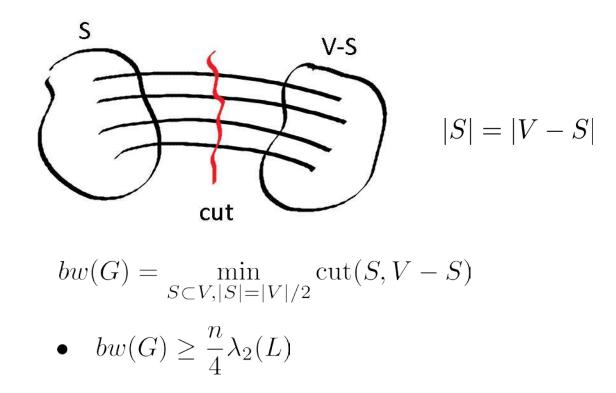
Bisection



Algorithm for finding sparse cuts: compute Fiedler vector, sort the vertices according to its values , and find the best cut .

Partitioning problem, Walshaw's partitioning archive, DIMACS competition [BMSSS] "Recent advances in graph partitioning", 2013

p-discrepancy

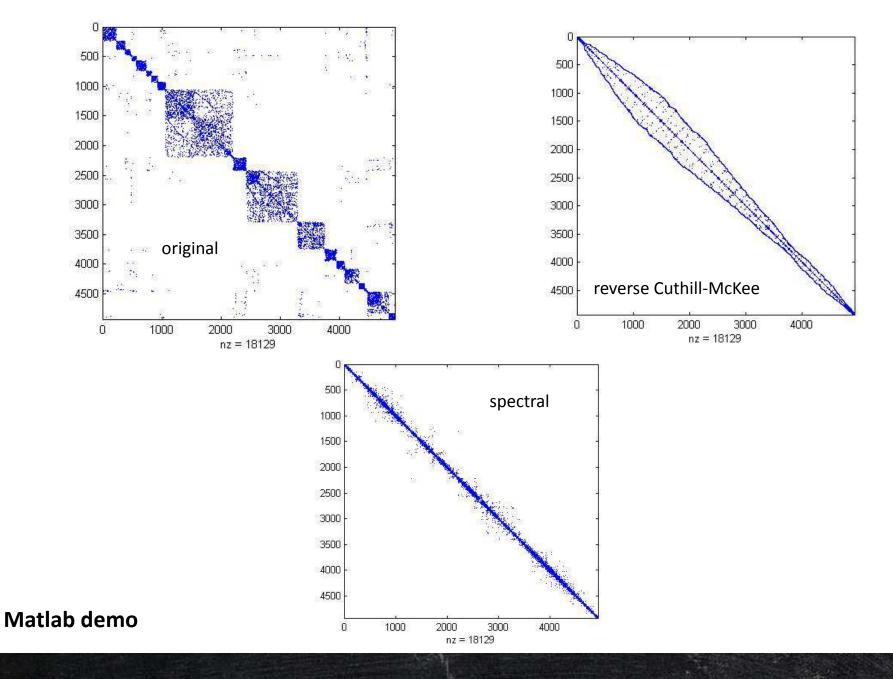
We define $p - discrepancy \sigma_p(G, \psi)$ of labeling ψ as

$$\sigma_p(G,\psi) = \left(\sum_{ij\in E} w_{ij}|\psi(i) - \psi(j)|^p\right)^{1/p} \text{ and } \sigma_\infty(G,\psi) = \max_{ij\in E} w_{ij}|\psi(i) - \psi(j)|$$

Finding minimum p - discrepancy (such as minimum linear arrangement, 2sum, bandwidth) is NP-hard. Basic facts:

$$\lambda_2 \frac{n(n^2 - 1)}{12} \le \sigma_2(G, \psi)^2 \le \lambda_n \frac{n(n^2 - 1)}{12}$$
$$\lambda_2 \frac{(n^2 - 1)}{6} \le \sigma_1(G, \psi) \le \lambda_n \frac{(n^2 - 1)}{6}$$

Homework: Juvan, Mohar "Optimal linear labelings and eigenvalues of graphs" (submit by 3/13)



Introduction to Network Science

Random Walks

Let $p_i(t)$ be the probability that the walk is at *i* at time *t*

$$p_i(t) = \sum_j \frac{A_{ij}}{d(j)} p_j(t-1) \text{ or } p(t) = AD^{-1}p(t-1)$$

Another useful form of this relation is

$$D^{-1/2}p(t) = \left(D^{-1/2}AD^{-1/2}\right)\left(D^{-1/2}p(t-1)\right)$$

As $t \to \infty$ the probability distribution is represented by $p = AD^{-1}p$ or

$$(I - AD^{-1})p = (D - A)D^{-1}p = LD^{-1}p = 0,$$

i.e., $D^{-1}p$ is an eigenvector of L with eval 0. **Example:** G is connected \Rightarrow there is only one eval $0 \Rightarrow D^{-1}p = \alpha 1$, i.e.,

$$p_i = d(i) / \sum_j d(j) = \frac{d(i)}{2m}$$

Intuition: high degree nodes are more likely to be visited.

First Passage Time

Q: what is the mean first passage time the random walk started at *i* reaches *j*? **Absorbing random walk** = random walk with one or more nodes we can move to but not leave We consider an absorbing random walk with **single absorbing vertex** *v*. Probability that rw has fpt exactly *t* is $p_v(t) - p_v(t-1)$, i.e., the mean is

$$\tau = \sum_{t=0}^{\infty} t(p_v(t) - p_v(t-1)).$$

For any
$$i \neq v \ p_i(t) = \sum_j \frac{A_{ij}}{d(j)} p_j(t-1) = \sum_{j \neq v} \frac{A_{ij}}{d(j)} p_j(t-1)$$
, i.e.,

 $p'(t) = A'D'^{-1}p'(t-1) = (A'D'^{-1})^t p'(0) \quad (' \text{ means } v \text{ is removed})$ Since $\sum_i p_i(t) = 1$ at all times

$$p_v(t) = 1 - \sum_{i \neq v} p_i(t) = 1 - 1^T p'(t)$$
 and

 $\tau = \sum_{t=0}^{\infty} t \mathbf{1}^T (p'_v(t-1) - p'_v(t-1)) = \mathbf{1}^T \left(I - A'D'^{-1} \right)^{-1} p'(0) = \dots = \mathbf{1}^T D'L'^{-1} p'(0)$

Random Models

• Model G(n, m) is a probability distribution P(G) over all graphs with n nodes and m edges.

Properties of model = properties of ensemble Examples:

• graph diameter l(G) means $\langle l \rangle = \sum_G P(G) l(G) = \frac{1}{\Omega} \sum_G l(G)$

• degree
$$\langle d(\cdot) \rangle = 2m/n$$

• Model G(n, p) - graphs with n nodes and independent probability p for placing an edge between two vertices (aka Erdös-Rényi model). Properties of model = properties of ensemble where G appears with prob

$$P(G) = p^m (1-p)^{\binom{n}{2}-m}$$

and probablity of drawing a graph with m edges from the ensemble is

$$P(m) = \binom{\binom{n}{2}}{m} p^m (1-p)^{\binom{n}{2}-m} \text{ and } \langle m \rangle = \sum_{m=0}^{\binom{n}{2}} m P(m) = \binom{n}{2} p$$

Introduction to Network analysis

• mean degree
$$\sum_{m=0}^{\binom{n}{2}} \frac{2m}{n} P(m) = \frac{2}{n} \binom{n}{2} p = (n-1)p = c$$

mean degree in a graph with exactly *m* edges

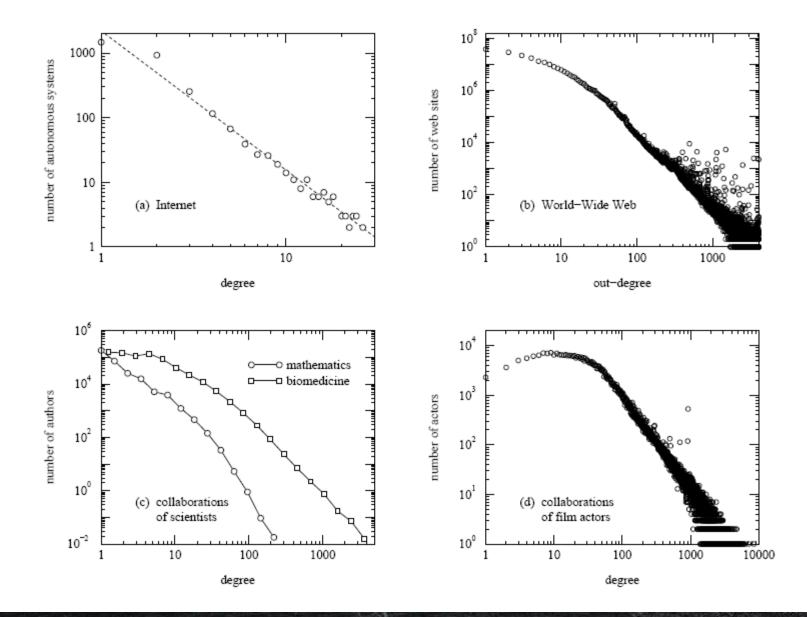
- degree distribution
 - node is connected to a particular k others $q_k = p^k (1-p)^{n-1-k}$
 - node is connected to exactly k others $p_k = \binom{n-1}{k} q_k$
 - in large-scale networks p = c/(n-1) can be very small, i.e.,

$$\ln((1-p)^{n-1-k}) = (n-1-k)\ln(1-c/(n-1)) \approx -(n-1-k)\frac{\infty}{n-1} \approx -c$$

Taylor series reminder: $\ln(1+\frac{1}{x}) = 2\left(A + \frac{1}{3}A^3 + \frac{1}{5}A^5 + \dots\right)$, where $A = \frac{1}{2x+1}$
also if $\binom{n-1}{k} = \frac{(n-1)!}{(n-1-k)!k!} \approx \frac{(n-1)^k}{k!}$ then

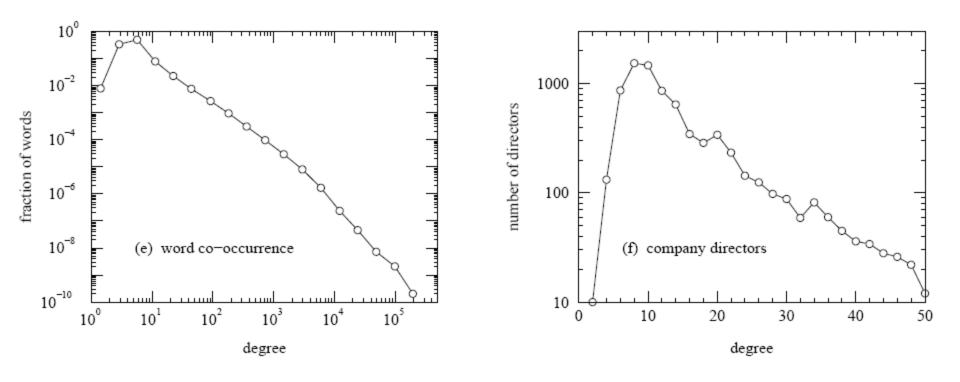
$$p_k = \frac{(n-1)^k}{k!} p^k e^{-c} = \frac{(n-1)^k}{k!} (\frac{c}{n-1})^k e^{-c} = e^{-c} \frac{c^k}{k!}$$

In contrast to the degree distribution in random model ...



Introduction to Network analysis

In contrast to the degree distribution in random model ...



Introduction to Network Analysis

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• clustering coefficient C = c/(n-1) = prob that any two nodes are neighbors

			clustering coefficient C	
network	n	z	measured	random graph
Internet (autonomous systems) ^a	6374	3.8	0.24	0.00060
World-Wide Web (sites) ^b	153127	35.2	0.11	0.00023
power grid ^c	4941	2.7	0.080	0.00054
biology collaborations ^d	1520251	15.5	0.081	0.000010
mathematics collaborations ^e	253339	3.9	0.15	0.000015
film actor collaborations ^f	449913	113.4	0.20	0.00025
company directors ^f	7673	14.4	0.59	0.0019
word co-occurrence ^g	460902	70.1	0.44	0.00015
neural network ^c	282	14.0	0.28	0.049
metabolic network ^h	315	28.3	0.59	0.090
food web ⁱ	134	8.7	0.22	0.065

Newman, "Random graphs as models of networks"