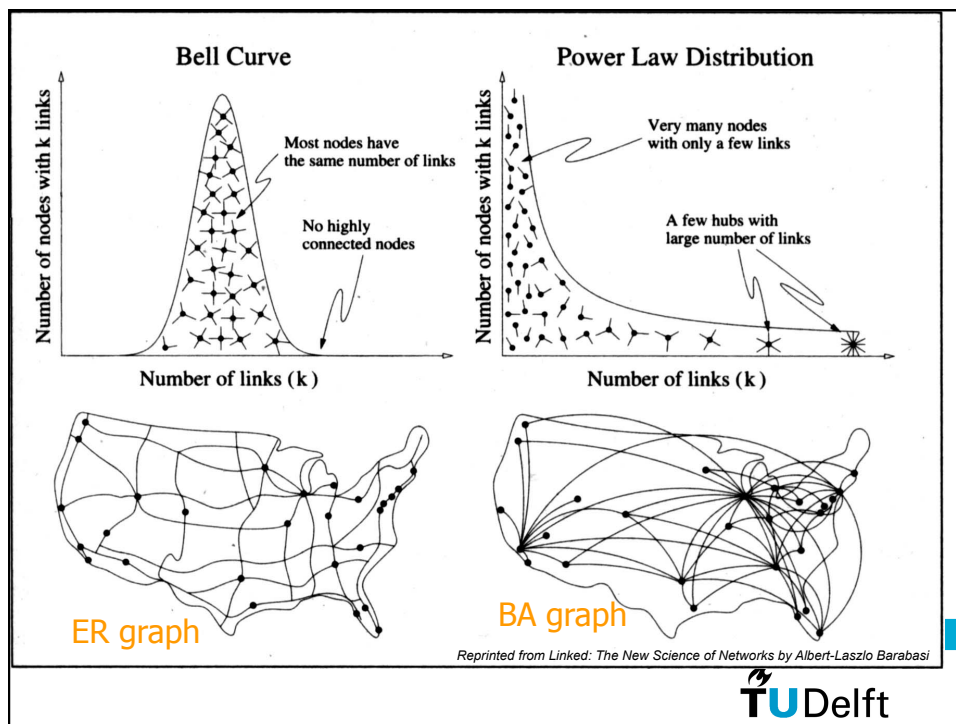
$$E[D^k] = \frac{\zeta(\tau-k)}{\zeta(\tau)} \text{ provided } \tau > k+1$$

The simplest family of “power law” graphs have been proposed by Barabasi-Albert:

- 1) start with n nodes
- 2) attach a new node with m links to a node proportionally to its degree
- 3) repeat 2) until size N is reached

This construction of “preferential attachment”, “rich get richer”, is observed in many large complex networks (webgraph, proteins, social relations, etc...)

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Mystery of “power laws”

Power law of a “property” appear if the “system” grows **exponentially**:

- if X grows exponentially with Y and Y has an exponential distribution, then X will have a power-law distribution (*Proof PA, p. 324*)

The exponential function $f(t)$ has a linear differential equation

$$\frac{df(t)}{dt} = af(t)$$

which essentially means "growing proportional to its size"

At phase transitions, quantities of interest also change in a “power law” fashion

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Observed common properties

- *small-world property*
 - average length of a path is short compared to the size N of the network ($E[H] = O(\log N)$)
- *scale-free degree distribution*
 - heavy tails (non-Gaussian behavior)
- *clustering and community structure*
 - network of networks
- *robustness to random node failure*
- *vulnerability to targeted hub attacks and cascading failures*

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Outline

Introduction

Graph metrics

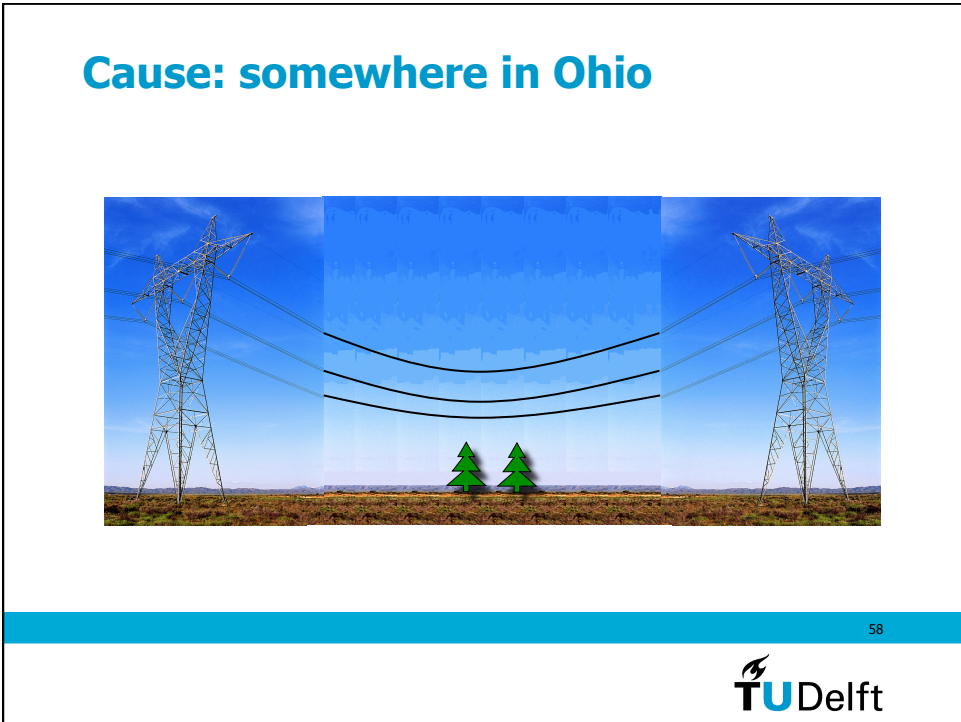
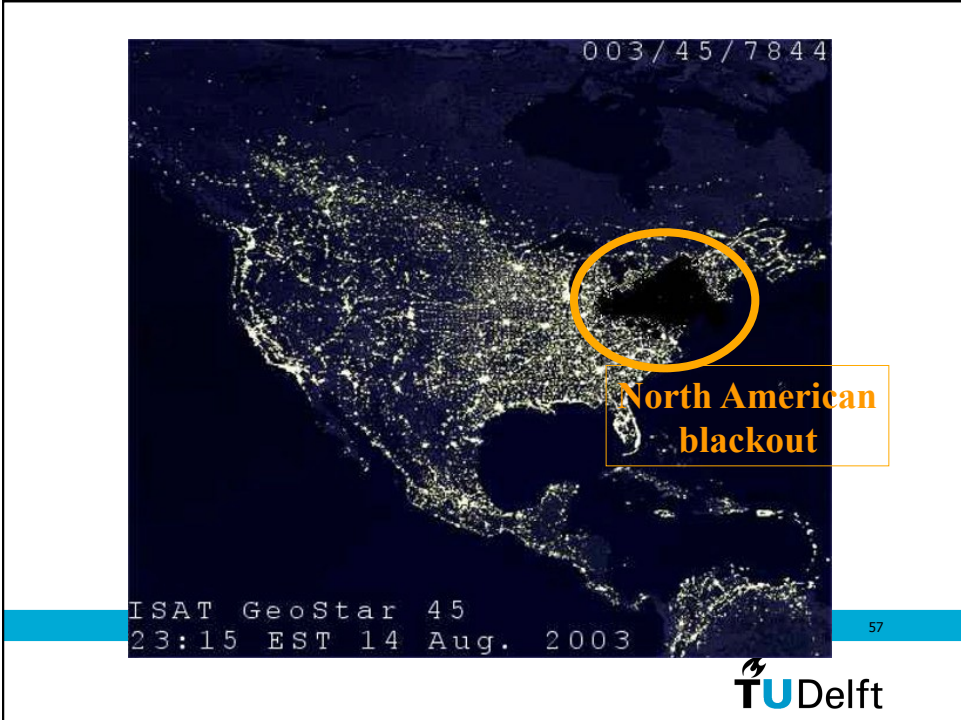
Spectrum

Network models

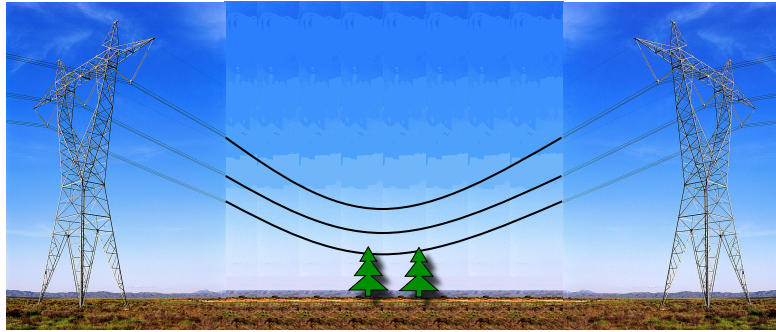
Attacks & failures

Framework for robustness



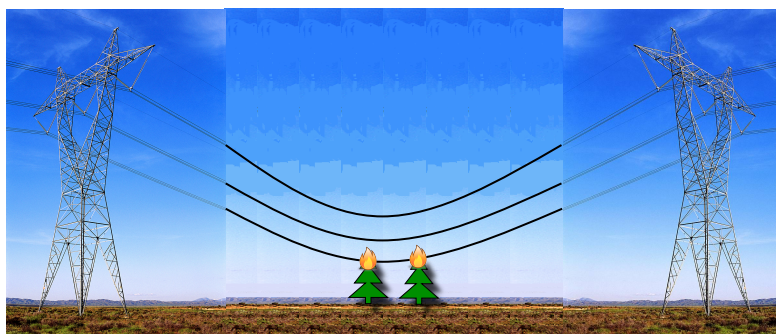


Cause: somewhere in Ohio



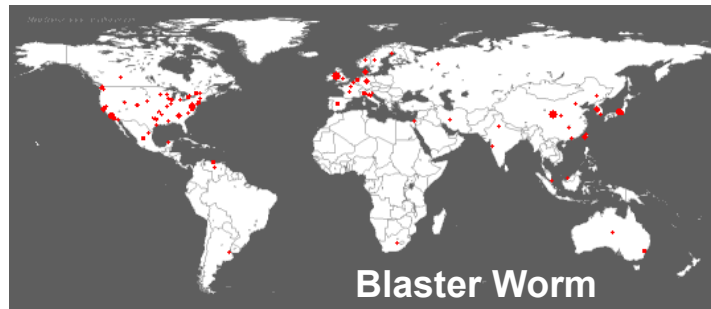
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Cause: somewhere in Ohio



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A few days earlier...



- “Alarm systems failed due to infection with Blaster Worm”

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Introduction (1/2)

- Society is critically depending on complex networks
 - Internet
 - Transportation networks
 - Energy networks
 - Communication networks
- Severe consequences if networks are disrupted
- Robustness is defined as the extent to which the complex network is able to cope with perturbations imposed on it

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Introduction (2/2)

- Examples of perturbations
 - Failures
 - Broken fibre cables
 - Malfunctioning switches
 - ...
 - Attacks
 - Denial-of-Service
 - Physical attack on Internet Exchange
 - ...
- Aim of this lecture: discuss examples of how graph-theoretic metrics can be used to quantify robustness

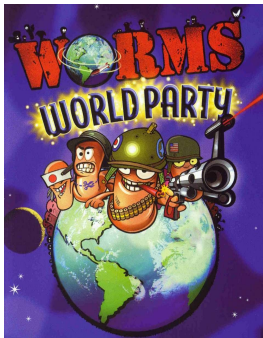
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Motivation for virus spread in networks

- Computer viruses
 - security threat to Internet
 - annoyance
 - very costly
 - Code Red worm: several billion \$\$ in damage
- Why do we care?
 - Understanding the spread of a virus is the first step in preventing it
 - How fast do we need to disinfect nodes so that the virus dies quickly? Which nodes?

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Applications of virus spread models



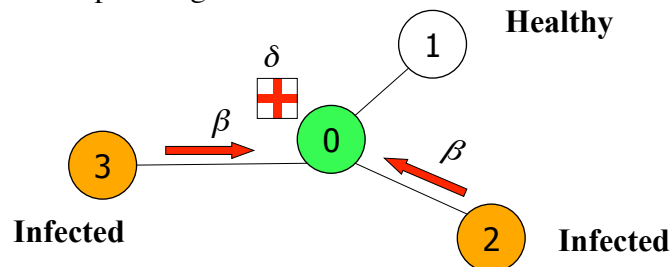
- Computer virus and worms modelling
- Epidemic algorithms
- Error propagation in networks
- Any self-replicating object on a dynamic network
- Emotions as infectious diseases in social networks

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Simple SIS model (1)

- Homogeneous birth (infection) rate β on all edges between infected and susceptible nodes
- Homogeneous death (curing) rate δ for infected nodes

$\tau = \beta / \delta$: effective spreading rate



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Simple SIS model (2)

- Each node j can be in either of the two states:

- “0”: healthy
- “1”: infected

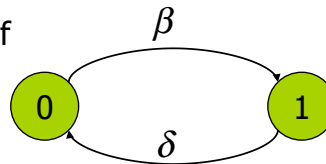
- Markov continuous time:

- infection rate β
- curing rate δ

- Mathematically:

- X_j is the state of node j

- infinitesimal generator $Q_j(t) = \begin{bmatrix} -q_{1j} & q_{1j} \\ q_{2j} & -q_{2j} \end{bmatrix} = \begin{bmatrix} -q_{1j} & q_{1j} \\ \delta & -\delta \end{bmatrix}$

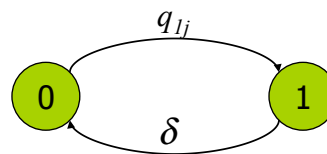


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Simple SIS model (3)

- Nodes are interconnected in graph:

$$Q_j(t) = \begin{bmatrix} -q_{1j} & q_{1j} \\ \delta & -\delta \end{bmatrix}$$



where the infection rate is due all infected neighbors of node j :

$$q_{1j}(t) = \beta \sum_{k=1}^N a_{jk} 1_{\{X_k(t)=1\}}$$

and where the adjacency matrix of the graph is

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1N} \\ a_{21} & a_{22} & \dots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \dots & a_{NN} \end{bmatrix}$$

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Simple SIS model (4)

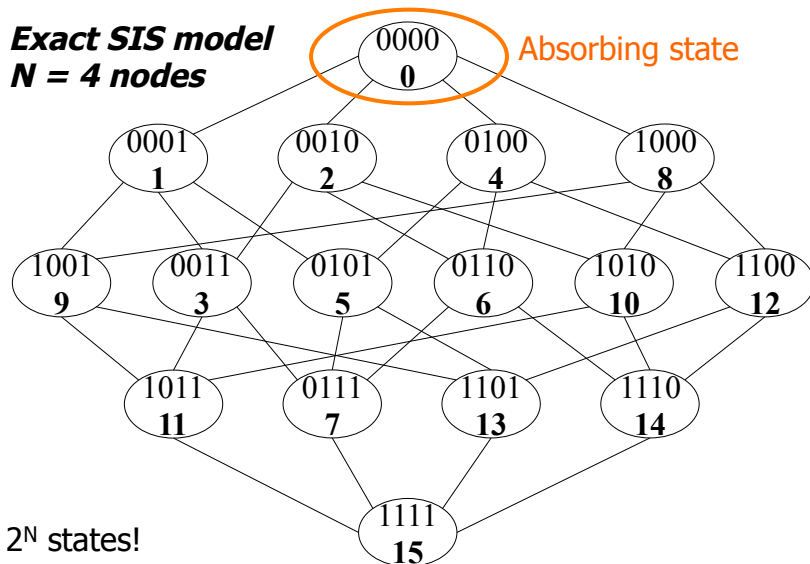
- Markov theory requires that the infinitesimal generator is a matrix whose elements are NOT random variables
- However, this is not the case in our simple model:

$$q_{1j}(t) = \beta \sum_{k=1}^N a_{jk} 1_{\{X_k(t)=1\}}$$

- By conditioning to each possible combination of infected states, we finally arrive to the exact Markov continuous SIS model
- *Drawback:* this exact model has 2^N states, where N is the number of nodes in the network.

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Exact SIS model
 $N = 4$ nodes



Simple SIS model (5): mean field

- The infinitesimal generator

$$Q_j(t) = \begin{bmatrix} -q_{1j} & q_{1j} \\ \delta & -\delta \end{bmatrix}$$

$$q_{1j}(t) = \beta \sum_{k=1}^N a_{jk} 1_{\{X_k(t)=1\}}$$

is replaced by its mean (**the only approximation!**)

$$Q_j = \begin{bmatrix} -E[q_{1j}] & E[q_{1j}] \\ \delta & -\delta \end{bmatrix}$$

$$E[q_{1j}(t)] = \beta \sum_{k=1}^N a_{jk} \Pr[\{X_k(t)=1\}]$$

- Being able now to apply ordinary Markov theory, we arrive at our **N-intertwined model for virus spread**

$$\begin{cases} \frac{dv_1}{dt} = (1-v_1)\beta \sum_{k=1}^N a_{1k}v_k - \delta v_1 \\ \frac{dv_2}{dt} = (1-v_2)\beta \sum_{k=1}^N a_{2k}v_k - \delta v_2 \\ \vdots \\ \frac{dv_N}{dt} = (1-v_N)\beta \sum_{k=1}^N a_{Nk}v_k - \delta v_N \end{cases}$$

where $v_k(t) = \Pr[X_k(t)=1]$

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N-intertwined virus spread model

- Non-linear matrix equation:

$$\frac{dV(t)}{dt} = \beta A \cdot V(t) - \text{diag}(v_i(t))(\beta A \cdot V(t) + \delta u)$$

where the vector $u^T = [1 \ 1 \ \dots \ 1]$ and $V^T = [v_1 \ v_2 \ \dots \ v_N]$

- Results:**

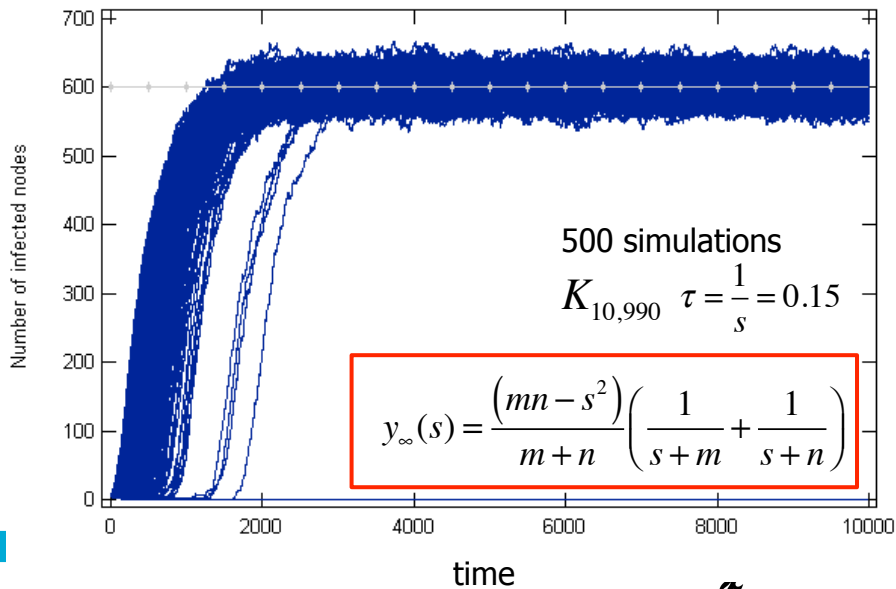
- Probability of infection v_k for each node k separately
- Number of infected nodes in the steady state
- Phase transition phenomena for any network (largest eigenvalue of the adjacency matrix A)
- Analytic computations feasible:
 - expansions of v_k as a function of the effective infection rate around the epidemic threshold and around infinity

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P. Van Mieghem, J. Omic, R. E. Kooij, "Virus Spread in Networks", IEEE/ACM Transaction on Networking, Vol. 17, No. 1, pp. 1-14, (2009).



Simulations



Kephart-White model

Assume perfect homogeneity & symmetry: a graph of degree r

$$\begin{cases} \frac{dv_1}{dt} = (1 - v_1)\beta \sum_{k=1}^N a_{1k}v_k - \delta v_1 \\ \frac{dv_2}{dt} = (1 - v_2)\beta \sum_{k=1}^N a_{2k}v_k - \delta v_2 \\ \vdots \\ \frac{dv_N}{dt} = (1 - v_N)\beta \sum_{k=1}^N a_{Nk}v_k - \delta v_N \end{cases}$$



$$\frac{dv}{dt} = (1 - v)\beta r v - \delta v$$

steady-state

$$v = 1 - \frac{1}{r\tau} \quad \text{where} \quad \tau = \frac{\beta}{\delta}$$

threshold

$$\tau \geq \tau_c = \frac{1}{r} \quad \text{then} \quad v \geq 0$$

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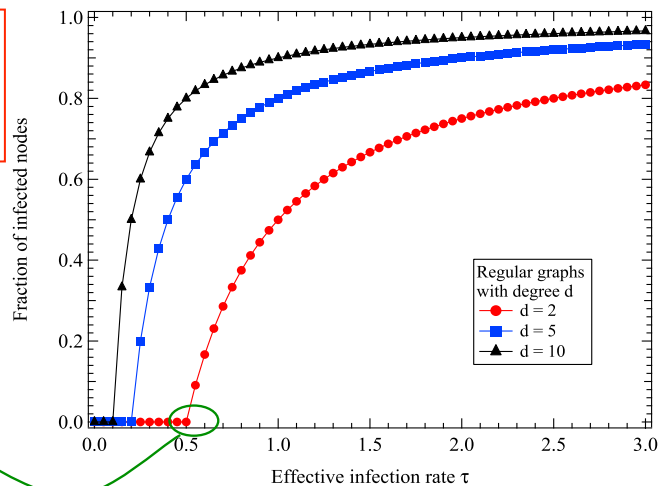
J. O. Kephart and S. R. White, "Directed-graph epidemiological models of computer viruses," *Proc. IEEE Comput. Soc. Symp. Research in Security and Privacy*, May 1991, pp. 343–359.

What is so interesting about epidemics?

β : infection rate per link
 δ : curing rate per node
 $\tau = \beta / \delta$: effective spreading rate

- Final epidemic state
- Rate of propagation
- Epidemic threshold

$$\tau_c = \frac{1}{\lambda_1(A)}$$



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$$E[D] = \frac{2L}{N} \leq \lambda_1(A) \leq d_{\max}$$

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Affecting the epidemic threshold

- Degree-preserving rewiring
 - Changing the assortativity of the graph
 - Van Mieghem, P., H. Wang, X. Ge, S. Tang and F. A. Kuipers, 2010, "[Influence of Assortativity and Degree-preserving Rewiring on the Spectra of Networks](#)", The European Physical Journal B, vol. 76, No. 4, pp. 643-652.
- Removing links/nodes (optimal way is NP-complete)
 - Van Mieghem, P., D. Stevanovic, F. A. Kuipers, C. Li, R. van de Bovenkamp, D. Liu and H. Wang, 2011, "[Decreasing the spectral radius of a graph by link removals](#)", Physical Review E, Vol. 84, No. 1, July, p. 016101.
- Quarantining: Removing inter-module links
 - Omic, J., J. Martin Hernandez and P. Van Mieghem, 2010, "[Network protection against worms and cascading failures using modularity partitioning](#)", 22nd International Teletraffic Congress (ITC 22), September 7-9, Amsterdam, Netherlands.

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E.R. van Dam, R.E. Kooij, The minimal spectral radius of graphs with a given diameter, *Linear Algebra and its Applications*, 423, 2007, pp. 408-419.

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Outline



Introduction

Graph metrics

Spectrum

Network models

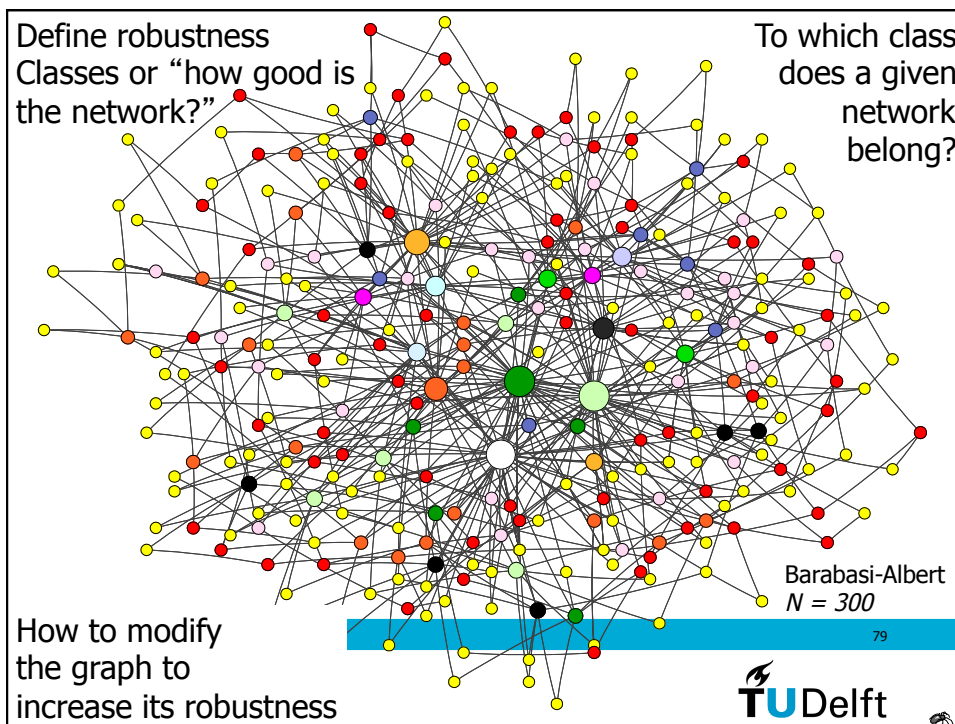
Attacks & failures

Framework for robustness



ResumeNet

**A framework for network robustness:
the R-model**

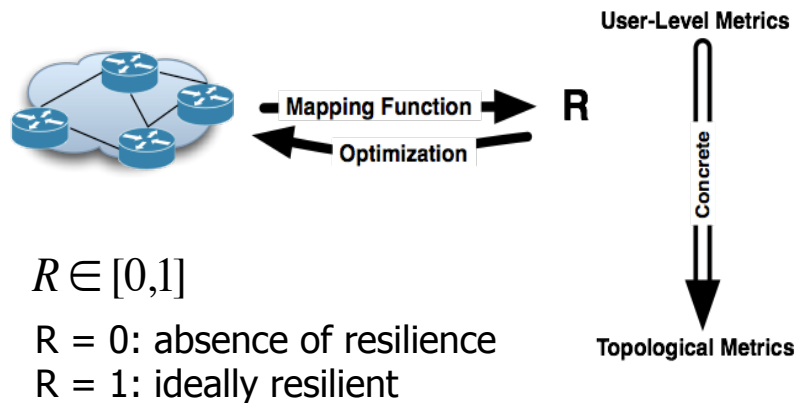


Network: topology + service(s)

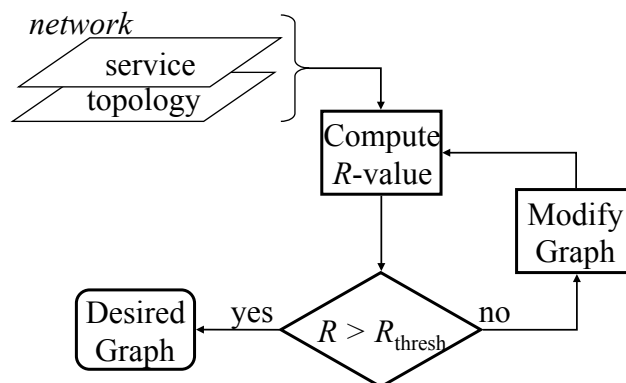
- Topology (or network infrastructure):
 - graph G with N nodes and L links
 - link weights
 - “hardware”
- Service:
 - more abstract and less clearly defined
 - uses the network infrastructure to transport items (e.g. email service, telephony, video, cars on roads, neurons in brain, etc.)
 - “software”
- Topology and service
 - own specifications
 - service is often designed independently of the topology
 - often more than 1 service on a same topology

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High-Level Goal: Express Network Resilience in a Number R



Simple framework



Goals:

1. define “ R -value” that characterizes the level of robustness in *any* network
2. compute the R -value
3. robustness classes (understanding): which R is desirable and what is R_{thresh}

R-model

$$R = \sum_{k=1}^m s_k t_k = s \cdot t \quad (0 \leq R \leq 1)$$

- s : the service vector with m components (interpreted as weights)
 t : the topology vector where each component is a metric
(e.g. average degree, clustering coefficient, algebraic connectivity, minimum degree, diameter/hopcount, betweenness, etc...)
- Normalization: $R = 0$ (absence of network robustness)
 $R = 1$ (perfect robustness)
 - **Linear**:
 - simplest m -dim expression & geometric interpretation (vector)
 - expectation $E[R]$ easy
 - no constraints on component values (else linear programming model)

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P. Van Mieghem, C. Doerr, H. Wang, J. Martin Hernandez, D. Hutchison, M. Karaliopoulos and R. E. Kooij, 2010, "[A Framework for Computing Topological Network Robustness](#)", Delft University of Technology, report20101218.



Issues with R-model

- dimension m : trade-off between accuracy and computational complexity (*not problematic, consensus*)
- orthogonality of the metrics (*fundamental problem*)
 - each metric should ideally be a basis vector in m -dim space
 - almost all topology metrics are dependent
 - degree of dependence depends on the graph
 - *Solution*: no metrics, but matrices (adjacency A , incidence B , Laplacian Q) or spectra (graph theory)?
- **Normalization** of graphs: how to compare graphs with different number of nodes and links?
- unclear how to map a service onto a service vector (recall s_k is projection of s on k -th metric)

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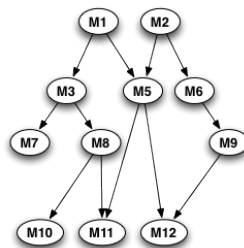
Which metrics to choose?

- Which metrics to choose is still an open question
 - Decomposition problem
 - Dependency problem
 - Normalization problem

User-Level Metrics



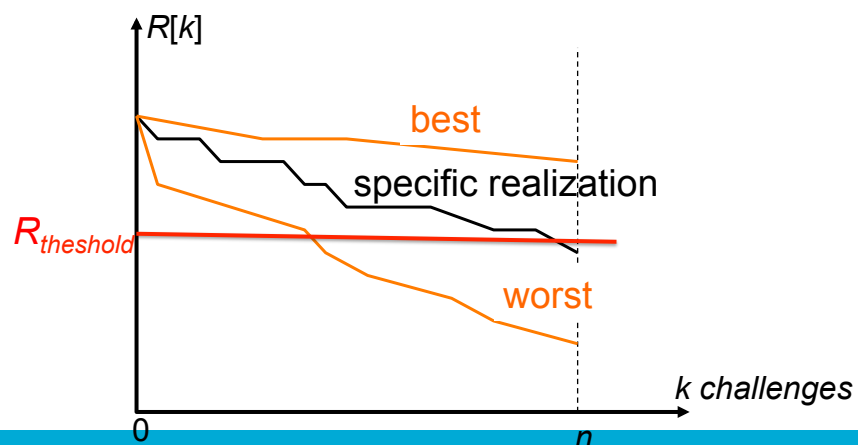
Topological Metrics



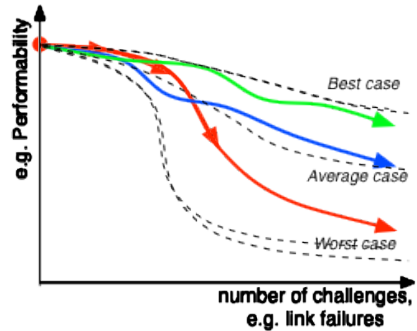
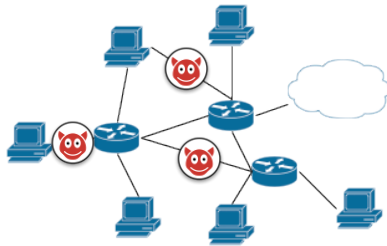
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R as a function of “challenges”

- resilience is related to the network’s capability to withstand perturbations from the outside during a given time interval

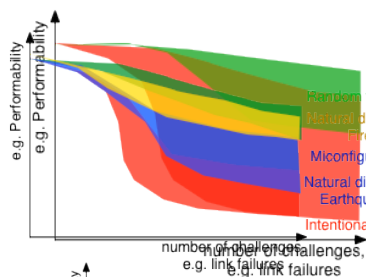


Understanding the Series of Events: Metric Envelopes

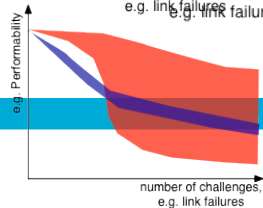


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Understanding the Series of Events: Comparing Metric Envelopes

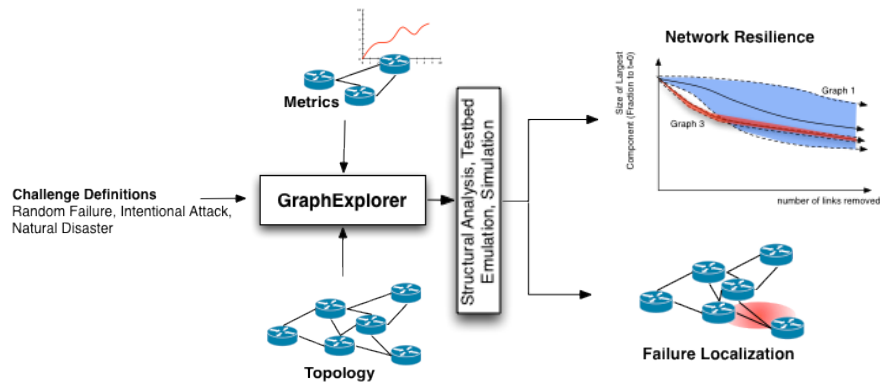


- Comparing resilience based on metric envelopes give a visual explanation of the network degradation process
- Depending on the application domain a more bounded envelope might be preferable
- The effect of various failure sources on the evaluated metric can be revealed



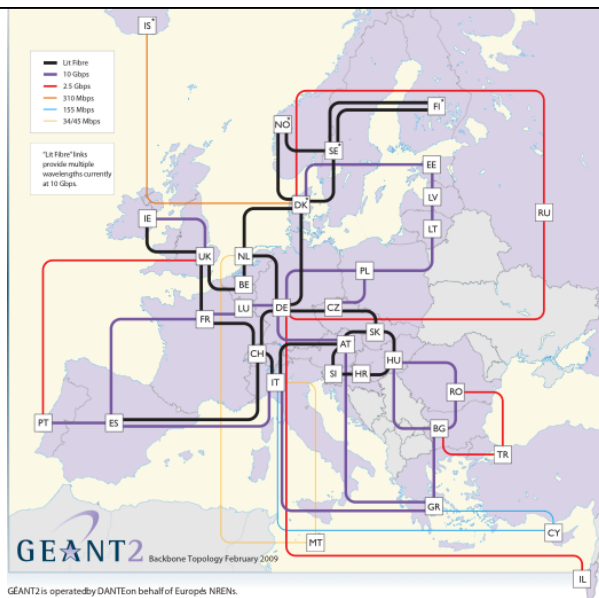
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Computational Approach to a Measuring Resilience



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Case Study: A Wireless GEANT2



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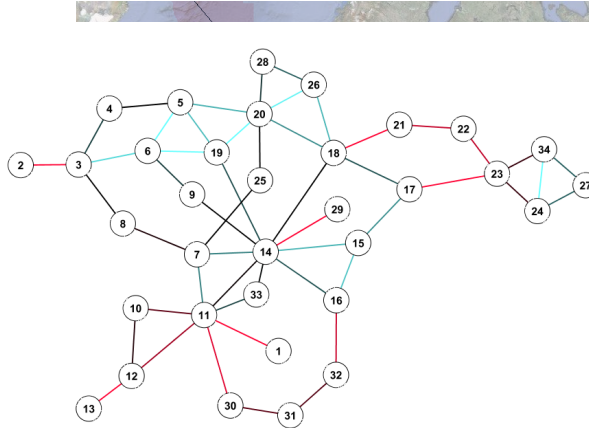
Show case for:

- Regional Challenges
- Fine-Grained, Intuitive Failures

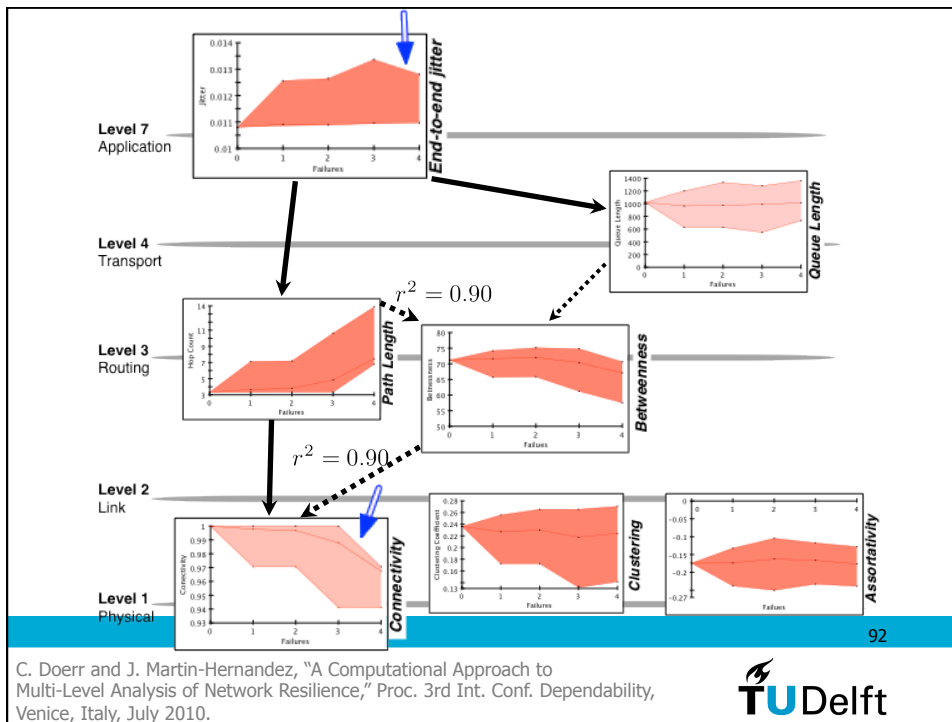
W-GEANT2: Where are the weak points?

- Risk map indicates which areas are most vulnerable to challenges

Impact map visualizes the effect of a particular failure on the network as a whole



Let's take a deeper look:
What concretely would happen?



C. Doerr and J. Martin-Hernandez, "A Computational Approach to Multi-Level Analysis of Network Resilience," Proc. 3rd Int. Conf. Dependability, Venice, Italy, July 2010.



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Spectrum

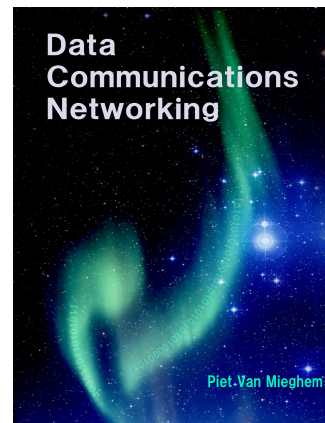
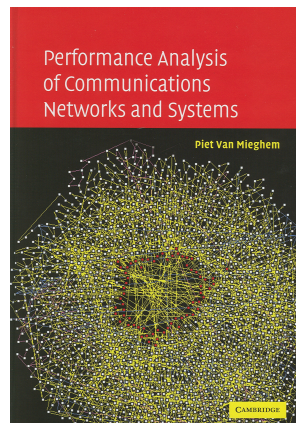
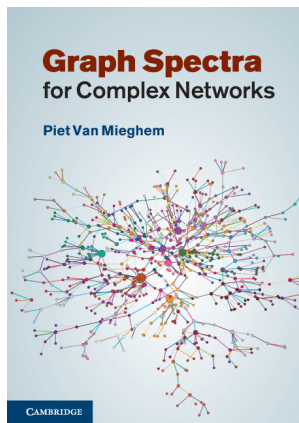
Network models

Attacks & failures

Framework for robustness



Books



Articles: <http://www.nas.ewi.tudelft.nl>

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Sixth International Workshop on Self-Organizing Systems
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