

Best spreader node in a graph

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Outline



Background: Electrical matrix equations

New graph metrics

Best nodal spreader



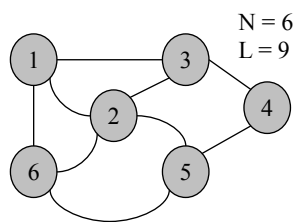
Function of network

- Usually, the function of a network is related to the *transport of items over its underlying graph*
- In man-made infrastructures: two major types of transport
 - Item is a **flow** (e.g. electrical current, water, gas,...)
 - Item is a **packet** (e.g. IP packet, car, container, postal letter,...)
- **Flow equations (physical laws)** determine transport (Maxwell equations (Kirchoff & Ohm), hydrodynamics, Navier-Stokes equation (turbulent, laminar flow equations, etc.))
- **Protocols** determine transport of packets (IP protocols and IETF standards, car traffic rules, etc.)

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Adjacency matrix A



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

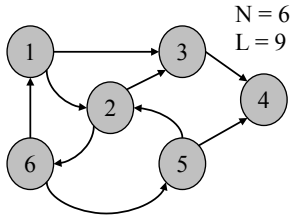
For an undirected graph: $A = A^T$ is symmetric

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

if there is a link between node i and j , then $a_{ij} = 1$
else $a_{ij} = 0$



Incidence matrix B



$N = 6$
 $L = 9$

- Label links (e.g.: $l_1 = (1,2)$, $l_2 = (1,3)$, $l_3 = (1,6)$, $l_4 = (2,3)$, $l_5 = (2,5)$, $l_6 = (2,6)$, $l_7 = (3,4)$, $l_8 = (4,5)$, $l_9 = (5,6)$)
- Col k for link $l_k = (i,j)$ is zero, except:
source node $i = 1 \rightarrow b_{ik} = 1$
destination node $j = -1 \rightarrow b_{jk} = -1$

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

Col sum B is zero: $u^T B = 0$

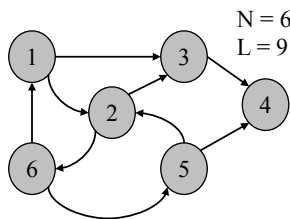
where the all-one vector $u = (1,1,\dots,1)$

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B specifies the directions of links



Laplacian matrix Q



$N = 6$
 $L = 9$

$$Q_{N \times N} = \begin{bmatrix} 3 & -1 & -1 & 0 & 0 & -1 \\ -1 & 4 & -1 & 0 & -1 & -1 \\ -1 & -1 & 3 & -1 & 0 & 0 \\ 0 & 0 & -1 & 2 & -1 & 0 \\ 0 & -1 & 0 & -1 & 3 & -1 \\ -1 & -1 & 0 & 0 & -1 & 3 \end{bmatrix}$$

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

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

Since BB^T is symmetric, so are A and Q . Although B specifies directions, A and Q lost this info here.

Basic property: $Qu = 0$

u is an eigenvector of Q
Belonging to eigenvalue $\mu = 0$

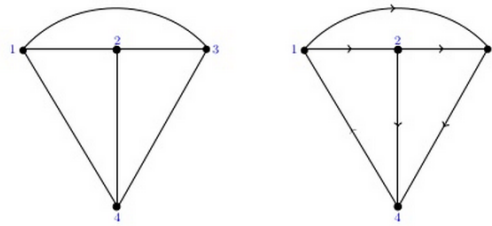
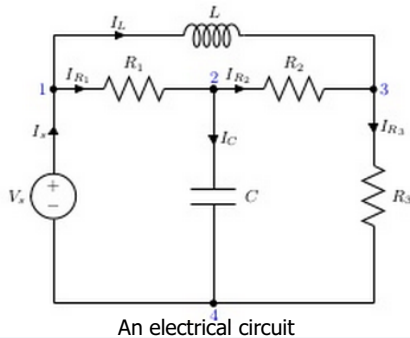
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$$Qu = BB^T u = 0 \quad \text{because} \quad 0 = u^T B = B^T u$$



Electrical Circuits as Graphs

- An electrical circuit can be represented as a graph $G(N,L)$:
 - Terminals, buses Nodes
 - Lines, branches Links



North-Eastern Hill University, EE-304 Electrical Network Theory [Class Notes1](#) - 2013



Analysis of Electrical Circuits

- Find all link currents (y_{ij}) and node voltages (v_i) from the known parameters in the network
- **Two important laws apply:**

Kirchhoff's Current Law (a conservation law): The sum of all the directed currents at each node i in a circuit equals zero:

$$\sum_{j \in \text{neighbors}(i)} y_{ij} = \sum_{j=1}^N a_{ij} y_{ij} = 0$$

Ohm's Law: The current through a conductor equals the potential difference over the conductor multiplied by its resistance. For any link between two nodes i and j with a resistance r_{ij} :

$$v_i - v_j = r_{ij} y_{ij}$$

Recall that $A = A^T$: thus $a_{ij} = a_{ji}$; A represents link existence; B specifies link directionality and the link current obeys $y_{ij} = -y_{ji}$. Both the vector v and y can have negative components.



Current-voltage relation for any graph

Ohm's Law: $v_i - v_j = r_{ij} y_{ij}$ \longrightarrow $y_{ij} = \frac{1}{r_{ij}} (v_i - v_j)$

Kirchhoff's law (conservation law): $x_i = \sum_{j \in \text{neighbors}(i)} y_{ij} = \sum_{j=1}^N a_{ij} y_{ij}$

Substituting Ohm's law into Kirchhoff's law:

$$x_i = \sum_{j=1}^N \frac{a_{ij}}{r_{ij}} (v_i - v_j) = v_i \sum_{j=1}^N \frac{a_{ij}}{r_{ij}} - \sum_{j=1}^N \frac{a_{ij}}{r_{ij}} v_j$$

We define a weighted Laplacian by $\tilde{Q} = \tilde{\Delta} - \tilde{A}$, where the elements in the weighted adjacency matrix \tilde{A} are $\tilde{a}_{ij} = \frac{1}{r_{ij}} a_{ij}$

Finally: $x = \tilde{Q}v$

Clearly, if all $r_{ij} = 1$, then $\tilde{Q} = Q$



Pseudo-inverse of the Laplacian (1)

Since $\det Q = 0$, we **cannot** solve $x = Qv$ as $v = Q^{-1}x$

The spectral decomposition of the Laplacian: $Q = ZMZ^T$
 where Z is the orthogonal eigenvector matrix ($Z^T Z = Z Z^T = I$)
 and M is the diagonal matrix with the ordered eigenvalues

$$\mu_1 \geq \mu_2 \geq \dots \geq \mu_{N-1} \geq \mu_N = 0$$

Expanding $Q = ZMZ^T$: $Q = \sum_{k=1}^N \mu_k z_k z_k^T = \sum_{k=1}^{N-1} \mu_k z_k z_k^T + \frac{\mu_N}{N} uu^T = \sum_{k=1}^{N-1} \mu_k z_k z_k^T$

Since G is connected, $\mu_k > 0$ for $0 < k < N$, so that the matrix

$$\hat{Q}^{-1} = \sum_{k=1}^{N-1} \frac{1}{\mu_k} z_k z_k^T$$

exists and is called the pseudo-inverse of Q .

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Pseudo-inverse of the Laplacian (2)

The pseudo-inverse of Q

$$\hat{Q}^{-1} = \sum_{k=1}^{N-1} \frac{1}{\mu_k} z_k z_k^T$$

obeys

$$\hat{Q}^{-1}Q = Q\hat{Q}^{-1} = I - \frac{1}{N}J$$

Indeed, use orthogonality $z_k^T z_j = \delta_{kj}$ and $Z^T Z = Z Z^T = I$

$$\hat{Q}^{-1}Q = \sum_{k=1}^{N-1} \frac{1}{\mu_k} z_k z_k^T \sum_{j=1}^{N-1} \mu_j z_j z_j^T = \sum_{k=1}^{N-1} \sum_{j=1}^{N-1} \mu_j \frac{1}{\mu_k} z_k (z_k^T z_j) z_j^T = \sum_{k=1}^{N-1} z_k z_k^T = I - \frac{u}{\sqrt{N}} \frac{u^T}{\sqrt{N}} = I - \frac{1}{N}J$$

An alternative form is $\hat{Q}^{-1} = (Q + \alpha J)^{-1} - \frac{1}{N^2}J$ for any $\alpha \neq 0$

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P. Van Mieghem, Graph Spectra for Complex Networks, Cambridge University Press, 2010, p.203-206



Matrix Representations of the Basic Laws

Using the pseudo-inverse on $x = Qv$

$$\hat{Q}^{-1}x = \hat{Q}^{-1}Qv = \left(I - \frac{1}{N}J\right)v$$

Further $\left(I - \frac{1}{N}J\right)v = v - u \left(\frac{u^T v}{N}\right) = v - v_{average}u$

Hence, from the spectral decomposition of the Laplacian matrix

$$Q = \sum_{k=1}^N \mu_k z_k z_k^T$$

the pseudo-inverse is constructed as $\hat{Q}^{-1} = \sum_{k=1}^{N-1} \frac{1}{\mu_k} z_k z_k^T$

The potential vector v is determined from the injected current vector x

$$v - v_{average}u = \hat{Q}^{-1}x \quad \longrightarrow \quad \begin{aligned} &\bullet \text{ Only potential differences matter!} \\ &\bullet \text{ Choose e.g. } v_{average} = 0 \end{aligned}$$

Observe that $u^T \hat{Q}^{-1} = 0$ so that $u^T v - v_{average} u^T u = 0 \quad \longrightarrow \quad v_{average} = \frac{u^T v}{N}$

Effective Resistance Matrix Ω

We consider a network in which a flow with magnitude I_c is injected in node a and the flow leaves the network at node b

The injected current vector $x = I_c (e_a - e_b)$, where the basic vector e_k has components $(e_k)_j = \delta_{kj}$

The general voltage-injected current vector relation $v = \hat{Q}^{-1}x$

shows
$$v = I_c \hat{Q}^{-1} (e_a - e_b)$$

The aim is to determine the effective resistance matrix Ω with elements ω_{ab} that satisfy $v_a - v_b = I_c \omega_{ab}$

Since $v_a - v_b = (e_a - e_b)^T v$, we have $v_a - v_b = I_c (e_a - e_b)^T \hat{Q}^{-1} (e_a - e_b)$



$$\omega_{ab} = (e_a - e_b)^T \hat{Q}^{-1} (e_a - e_b)$$

P. Van Mieghem, Graph Spectra for Complex Networks,
Cambridge University Press, 2010, p.203-206



Effective Resistance Matrix Ω

Multiplying out
$$\omega_{ab} = (e_a - e_b)^T \hat{Q}^{-1} (e_a - e_b)$$

yields
$$\omega_{ab} = (\hat{Q}^{-1})_{aa} + (\hat{Q}^{-1})_{bb} - 2(\hat{Q}^{-1})_{ab}$$

so that the effective resistance matrix is

$$\Omega = u \zeta^T + \zeta u^T - 2\hat{Q}^{-1}$$

where the vector ζ is

$$\zeta = \left((\hat{Q}^{-1})_{11}, (\hat{Q}^{-1})_{22}, \dots, (\hat{Q}^{-1})_{NN} \right)$$



Effective Resistance Matrix Ω

Properties of $\Omega = u\xi^T + \xi u^T - 2\hat{Q}^{-1}$

1. Symmetric: $\Omega^T = \Omega$
 2. All diagonal elements of Ω are zero
 3. Triangular inequality: $\omega_{ij} \leq \omega_{ik} + \omega_{kj}$
- } Distance matrix

The effective graph resistance is defined as $R_G = \frac{1}{2} u^T \Omega u$

R_G measures the difficulty of transport in a graph G: low R_G corresponds to a "good conducting" network (i.e. low resistance to flows)

Since $u^T \hat{Q}^{-1} u = 0$ (each eigenvector z_k with $k < N$ is orthogonal to $z_N = u$)

we find $R_G = Nu^T \xi = N \text{trace}(\hat{Q}^{-1}) = N \sum_{k=1}^{N-1} \frac{1}{\mu_k}$

Ellens, W., F. A. Spijksma, P. Van Mieghem, A. Jamakovic and R. E. Kooij, 2011, "Effective Graph Resistance", Linear Algebra and its Applications, Vol. 435, pp. 2491-2506.



More general than resistor networks

$x(s) = Q(s)v(s)$ for link impedances $r_l + sL_l + \frac{1}{s}C_l$

Processes 'proportional' to the network topology (graph)

The analogy with voltage is in brackets:

- water flow networks (height of water column)
- spring-mass systems (energy stored in spring)
- gas networks (pressure)
- warmth diffusion in networks (temperature)

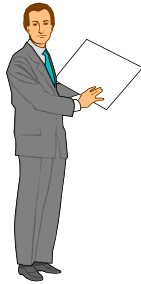
Processes described by a weighted Laplacian

- Any Markovian continuous-time processes, where the infinitesimal generator is minus a weighted Laplacian of the Markov state graph)

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P. Van Mieghem, K. Devriendt and H. Cetinay, "Pseudo-inverse of the Laplacian and best spreader node in a network", unpublished, 2017



New electrical matrix equations

Recall the inverse current-voltage relations

$$x = Qv$$

$$v = Q^{\$}x$$

Matrix Ohm law:

$$v = -\frac{1}{2N}(NI - J)\Omega x$$

where the effective resistance matrix is denoted by Ω

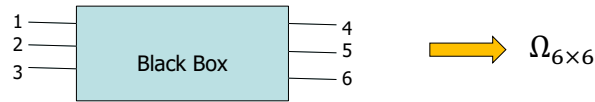
Power \wp dissipated in the network: $\wp = -\frac{1}{2}x^T\Omega x$

Current/flow eigenvalue equation: $Q\Omega x = -2x$

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Relation between "function" and "structure" of a network



Block inverse (*inspired by Fiedler, "Geometry of Laplacian", LAA, 1998*):

$$\begin{bmatrix} 0 & u^T \\ u & \Omega \end{bmatrix} = -2 \begin{bmatrix} \zeta^T Q \zeta + \frac{4R_G}{N^2} & -\left(Q\zeta + \frac{2}{N}u\right)^T \\ -\left(Q\zeta + \frac{2}{N}u\right) & Q \end{bmatrix}^{-1}$$

where $\left(Q\zeta + \frac{2}{N}u\right)$ is the eigenvector of $Q\Omega$ belonging to the zero eigenvalue.

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$$\xi = \left((Q^s)_{11}, (Q^s)_{22}, \dots, (Q^s)_{NN} \right)$$



Geometry

Spectral decomposition: $Q^s = ZM^s Z^T = \left(Z\sqrt{M^s}\right) \left(Z\sqrt{M^s}\right)^T$

The matrix $S^s = \left(Z\sqrt{M^s}\right)^T$ has rank $N-1$ (row $N=0$ due to $\mu_N = 0$)

The i -th column vector $s_i =$ point p_i in $(N-1)$ -dim space AND

$$\|s_i - s_j\|_2^2 = \omega_{ij}$$

All N points p_j form a hyperacute simplex with volume V_G

$$V_G = \frac{1}{N! \sqrt{2\xi}}$$

where the number of (weighted) spanning trees ξ is

$$\xi = \frac{1}{N} \prod_{k=1}^{N-1} \mu_k$$

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K. Menger, "New foundation of Euclidean geometry",
American Journal of Mathematics, 53(4):721-745, 1931



Graph metrics

The volume V_G (or the weighted complexity)

$$\xi = \frac{1}{N} \prod_{k=1}^{N-1} \mu_k = \frac{1}{2(N! V_G)^2}$$

provides similar information as the effective graph resistance

$$R_G = N \sum_{k=1}^{N-1} \mu_k$$

by concavity of $\log(x)$ function:

Small volume \rightarrow large number of spanning trees
 \rightarrow good conductance
 \rightarrow low effective graph resistance

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Graph metrics

$$\text{Average } \frac{1}{N} \sum_{k=1}^N \zeta_k = \frac{R_G}{N^2} \quad \longrightarrow \quad R_G = N \sum_{k=1}^{N-1} \frac{1}{\mu_k}$$

R_G is the effective graph resistance

$$\text{Variance } \frac{1}{N} \sum_{k=1}^N \left(\zeta_k - \frac{R_G}{N^2} \right)^2 \leq \frac{\nabla R}{N^2} \quad \longrightarrow \quad \nabla R = (N-1) \sum_{k=1}^{N-1} \frac{1}{\mu_k^2} - \left(\sum_{k=1}^{N-1} \frac{1}{\mu_k} \right)^2$$

Most ζ_k lie in the interval $\left(\frac{R_G}{N^2} - \frac{\sqrt{\nabla R}}{N}, \frac{R_G}{N^2} + \frac{\sqrt{\nabla R}}{N} \right)$

$\longrightarrow \nabla R$ reflects the nodal spreading heterogeneity in the graph

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$$\xi = \left((Q^s)_{11}, (Q^s)_{22}, \dots, (Q^s)_{NN} \right)$$

Open problem: when is $Q^\$$ a (weighted) Laplacian?

1. $(Q^\$)_{ii} \geq (Q^\$)_{ij}$

2. $(Q^\$)_{ii} (Q)_{ii} \geq \left(1 - \frac{1}{N}\right)^2$ \longrightarrow Similar to Heisenberg's uncertainty relation

\longrightarrow $R_G \geq (N - 1)^2 E \left[\frac{1}{D} \right]$

3. $(\widehat{Q}^{-1})_{ii} \leq \frac{1}{d_i} \left(1 - \frac{1}{N}\right) + \max_{k \neq i} (\widehat{Q}^{-1})_{ik}$

4. If \widehat{Q}^{-1} is a weighted Laplacian then

$$\frac{1}{d_i} \left(1 - \frac{1}{N}\right)^2 \leq (\widehat{Q}^{-1})_{ii} \leq \frac{1}{d_i} \left(1 - \frac{1}{N}\right)$$

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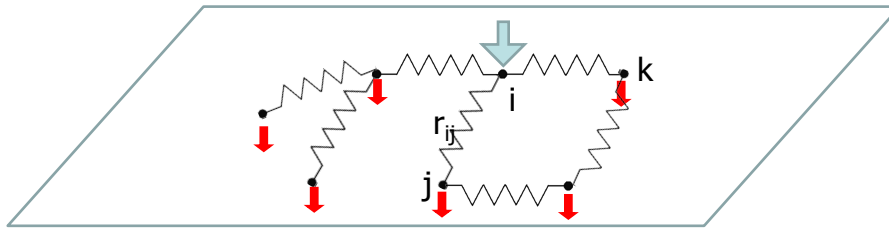
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Background: Electrical matrix equations

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Best nodal spreader



Inverses: $x = Qv$ and $v = Q^s x$ with the convention for voltages $u^T v = 0$

Q : weighted Laplacian of the graph

Q^s : pseudo-inverse of the weighted Laplacian: $Q \cdot Q^s = Q^s \cdot Q = I - 1/N J$

x : vector with external nodal current

v : vector with nodal potentials

$$v_i = (Q^s)_{ii} \quad \text{If } x = e_i - 1/N u$$

The best spreader is the node k with minimum $(Q^s)_{kk}$

$$\xi = ((Q^s)_{11}, (Q^s)_{22}, \dots, (Q^s)_{NN})$$

Interpretation: best spreader node

Inverses: $x = Qv$ and $v = Q^s x$

Clearly: $u^T x = 0$ and $u^T v = 0$

$$v_i = (Q^s)_{ii} \quad \text{is same as} \quad (Q^s)_{ii} = v_i - u^T v = \frac{1}{N} \sum_{k=1}^N (v_i - v_k)$$

The best spreader minimizes the sum of potential differences *between its and all other node potentials*



"closeness" minimization of average distance to all other nodes



best spreader lies in center of "gravity"

$$\xi = ((Q^s)_{11}, (Q^s)_{22}, \dots, (Q^s)_{NN})$$

Closeness Cl_i and $(Q^s)_{ii}$

Closeness Cl_i of a node i is the reciprocal of the total hopcount of all shortest path at this node i to all other nodes in the graph G :

$$Cl_i = \frac{1}{\sum_{j \in G \setminus \{i\}} H(P_{i \rightarrow j}^*)}$$

Concept of distance in both Cl_i and $(Q^s)_{ii}$

- All paths [$(Q^s)_{ii}$] versus only the shortest path [Cl_i]
- $(Q^s)_{ii}$ lowerbounds Cl_i
($(Q^s)_{ii} = Cl_i$ in trees with unit link weights)

$(Q^s)_{ii}$ is more analytically tractable than a shortest path computation (closeness)

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P. Van Mieghem, Performance Analysis of Complex Networks and Systems, Cambridge University Press, 2014, p. 370

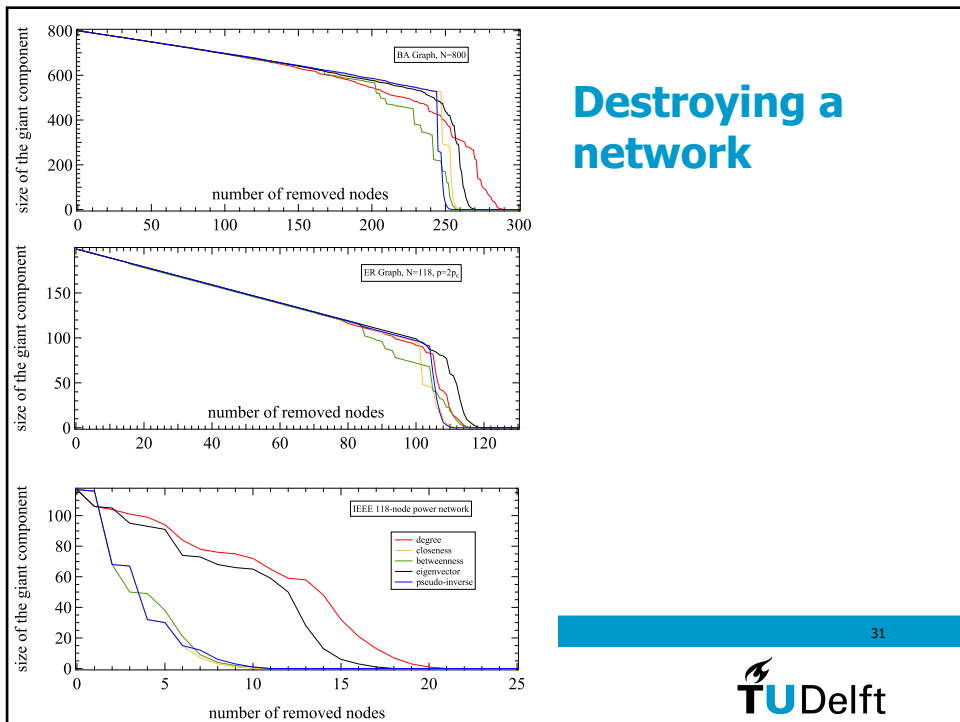
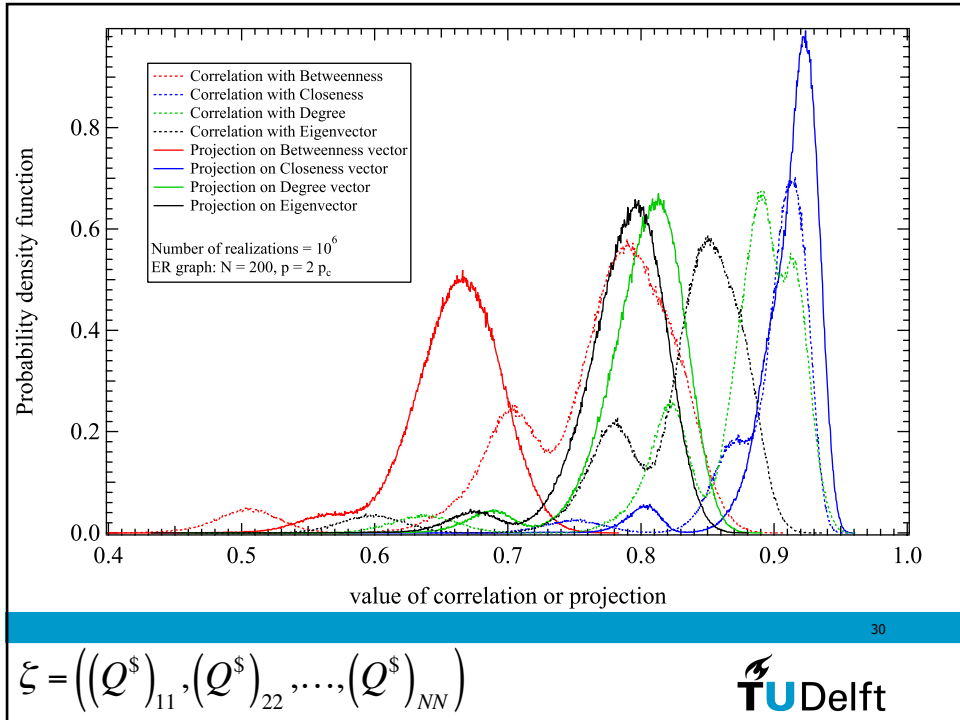


Contemplation: best spreader node

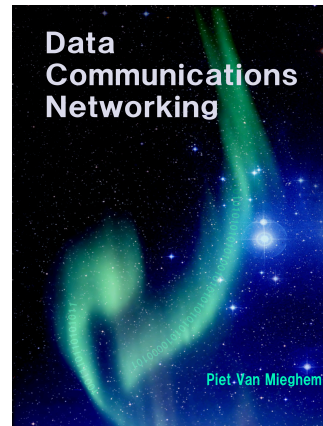
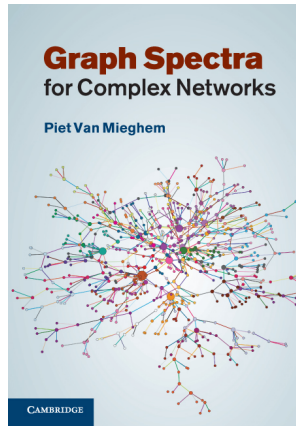
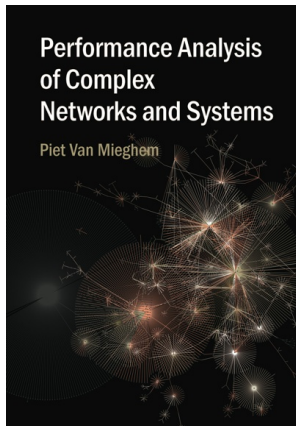
- *Valid for any weighted Laplacian*
 - Not heuristic, but based on the **law of conservation**
 - If resistances $r_{ij} = 1$: pure graph focus
 - **The infinitesimal generator of a continuous-time Markov chain (MC) is minus a weighted Laplacian (which is not necessarily symmetric!)**
 - Huge potential as nearly all processes can be approximated by a MC, provided the state space is sufficiently large
- *Interpretations:*
 - Ranking of nodes according to “diffusive centrality” or dynamic connectivity to all others
 - Resilience/Robustness: Safe-guarding nodes in this ranking to secure dynamic processes

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Books



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

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Thank You

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