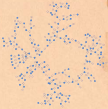
Assortativity and Mixing

Complex Networks
CSYS/MATH 303, Spring, 2011

Prof. Peter Dodds

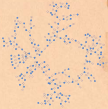
Department of Mathematics & Statistics
Center for Complex Systems
Vermont Advanced Computing Center
University of Vermont



Outline

Basic idea:

- Random networks with arbitrary degree distributions cover much territory but do not represent all networks.
- Moving away from pure random networks was a key first step.
- We can extend in many other directions and a natural one is to introduce correlations between different kinds of nodes.
- Node attributes may be anything, e.g.:
  1. degree
  2. demographics (age, gender, etc.)
  3. group affiliation
- We speak of mixing patterns, correlations, biases...
- Networks are still random at base but now have more global structure.
- Build on work by Newman [4, 5], and Boguñá and Serano. [1].



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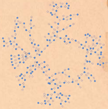

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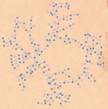

General mixing between node categories

- Assume types of nodes are countable, and are assigned numbers 1, 2, 3, ...
- Consider networks with directed edges.

$$e_{\mu\nu} = \mathbf{Pr}\left(\begin{array}{l}\text{an edge connects a node of type } \mu \\ \text{to a node of type } \nu\end{array}\right)$$

$$a_{\mu} = \mathbf{Pr}(\text{an edge comes from a node of type } \mu)$$

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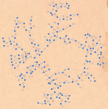
- Write $\mathbf{E} = [e_{\mu\nu}]$, $\vec{a} = [a_{\mu}]$, and $\vec{b} = [b_{\nu}]$.
- Requirements:

$$\sum_{\mu\ \nu} e_{\mu\nu} = 1, \quad \sum_{\nu} e_{\mu\nu} = a_{\mu}, \text{ and} \sum_{\mu} e_{\mu\nu} = b_{\nu}.$$



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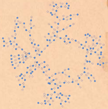

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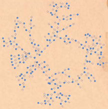

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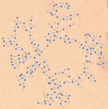

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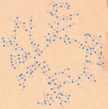

Notes:

- Varying $e_{\mu\nu}$ allows us to move between the following:

  1. Perfectly assortative networks where nodes only connect to like nodes, and the network breaks into subnetworks.
     Requires $e_{\mu\nu} = 0$ if $\mu \neq \nu$ and $\sum_{\mu} e_{\mu\mu} = 1$.
  2. Uncorrelated networks (as we have studied so far)
     For these we must have independence: $e_{\mu\nu} = a_{\mu} b_{\nu}$.
  3. Disassortative networks where nodes connect to nodes distinct from themselves.

- Disassortative networks can be hard to build and may require constraints on the $e_{\mu\nu}$.
- Basic story: level of assortativity reflects the degree to which nodes are connected to nodes within their group.

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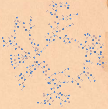

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Correlation coefficient:

- Quantify the level of assortativity with the following assortativity coefficient [5]:

$$r = \frac{\sum_\mu e_{\mu\mu} - \sum_\mu a_\mu b_\mu}{1 - \sum_\mu a_\mu b_\mu} = \frac{\mathrm{Tr}\,\mathbf{E} - ||E^2||_1}{1 - ||E^2||_1}$$

  where $||\cdot||_1$ is the 1-norm = sum of a matrix's entries.

- $\mathrm{Tr}\,\mathbf{E}$ is the fraction of edges that are within groups.
- $||E^2||_1$ is the fraction of edges that would be within groups if connections were random.
- $1 - ||E^2||_1$ is a normalization factor so $r_{\max} = 1$.
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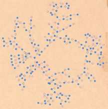

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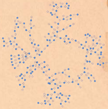

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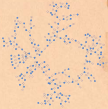

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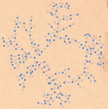

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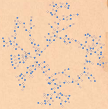

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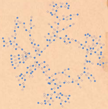

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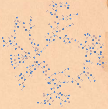
Notes:

- $r = -1$ is inaccessible if three or more types are present.
- Disassortative networks simply have nodes connected to unlike nodes—no measure of how unlike nodes are.
- Minimum value of r occurs when all links between non-like nodes: $\mathrm{Tr}\, \mathbf{e}_{\mu\mu} = 0$.
- $$r_{\min} = \frac{-\|E^2\|_1}{1 - \|E^2\|_1}$$

  where $-1 \le r_{\min} < 0$.



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Correlation coefficient:

Notes:

- $r = -1$ is inaccessible if three or more types are present.
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- Minimum value of r occurs when all links between non-like nodes: $\mathrm{Tr}\, \mathbf{e}_{\mu\mu} = 0$.
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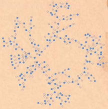

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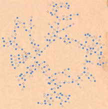

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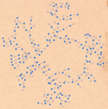

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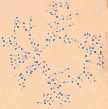

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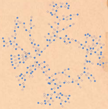

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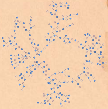

Degree-degree correlations

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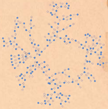

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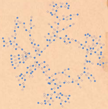

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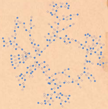

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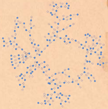

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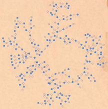

Degree-degree correlations

- Notation reconciliation for undirected networks:

$$r = \frac{\sum_{j\,k} j\,k(e_{jk} - R_j R_k)}{\sigma_R^2}$$

where, as before, R_k is the probability that a randomly chosen edge leads to a node of degree $k+1$, and

$$\sigma_R^2 = \sum_j j^2 R_j - \left[\sum_j j R_j\right]^2 .$$

Degree-degree correlations

Error estimate for r:

- Remove edge i and recompute r to obtain r_i.
- Repeat for all edges and compute using the jackknife method (⊞) [2]

$$\sigma_r^2 = \sum_i (r_i - r)^2.$$

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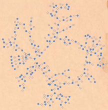
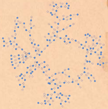


Measurements of degree-degree correlations

Group		Network	Type	Size n	Assortativity r	Error σ_r
Social	a	Physics coauthorship	undirected	52 909	0.363	0.002
	a	Biology coauthorship	undirected	1 520 251	0.127	0.0004
	b	Mathematics coauthorship	undirected	253 339	0.120	0.002
	c	Film actor collaborations	undirected	449 913	0.208	0.0002
	d	Company directors	undirected	7 673	0.276	0.004
	e	Student relationships	undirected	573	−0.029	0.037
	f	Email address books	directed	16 881	0.092	0.004
Technological	g	Power grid	undirected	4 941	−0.003	0.013
	h	Internet	undirected	10 697	−0.189	0.002
	i	World Wide Web	directed	269 504	−0.067	0.0002
	j	Software dependencies	directed	3 162	−0.016	0.020
Biological	k	Protein interactions	undirected	2 115	−0.156	0.010
	l	Metabolic network	undirected	765	−0.240	0.007
	m	Neural network	directed	307	−0.226	0.016
	n	Marine food web	directed	134	−0.263	0.037
	o	Freshwater food web	directed	92	−0.326	0.031

- Social networks tend to be assortative (homophily)
- Technological and biological networks tend to be disassortative



Spreading on degree-correlated networks

- Next: Generalize our work for random networks to degree-correlated networks.
- As before, by allowing that a node of degree k is activated by one neighbor with probability B_{k1}, we can handle various problems:
  1. find the giant component size.
  2. find the probability and extent of spread for simple disease models.
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- Goal: Find $f_{n,j}$ = **Pr** an edge emanating from a degree $j+1$ node leads to a finite active subcomponent of size n.
- Repeat: a node of degree k is in the game with probability B_{k1}.
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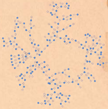

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$$F_j(x;\vec{B}_1) = x^0 \sum_{k=0}^{\infty} \frac{e_{jk}}{R_j}(1 - B_{k+1,1}) + x \sum_{k=0}^{\infty} \frac{e_{jk}}{R_j} B_{k+1,1} \left[F_k(x;\vec{B}_1) \right]^k .$$

- First term = **Pr** that the first node we reach is not in the game.
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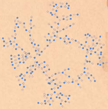

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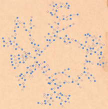

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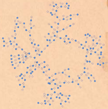

Spreading on degree-correlated networks

- Differentiate $F_j(x;\vec{B}_1)$, set $x = 1$, and rearrange.
- We use $F_k(1;\vec{B}_1) = 1$ which is true when no giant component exists. We find:

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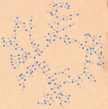

Spreading on degree-correlated networks

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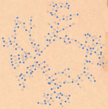

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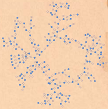


Spreading on degree-correlated networks

- In matrix form, we have

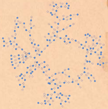
$$\mathbf{A}_{\mathbf{E},\vec{B}_1} \vec{F}'(1;\vec{B}_1) = \mathbf{E}\vec{B}_1$$

where

$$\left[\mathbf{A}_{\mathbf{E},\vec{B}_1}\right]_{j+1,k+1} = \delta_{jk} R_k - k B_{k+1,1} e_{jk},$$

$$\left[\vec{F}'(1;\vec{B}_1)\right]_{k+1} = F'_k(1;\vec{B}_1),$$

$$[\mathbf{E}]_{j+1,k+1} = e_{jk}, \text{ and } \left[\vec{B}_1\right]_{k+1} = B_{k+1,1}.$$



Spreading on degree-correlated networks

- So, in principle at least:

$$\vec{F}'(1;\vec{B}_1) = \mathbf{A}^{-1}_{\mathbf{E},\vec{B}_1}\,\mathbf{E}\vec{B}_1.$$

- Now: as $\vec{F}'(1;\vec{B}_1)$, the average size of an active component reached along an edge, increases, we move towards a transition to a giant component.
- Right at the transition, the average component size explodes.
- Exploding inverses of matrices occur when their determinants are 0.
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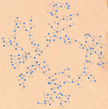

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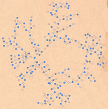

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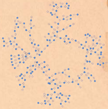

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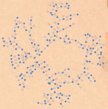

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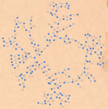

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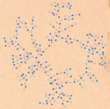

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We'll next find two more pieces:

1. P_{trig}, the probability of starting a cascade
2. S, the expected extent of activation given a small seed.

Triggering probability:

- Generating function:

$$H(x; \vec{B}_1) = x \sum_{k=0}^{\infty} P_k \left[F_{k-1}(x; \vec{B}_1) \right]^k .$$

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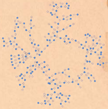

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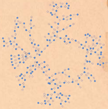

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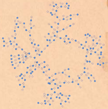

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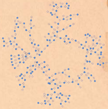

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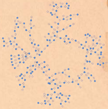

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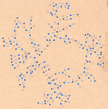

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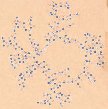

Spreading on degree-correlated networks

- Truly final piece: Find final size using approach of Gleeson [3], a generalization of that used for uncorrelated random networks.
- Need to compute $\theta_{j,t}$, the probability that an edge leading to a degree j node is infected at time t.
- Evolution of edge activity probability:

$$\theta_{j,t+1} = G_j(\vec{\theta}_t) = \phi_0 + (1-\phi_0)\times$$

$$\sum_{k=1}^{\infty} \frac{e_{j-1,k-1}}{R_{j-1}} \sum_{i=0}^{k-1} \binom{k-1}{i} \theta_{k,t}^{i} (1-\theta_{k,t})^{k-1-i} B_{ki}.$$

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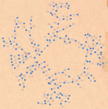

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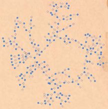

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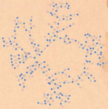

Spreading on degree-correlated networks

- As before, these equations give the actual evolution of ϕ_t for synchronous updates.
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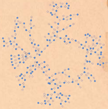

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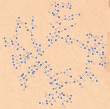

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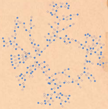
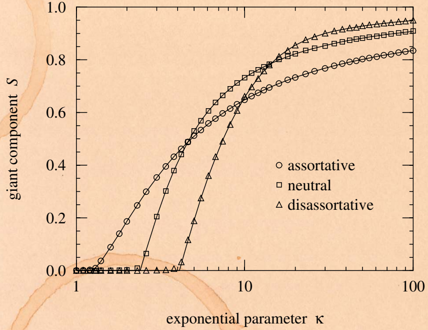


How the giant component changes with assortativity:



from Newman, 2002 [4]

- More assortative networks percolate for lower average degrees
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