Random Networks Complex Networks, CSYS/MATH 303, Spring, 2010

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







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Pure, abstract random networks:

- Consider set of all networks with N labelled nodes and m edges.
- Standard random network = randomly chosen network from this set.
- ▶ To be clear: each network is equally probable.
- Sometimes equiprobability is a good assumption, but it is always an assumption.
- Known as Erdős-Rényi random networks or ER graphs.

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Some features:

Number of possible edges:

$$0 \le m \le \binom{N}{2} = rac{N(N-1)}{2}$$

- Given *m* edges, there are
 ^N
 ^(N)
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- Crazy factorial explosion for $1 \ll m \ll \binom{N}{2}$.
- Limit of m = 0: empty graph.
- Limit of $m = \binom{N}{2}$: complete or fully-connected graph.
- Real world: links are usually costly so real networks are almost always sparse.

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- Two probablistic methods (we'll see a third later on)
- 1. Connect each of the $\binom{N}{2}$ pairs with appropriate probability *p*.
 - Useful for theoretical work.
- 2. Take *N* nodes and add exactly *m* links by selecting edges without replacement.
 - Algorithm: Randomly choose a pair of nodes i and j, i ≠ j, and connect if unconnected; repeat until all m edges are allocated.
 - Best for adding relatively small numbers of links (most cases).
 - 1 and 2 are effectively equivalent for large N.

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A few more things:

For method 1, # links is probablistic:

$$\langle m \rangle = p \binom{N}{2} = p \frac{1}{2} N(N-1)$$

So the expected or average degree is

$$\langle k \rangle = \frac{2 \langle m \rangle}{N}$$

$$=\frac{2}{N}p\frac{1}{2}N(N-1)=\frac{2}{N}p\frac{1}{2}N(N-1)=p(N-1).$$

- Which is what it should be...
- If we keep $\langle k \rangle$ constant then $p \propto 1/N \to 0$ as $N \to \infty$.

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Random networks: examples

Next slides: Example realizations of random networks

- ► *N* = 500
- ▶ Vary *m*, the number of edges from 100 to 1000.
- Average degree $\langle k \rangle$ runs from 0.4 to 4.
- Look at full network plus the largest component.

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N = 500, number of edges m = 100average degree $\langle k \rangle = 0.4$

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entire network:



N = 500, number of edges m = 200average degree $\langle k \rangle = 0.8$

largest component:

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entire network:



N = 500, number of edges m = 230average degree $\langle k \rangle = 0.92$

largest component:

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entire network:



N = 500, number of edges m = 240average degree $\langle k \rangle = 0.96$

largest component:

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N = 500, number of edges m = 250average degree $\langle k \rangle = 1$

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entire network:



N = 500, number of edges m = 260average degree $\langle k \rangle = 1.04$

largest component:

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entire network:



largest component:

N = 500, number of edges m = 280average degree $\langle k \rangle = 1.12$

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entire network:



largest component:



N = 500, number of edges m = 300average degree $\langle k \rangle = 1.2$ Random Networks

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entire network:



largest component:

N = 500, number of edges m = 500average degree $\langle k \rangle = 2$

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N = 500, number of edges m = 1000average degree $\langle k \rangle = 4$

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Random networks: examples for N=500









m = 100 $\langle k \rangle = 0.4$



m = 230 $\langle k \rangle = 0.92$



m = 250 $\langle k \rangle = 1$



m = 260

 $\langle k \rangle = 1.04$



m = 280

 $\langle k \rangle = 1.12$



m = 300

 $\langle k \rangle = 1.2$



m = 500

 $\langle k \rangle = 2$



m = 1000 $\langle k \rangle = 4$

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Random networks: largest components



m = 100 $\langle k \rangle = 0.4$

m = 260

 $\langle k \rangle = 1.04$



m = 280

 $\langle k \rangle = 1.12$

m = 200 $\langle k \rangle = 0.8$

m = 230 $\langle k \rangle = 0.92$

m = 300

 $\langle k \rangle = 1.2$



m = 240 $\langle k \rangle = 0.96$

m = 500

 $\langle k \rangle = 2$

m = 250 $\langle k \rangle = 1$

m = 1000

 $\langle k \rangle = 4$



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Random networks: examples for N=500







m = 250

 $\langle k \rangle = 1$

m = 250 $\langle k \rangle = 1$

m = 250

 $\langle k \rangle = 1$



m = 250 $\langle k \rangle = 1$



m = 250 $\langle k \rangle = 1$ m = 250 $\langle k \rangle = 1$





m = 250 $\langle k \rangle = 1$



m = 250

 $\langle k \rangle = 1$

m = 250 $\langle k \rangle = 1$

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Random networks: largest components





m = 250 $\langle k \rangle = 1$ m = 250 $\langle k \rangle = 1$





m = 250 $\langle k \rangle = 1$

m = 250

 $\langle k \rangle = 1$







 $\langle k \rangle = 1$

m = 250 $\langle k \rangle = 1$



m = 250 $\langle k \rangle = 1$



m = 250 $\langle k \rangle = 1$

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Clustering:

- For method 1, what is the clustering coefficient for a finite network?
- Consider triangle/triple clustering coefficient (Newman^[1]):

 $C_2 = \frac{3 \times \# \text{triangles}}{\# \text{triples}}$

- Recall: C₂ = probability that two nodes are connected given they have a friend in common.
- For standard random networks, we have simply that

 $C_2 = p$

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Clustering:

- So for large random networks (N → ∞), clustering drops to zero.
- Key structural feature of random networks is that they locally look like branching networks (no loops).

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Degree distribution:

- Recall p_k = probability that a randomly selected node has degree k.
- Consider method 1 for constructing random networks: each possible link is realized with probability p.
- Now consider one node: there are 'N − 1 choose k' ways the node can be connected to k of the other N − 1 nodes.
- ► Each connection occurs with probability p, each non-connection with probability (1 - p).
- Therefore have a binomial distribution:

$$P(k;p,N) = \binom{N-1}{k} p^k (1-p)^{N-1-k}.$$

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Frame 29/89

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Limiting form of P(k; p, N):

- Our degree distribution: $P(k; p, N) = \binom{N-1}{k} p^k (1-p)^{N-1-k}$
- What happens as $N \to \infty$?
- We must end up with the normal distribution right?
- If p is fixed, then we would end up with a Gaussian with average degree ⟨k⟩ ≃ pN → ∞.
- But we want to keep $\langle k \rangle$ fixed...
- ▶ So examine limit of P(k; p, N) when $p \to 0$ and $N \to \infty$ with $\langle k \rangle = p(N-1) = \text{constant}$.

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• Substitute $p = \frac{\langle k \rangle}{N-1}$ into P(k; p, N) and hold k fixed:

$$P(k; p, N) = \binom{N-1}{k} \left(\frac{\langle k \rangle}{N-1}\right)^k \left(1 - \frac{\langle k \rangle}{N-1}\right)^{N-1-k}$$

$$=\frac{(N-1)!}{k!(N-1-k)!}\frac{\langle k\rangle^k}{(N-1)^k}\left(1-\frac{\langle k\rangle}{N-1}\right)^{N-1-k}$$

$$=\frac{(N-1)(N-2)\cdots(N-k)}{k!}\frac{\langle k\rangle^k}{(N-1)^k}\left(1-\frac{\langle k\rangle}{N-1}\right)^{N-1-k}$$

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Substitute $p = \frac{\langle k \rangle}{N-1}$ into P(k; p, N) and hold k fixed:

$$P(k; p, N) = \binom{N-1}{k} \left(\frac{\langle k \rangle}{N-1}\right)^k \left(1 - \frac{\langle k \rangle}{N-1}\right)^{N-1-k}$$

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$$=\frac{(N-1)(N-2)\cdots(N-k)}{k!}\frac{\langle k\rangle^k}{(N-1)^k}\left(1-\frac{\langle k\rangle}{N-1}\right)^{N-1-k}$$

$$=\frac{N^{k}(1-\frac{1}{N})\cdots(1-\frac{k}{N})}{k!N^{k}}\frac{\langle k\rangle^{k}}{(1-\frac{1}{N})^{k}}\left(1-\frac{\langle k\rangle}{N-1}\right)^{N-1-k}$$

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$$=\frac{\cancel{k}}{\cancel{k!}}\frac{(1-\frac{1}{N})\cdots(1-\frac{k}{N})}{\cancel{k!}}\frac{\langle k\rangle^{k}}{(1-\frac{1}{N})^{k}}\left(1-\frac{\langle k\rangle}{N-1}\right)^{N-1-k}$$

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$$=\frac{(N-1)(N-2)\cdots(N-k)}{k!}\frac{\langle k\rangle^k}{(N-1)^k}\left(1-\frac{\langle k\rangle}{N-1}\right)^{N-1-k}$$

$$\simeq \frac{\mathcal{M}^{k}(1-\frac{1}{N})\cdots(1-\frac{k}{N})}{k!\mathcal{M}^{k}}\frac{\langle k\rangle^{k}}{(1-\frac{1}{N})^{k}}\left(1-\frac{\langle k\rangle}{N-1}\right)^{N-1-k}$$

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References

We are now here:

$$P(k; p, N) \simeq \frac{\langle k \rangle^k}{k!} \left(1 - \frac{\langle k \rangle}{N-1}\right)^{N-1-k}$$

Now use the excellent result:

$$\lim_{n\to\infty}\left(1+\frac{x}{n}\right)^n=e^x$$

(Use l'Hôpital's rule to prove.)

ldentifying n = N - 1 and $x = -\langle k \rangle$:

$$P(k;\langle k\rangle) \simeq \frac{\langle k\rangle^k}{k!} e^{-\langle k\rangle} \left(1 - \frac{\langle k\rangle}{N-1}\right)^{-k} \to \frac{\langle k\rangle^k}{k!} e^{-\langle k\rangle}$$

▶ This is a Poisson distribution (\boxplus) with mean $\langle k \rangle$.

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- So... standard random networks have a Poisson degree distribution
- Generalize to arbitrary degree distribution P_k .
- Also known as the configuration model^[1].
- Can generalize construction method from ER random networks.
- Assign each node a weight w from some distribution P_w and form links with probability

 $P(\text{link between } i \text{ and } j) \propto w_i w_j.$

- But we'll be more interested in
 - Randomly wiring up (and rewiring) already existing nodes with fixed degrees.
 - Examining mechanisms that lead to networks with certain degree distributions.

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 - Randomly wiring up (and rewiring) already existing nodes with fixed degrees.
 - Examining mechanisms that lead to networks with certain degree distributions.

Random Networks

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- So... standard random networks have a Poisson degree distribution
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Coming up:

Example realizations of random networks with power law degree distributions:

- ► *N* = 1000.
- $P_k \propto k^{-\gamma}$ for $k \ge 1$.
- Set $P_0 = 0$ (no isolated nodes).
- Vary exponent γ between 2.10 and 2.91.
- Again, look at full network plus the largest component.
- Apart from degree distribution, wiring is random.

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Random networks: examples for N=1000



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Random Networks

Random networks: largest components











 $\gamma = 2.1$ $\langle k \rangle = 3.448$

 $\gamma = 2.55$

(k) = 1.712

 $\gamma = 2.19$ $\langle k \rangle = 2.986$

 $\gamma = 2.64$

 $\langle k \rangle = 1.6$



 $\gamma = 2.37$ $\langle k \rangle = 2.504$ $\begin{array}{l} \gamma = 2.46 \\ \langle k \rangle = 1.856 \end{array}$









 $\gamma = 2.73$ $\langle k \rangle = 1.862$ $\gamma = 2.82$ $\langle k \rangle = 1.386$ $\gamma = 2.91$ $\langle k \rangle = 1.49$

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Normalization: we must have

$$\sum_{k=0}^{\infty} P(k; \langle k \rangle) = 1$$

► Checking:

$$\sum_{k=0}^{\infty} P(k; \langle k \rangle) = \sum_{k=0}^{\infty} \frac{\langle k \rangle^k}{k!} e^{-\langle k \rangle}$$

$$=e^{-\langle k
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$$=e^{-\langle k
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- The variance of degree distributions for random networks turns out to be very important.
- Use calculation similar to one for finding (k) to find the second moment:

$$\langle k^2 \rangle = \langle k \rangle^2 + \langle k \rangle.$$

Variance is then

 $\sigma^{2} = \langle \boldsymbol{k}^{2} \rangle - \langle \boldsymbol{k} \rangle^{2} = \langle \boldsymbol{k} \rangle^{2} + \langle \boldsymbol{k} \rangle - \langle \boldsymbol{k} \rangle^{2} = \langle \boldsymbol{k} \rangle.$

- So standard deviation σ is equal to $\sqrt{\langle k \rangle}$.
- Note: This is a special property of Poisson distribution and can trip us up...

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- The degree distribution P_k is fundamental for our description of many complex networks
- Again: P_k is the degree of randomly chosen node.
- A second very important distribution arises from choosing randomly on edges rather than on nodes
- ▶ Define Q_k to be the probability the node at a random end of a randomly chosen edge has degree k.
- Now choosing nodes based on their degree (i.e., size):



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 $Q_k = \frac{kP_k}{\sum_{k'=0}^{\infty} k'P_{k'}} = \frac{kP_k}{\langle k \rangle}.$

 $Q_k \propto k P_k$

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- For random networks, Q_k is also the probability that a friend (neighbor) of a random node has k friends.
- Useful variant on Q_k :

 R_k = probability that a friend of a random node has k other friends.

$$R_{k} = \frac{(k+1)P_{k+1}}{\sum_{k'=0}(k'+1)P_{k'+1}} = \frac{(k+1)P_{k+1}}{\langle k \rangle}$$

- Equivalent to friend having degree k + 1.
- Natural question: what's the expected number of other friends that one friend has?

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Frame 42/89

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$$\langle \mathbf{k} \rangle_{\mathbf{R}} = \sum_{k=0}^{\infty} \mathbf{k} \mathbf{R}_{k} = \sum_{k=0}^{\infty} k \frac{(k+1)P_{k-1}}{\langle k \rangle}$$
$$= \frac{1}{\langle k \rangle} \sum_{k=1}^{\infty} k(k+1)P_{k+1}$$

$$=\frac{1}{\langle k\rangle}\sum_{k=1}^{\infty}\left((k+1)^2-(k+1)\right)P_{k+1}$$

(where we have sneakily matched up indices)

$$=rac{1}{\langle k
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 (using j = k+1)

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- ► Note: our result, \langle k \rangle_R = \frac{1}{\langle k \rangle} \left(\langle k^2 \rangle \langle k \rangle \right), is true for all random networks, independent of degree distribution.
- For standard random networks, recall

$$\langle k^2 \rangle = \langle k \rangle^2 + \langle k \rangle.$$

► Therefore:

$$\langle k \rangle_R = \frac{1}{\langle k \rangle} \left(\langle k \rangle^2 + \langle k \rangle - \langle k \rangle \right) = \langle k \rangle$$

- Again, neatness of results is a special property of the Poisson distribution.
- So friends on average have $\langle k \rangle$ other friends, and $\langle k \rangle + 1$ total friends...

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Reason #1:

Average # friends of friends per node is

$$\langle \mathbf{k}_2 \rangle = \langle \mathbf{k} \rangle \times \langle \mathbf{k} \rangle_{\mathbf{R}} = \langle \mathbf{k} \rangle \frac{1}{\langle \mathbf{k} \rangle} \left(\langle \mathbf{k}^2 \rangle - \langle \mathbf{k} \rangle \right) = \langle \mathbf{k}^2 \rangle - \langle \mathbf{k} \rangle.$$

- Key: Average depends on the 1st and 2nd moments of P_k and not just the 1st moment.
- ► Three peculiarities:
 - 1. We might guess $\langle k_2 \rangle = \langle k \rangle (\langle k \rangle 1)$ but it's actually $\langle k(k-1) \rangle$.
 - 2. If P_k has a large second moment, then $\langle k_2 \rangle$ will be big.
 - (e.g., in the case of a power-law distribution)
 - 3. Your friends are different to you...

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Reason #1:

Average # friends of friends per node is

$$\langle \mathbf{k}_2 \rangle = \langle \mathbf{k} \rangle \times \langle \mathbf{k} \rangle_{\mathbf{R}} = \langle \mathbf{k} \rangle \frac{1}{\langle \mathbf{k} \rangle} \left(\langle \mathbf{k}^2 \rangle - \langle \mathbf{k} \rangle \right) = \langle \mathbf{k}^2 \rangle - \langle \mathbf{k} \rangle.$$

- Key: Average depends on the 1st and 2nd moments of P_k and not just the 1st moment.
- Three peculiarities:
 - 1. We might guess $\langle k_2 \rangle = \langle k \rangle (\langle k \rangle 1)$ but it's actually $\langle k(k-1) \rangle$.
 - If *P_k* has a large second moment, then ⟨*k*₂⟩ will be big. (e.g., in the case of a power-law distribution)
 Your friends are different to you

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 - 3. Your friends are different to you...

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More on peculiarity #3:

A node's average # of friends: (k)

- Friend's average # of friends: $\frac{\langle k^2 \rangle}{\langle k \rangle}$
- ► Comparison:

$$\frac{\langle k^2 \rangle}{\langle k \rangle} = \langle k \rangle \frac{\langle k^2 \rangle}{\langle k \rangle^2} = \langle k \rangle \frac{\sigma^2 + \langle k \rangle^2}{\langle k \rangle^2} = \langle k \rangle \left(1 + \frac{\sigma^2}{\langle k \rangle^2} \right)$$

- So only if everyone has the same degree (variance= σ² = 0) can a node be the same as it friends.
- Intuition: for random networks, the more connected a node, the more likely it is to be chosen as a friend.

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(Big) Reason #2:

- ⟨k⟩_R is key to understanding how well random networks are connected together.
- e.g., we'd like to know what's the size of the largest component within a network.
- As N → ∞, does our network have a giant component?
- Defn: Component = connected subnetwork of nodes such that ∃ path between each pair of nodes in the subnetwork, and no node outside of the subnetwork is connected to it.
- ▶ Defn: Giant component = component that comprises a non-zero fraction of a network as $N \rightarrow \infty$.
- Note: Component = Cluster

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Giant component:

- A giant component exists if when we follow a random edge, we are likely to hit a node with at least 1 other outgoing edge.
- Equivalently, expect exponential growth in node number as we move out from a random node.
- All of this is the same as requiring $\langle k \rangle_R > 1$.
- Giant component condition (or percolation condition):

$$\langle k \rangle_R = rac{\langle k^2
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- Again, see that the second moment is an essential part of the story.
- Equivalent statement: $\langle k^2 \rangle > 2 \langle k \rangle$

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- Equivalent statement: (k²) > 2(k)

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SQC.

Standard random networks:

• Recall
$$\langle k^2 \rangle = \langle k \rangle^2 + \langle k \rangle$$
.

Condition for giant component:

$$\langle k \rangle_R = \frac{\langle k^2 \rangle - \langle k \rangle}{\langle k \rangle} = \frac{\langle k \rangle^2 + \langle k \rangle - \langle k \rangle}{\langle k \rangle} = \langle k \rangle$$

- ► Therefore when ⟨k⟩ > 1, standard random networks have a giant component.
- When $\langle k \rangle < 1$, all components are finite.
- Fine example of a continuous phase transition (\boxplus) .
- We say $\langle k \rangle = 1$ marks the critical point of the system.

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Standard random networks:

• Recall
$$\langle k^2 \rangle = \langle k \rangle^2 + \langle k \rangle$$
.

Condition for giant component:

$$\langle k \rangle_R = \frac{\langle k^2 \rangle - \langle k \rangle}{\langle k \rangle} = \frac{\langle k \rangle^2 + \langle k \rangle - \langle k \rangle}{\langle k \rangle} = \langle k \rangle$$

- ► Therefore when ⟨k⟩ > 1, standard random networks have a giant component.
- When $\langle k \rangle < 1$, all components are finite.
- Fine example of a continuous phase transition (\boxplus) .
- We say $\langle k \rangle = 1$ marks the critical point of the system.

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Random networks with skewed P_k :

• e.g, if $P_k = ck^{-\gamma}$ with 2 < γ < 3 then

$$\langle k^2
angle = c \sum_{k=0}^{\infty} k^2 k^{-\gamma}$$

$$\sim \int_{x=0}^{\infty} x^{2-\gamma} \mathrm{d}x$$

$$\propto x^{3-\gamma}\Big|_{x=0}^{\infty} = \infty \quad (>\langle k \rangle).$$

- So giant component always exists for these kinds of networks.
- ► Cutoff scaling is k⁻³: if γ > 3 then we have to look harder at ⟨k⟩_R.

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And how big is the largest component?

- Define S₁ as the size of the largest component.
- Consider an infinite ER random network with average degree (k).
- ▶ Let's find S₁ with a back-of-the-envelope argument.
- Define δ as the probability that a randomly chosen node does not belong to the largest component.
- Simple connection: $\delta = 1 S_1$.
- Dirty trick: If a randomly chosen node is not part of the largest component, then none of its neighbors are.
- ► So

$$\delta = \sum_{k=0}^{\infty} \boldsymbol{P}_k \delta^k$$

Substitute in Poisson distribution...

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Carrying on:



$$=e^{-\langle k
angle}\sum_{k=0}^{\infty}rac{(\langle k
angle\delta)^k}{k!}$$

$$= e^{-\langle k
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angle \delta} = e^{-\langle k
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▶ Now substitute in $\delta = 1 - S_1$ and rearrange to obtain:

$$S_1 = 1 - e^{-\langle k \rangle S_1}$$

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$$\delta = \sum_{k=0}^{\infty} P_k \delta^k = \sum_{k=0}^{\infty} \frac{\langle k \rangle^k}{k!} e^{-\langle k \rangle} \delta^k$$

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Frame 53/89

We can figure out some limits and details for S₁ = 1 − e^{-⟨k⟩S₁}.

First, we can write $\langle k \rangle$ in terms of S_1 :

$$\langle k \rangle = \frac{1}{S_1} \ln \frac{1}{1 - S_1}$$

• As
$$\langle k \rangle \rightarrow 0$$
, $S_1 \rightarrow 0$.

• As
$$\langle k \rangle \to \infty$$
, $S_1 \to 1$.

• Notice that at $\langle k \rangle = 1$, the critical point, $S_1 = 0$.

- Only solvable for S > 0 when $\langle k \rangle > 1$
- Really a transcritical bifurcation^[2].

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Turns out we were lucky ...

- Our dirty trick only works for ER random networks.
- The problem: We assumed that neighbors have the same probability δ of belonging to the largest component.
- But we know our friends are different from us...
- Works for ER random networks because $\langle k \rangle = \langle k \rangle_R$.
- We need a separate probability δ' for the chance that a node at the end of a random edge is part of the largest component.
- We can do this but we need to enhance our toolkit with Generatingfunctionology...^[3]
- (Well, not really but it's fun and we get all sorts of other things...)

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- Works for ER random networks because $\langle k \rangle = \langle k \rangle_R$.
- We need a separate probability δ' for the chance that a node at the end of a random edge is part of the largest component.
- We can do this but we need to enhance our toolkit with Generatingfunctionology...^[3]
- (Well, not really but it's fun and we get all sorts of other things...)

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- Idea: Given a sequence a₀, a₁, a₂,..., associate each element with a distinct function or other mathematical object.
- Well-chosen functions allow us to manipulate sequences and retrieve sequence elements.

Definition:

• The generating function (g.f.) for a sequence $\{a_n\}$ is

$$F(x) = \sum_{n=0}^{\infty} a_n x^n.$$

- Roughly: transforms a vector in R[∞] into a function defined on R¹.
- Related to Fourier, Laplace, Mellin, ...

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Frame 58/89

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Simple example

Rolling dice:

$$F^{(\Box)}(x) = \sum_{k=1}^{6} p_k x^k = \frac{1}{6} (x + x^2 + x^3 + x^4 + x^5 + x^6).$$

We'll come back to this simple example as we derive various delicious properties of generating functions.

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Take a degree distribution with exponential decay:

$$P_k = c e^{-\lambda k}$$

where $c = 1 - e^{-\lambda}$.

The generating function for this distribution is

$$F(x) = \sum_{k=0}^{\infty} P_k x^k = \sum_{k=0}^{\infty} c e^{-\lambda k} x^k = \frac{c}{1 - x e^{-\lambda k}}$$

- Notice that $F(1) = c/(1 e^{-\lambda}) = 1$.
- For probability distributions, we must always have F(1) = 1 since

$$F(1) = \sum_{k=0}^{\infty} P_k 1^k = \sum_{k=0}^{\infty} P_k = 1$$

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Average degree:

$$\langle \mathbf{k} \rangle = \sum_{k=0}^{\infty} \mathbf{k} \mathbf{P}_{\mathbf{k}} = \sum_{k=0}^{\infty} \mathbf{k} \mathbf{P}_{k} x^{k-1} \bigg|_{x=1}$$
$$= \frac{d}{dx} F(x) \bigg|_{x=1} = F'(1)$$

- In general, many calculations become simple, if a little abstract.
- For our exponential example:

$$F'(x) = \frac{(1 - e^{-\lambda})e^{-\lambda}}{(1 - xe^{-\lambda})^2}.$$

So:

$$\langle k \rangle = F'(1) = rac{e^{-\lambda}}{(1-e^{-\lambda})}.$$

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Useful pieces for probability distributions:

Normalization:

First moment:

$$\langle k \rangle = F'(1)$$

► Higher moments:

$$\langle k^n \rangle = \left(x \frac{\mathrm{d}}{\mathrm{d}x} \right)^n F(x) \Big|_{x=1}$$

kth element of sequence (general):

$$P_k = \frac{1}{k!} \frac{\mathrm{d}^k}{\mathrm{d}x^k} F(x) \Big|_{x=1}$$

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Useful pieces for probability distributions:

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F(1) = 1

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Edge-degree distribution

Recall our condition for a giant component:

$$\langle k \rangle_R = \frac{\langle k^2 \rangle - \langle k \rangle}{\langle k \rangle} > 1$$

- We first need the g.f. for R_k .
- We'll now use this notation:

 $F_P(x)$ is the g.f. for P_k . $F_B(x)$ is the g.f. for R_k .

Condition in terms of g.f. is:

 $\langle k \rangle_R = F'_R(1) > 1.$

▶ Now find how *F_R* is related to *F_P*...

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Condition in terms of g.f. is:

 $\langle k \rangle_R = F'_R(1) > 1.$

▶ Now find how *F_R* is related to *F_P*...

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Recall our condition for a giant component:

$$\langle k \rangle_R = \frac{\langle k^2 \rangle - \langle k \rangle}{\langle k \rangle} > 1$$

- We first need the g.f. for R_k .
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We have

$$F_{R}(x) = \sum_{k=0}^{\infty} \frac{R_{k}x^{k}}{k} = \sum_{k=0}^{\infty} \frac{(k+1)P_{k+1}}{\langle k \rangle} x^{k}.$$

Shift index to j = k + 1 and pull out $\frac{1}{\langle k \rangle}$:

$$F_R(x) = \frac{1}{\langle k \rangle} \sum_{j=1}^{\infty} j P_j x^{j-1} = \frac{1}{\langle k \rangle} \sum_{j=1}^{\infty} P_j \frac{\mathrm{d}}{\mathrm{d}x} x^j$$

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References

- Recall giant component condition is $\langle k \rangle_R = F'_R(1) > 1.$
- Since we have $F_R(x) = F'_P(x)/F'_P(1)$,





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- Since we have $F_R(x) = F'_P(x)/F'_P(1)$,

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Setting x = 1, our condition becomes



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$$rac{F_P''(1)}{F_P'(1)} > 1$$

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To figure out the size of the largest component (S_1) , we need more resolution on component sizes.

Definitions:

- π_n = probability that a random node belongs to a finite component of size n < ∞.</p>
- ρ_n = probability a random link leads to a finite subcomponent of size n < ∞.</p>

Local-global connection:

 $P_k, R_k \Leftrightarrow \pi_n,
ho_n$ neighbors \Leftrightarrow components

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G.f.'s for component size distributions:

$$F_{\pi}(x) = \sum_{n=0}^{\infty} \pi_n x^n$$
 and $F_{\rho}(x) = \sum_{n=0}^{\infty} \rho_n x^n$

The largest component:

Subtle key: F_π(1) is the probability that a node belongs to a finite component.

• Therefore:
$$S_1 = 1 - F_{\pi}(1)$$
.

Our mission, which we accept:

Find the four generating functions

 F_P, F_R, F_π , and F_ρ .

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Sneaky Result 1:

- Consider two random variables U and V whose values may be 0, 1, 2, ...
- ► Write probability distributions as U_k and V_k and g.f.'s as F_U and F_V.
- SR1: If a third random variable is defined as

$$W = \sum_{i=1}^{U} V^{(i)}$$
 with each $V^{(i)} \stackrel{d}{=} V$

then

$$F_W(x) = F_U(F_V(x))$$

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References
Write probability that variable W has value k as W_k .

 $W_k = \sum_{j=0} U_j \times \Pr(\text{sum of } j \text{ draws of variable } V = k)$

$$= \sum_{j=0}^{\infty} U_j \sum_{\substack{\{i_1, i_2, \dots, i_j\} \mid \\ i_1 + i_2 + \dots + i_j = k}} V_{i_1} V_{i_2} \cdots V_{i_j}$$

$$\therefore F_{W}(x) = \sum_{k=0}^{\infty} W_{k} x^{k} = \sum_{k=0}^{\infty} \sum_{j=0}^{\infty} U_{j} \sum_{\substack{\{i_{1}, i_{2}, \dots, i_{j}\} \mid \\ i_{1}+i_{2}+\dots+i_{j}=k}} V_{i_{1}} V_{i_{2}} \cdots V_{i_{j}} x^{k}$$

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References

Write probability that variable *W* has value *k* as W_k .

~

$$W_k = \sum_{j=0}^{\infty} U_j imes ext{Pr}(ext{sum of } j ext{ draws of variable } V = k)$$

$$=\sum_{j=0}^{\infty} U_{j} \sum_{\substack{\{i_{1},i_{2},...,i_{j}\} \mid \\ i_{1}+i_{2}+...+i_{j}=k}} V_{i_{1}} V_{i_{2}} \cdots V_{i_{j}}$$

$$\therefore F_{W}(x) = \sum_{k=0}^{\infty} W_{k} x^{k} = \sum_{k=0}^{\infty} \sum_{j=0}^{\infty} U_{j} \sum_{\substack{\{i_{1}, i_{2}, \dots, i_{j}\} \mid \\ i_{1}+i_{2}+\dots+i_{j}=k}} V_{i_{1}} V_{i_{2}} \cdots V_{i_{j}} x^{k}$$

$$= \sum_{j=0}^{\infty} U_j \sum_{k=0}^{\infty} \sum_{\substack{\{i_1, i_2, \dots, i_j\} \mid \\ i_1 + i_2 + \dots + i_j = k}} V_{i_1} x^{i_1} V_{i_2} x^{i_2} \cdots V_{i_j} x^{i_j}$$

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With some concentration, observe:

$$F_{W}(x) = \sum_{j=0}^{\infty} U_{j} \sum_{k=0}^{\infty} \sum_{\substack{\{i_{1},i_{2},...,i_{j}\} \mid \\ i_{1}+i_{2}+...+i_{j}=k}} V_{i_{1}} x^{i_{1}} V_{i_{2}} x^{i_{2}} \cdots V_{i_{j}} x^{i_{j}}}{x^{k} \text{ piece of } \left(\sum_{i'=0}^{\infty} V_{i'} x^{i'}\right)^{j}}$$

$$=\sum_{j=0}^{\infty} U_j (F_V(x))^j$$
$$=F_U (F_V(x)) \checkmark$$

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- Start with a random variable U with distribution U_k (k = 0, 1, 2, ...)
- SR2: If a second random variable is defined as

V = U + 1 then $F_V(x) = xF_U(x)$

• Reason: $V_k = U_{k-1}$ for $k \ge 1$ and $V_0 = 0$.

$$\therefore F_V(x) = \sum_{k=0}^{\infty} V_k x^k = \sum_{k=1}^{\infty} U_{k-1} x^k$$
$$= x \sum_{k=0}^{\infty} U_j x^j = x F_U(x) \cdot \sqrt{1-1}$$

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$$= x \sum_{k=0}^{\infty} U_{i} x^{j} = x F_{U}(x) \sqrt{1-x^{k}}$$

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Generalization of SR2:

▶ (1) If V = U + i then

 $F_V(x) = x^i F_U(x).$

▶ (2) If V = U - i then

 $F_V(x) = x^{-i} F_U(x)$



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- Goal: figure out forms of the component generating functions, *F_π* and *F_ρ*.
- π_n = probability that a random node belongs to a finite component of size *n*

 $\sum_{k=0}^{\infty} P_k \times \Pr\left(\begin{array}{c} \text{sum of sizes of subcomponents} \\ \text{at end of } k \text{ random links} = n-1 \end{array}\right)$

herefore:
$$F_{\pi}(x) = \underbrace{x}_{P}(F_{\rho}(x))$$

Extra factor of x accounts for random node itself.

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Therefore:
$$F_{\pi}(x) = \underbrace{x}_{\text{SP2}} \underbrace{F_{P}(F_{\rho}(x))}_{\text{SP3}}$$

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- *ρ_n* = probability that a random link leads to a finite subcomponent of size *n*.
- ► Invoke one step of recursion: p_n = probability that in following a random edge, the outgoing edges of the node reached lead to finite subcomponents of combined size n − 1,

 $= \sum_{k=0}^{\infty} R_k \times \Pr\left(\begin{array}{c} \text{sum of sizes of subcomponents} \\ \text{at end of } k \text{ random links} = n - 1 \end{array}\right)$

herefore:
$$F_{\rho}(x) = \underbrace{x}_{P_{R}} \underbrace{F_{R}(F_{\rho}(x))}_{P_{R}}$$

 Again, extra factor of x accounts for random node itself.

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- ρ_n = probability that a random link leads to a finite subcomponent of size n.
- ► Invoke one step of recursion: p_n = probability that in following a random edge, the outgoing edges of the node reached lead to finite subcomponents of combined size n − 1,

 $= \sum_{k=0}^{\infty} R_k \times \Pr\left(\begin{array}{c} \text{sum of sizes of subcomponents} \\ \text{at end of } k \text{ random links} = n-1 \end{array}\right)$

herefore:
$$F_{\rho}(x) = \underbrace{x}_{\rho} \underbrace{F_{R}(F_{\rho}(x))}_{\rho}$$

 Again, extra factor of x accounts for random node itself.

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Therefore:
$$F_{\rho}(x) = \underbrace{x}_{P_{R}} \underbrace{F_{R}(F_{\rho}(x))}_{P_{R}}$$

 Again, extra factor of x accounts for random node itself.

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Therefore:
$$F_{\rho}(x) = \underbrace{x}_{\text{SR2}} \underbrace{F_{R}(F_{\rho}(x))}_{\text{SR2}}$$

 Again, extra factor of x accounts for random node itself.

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We now have two functional equations connecting our generating functions:

 $F_{\pi}(x) = xF_{P}(F_{\rho}(x))$ and $F_{\rho}(x) = xF_{R}(F_{\rho}(x))$

- ► Taking stock: We know $F_P(x)$ and $F_R(x) = F'_P(x)/F'_P(1)$.
- We first untangle the second equation to find F_ρ
- We can do this because it only involves F_{ρ} and F_R .
- The first equation then immediately gives us F_π in terms of F_ρ and F_R.

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References

Remembering vaguely what we are doing:

Finding F_{π} to obtain the fractional size of the largest component $S_1 = 1 - F_{\pi}(1)$.

Set x = 1 in our two equations:

 $F_{\pi}(1) = F_{P}(F_{\rho}(1))$ and $F_{\rho}(1) = F_{R}(F_{\rho}(1))$

Solve second equation numerically for *F_ρ*(1).
 Plug *F_ρ*(1) into first equation to obtain *F_π*(1).

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Set x = 1 in our two equations:

 $F_{\pi}(1) = F_{P}(F_{\rho}(1))$ and $F_{\rho}(1) = F_{R}(F_{\rho}(1))$

Solve second equation numerically for *F*_ρ(1).
 Plug *F*_ρ(1) into first equation to obtain *F*_π(1).

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- Plug $F_{\rho}(1)$ into first equation to obtain $F_{\pi}(1)$.

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Example: Standard random graphs.

• We can show
$$F_P(x) = e^{-\langle k \rangle (1-x)}$$

 $\therefore F_R(x) = F'_P(x)/F'_P(1) = e^{-\langle k \rangle (1-x)}/e^{-\langle k \rangle (1-x')}|_{x'}$

 $=e^{-\langle k\rangle(1-x)}=F_P(x)$...aha!

- ► RHS's of our two equations are the same.
 ► So F_π(x) = F_ρ(x) = xF_R(F_ρ(x)) = xF_R(F_π(x))
- Why our dirty (but wrong) trick worked earlier...

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Example: Standard random graphs.

• We can show $F_P(x) = e^{-\langle k \rangle (1-x)}$

$$\therefore F_{\mathcal{B}}(x) = F_{\mathcal{P}}'(x)/F_{\mathcal{P}}'(1) = e^{-\langle k \rangle (1-x)}/e^{-\langle k \rangle (1-x')}|_{x'=1}$$

$$= e^{-\langle k \rangle (1-x)} = F_P(x)$$
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$$1-S_1=e^{-\langle k
angle S_1}$$

Or: $\langle k
angle = rac{1}{S_1} \ln rac{1}{1-S_1}$

▶ Just as we found with our dirty trick

Again, we (usually) have to resort to numerics ...

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References

• We are down to

$$F_{\pi}(x) = xF_{R}(F_{\pi}(x))$$
 and $F_{R}(x) = e^{-\langle k \rangle (1-x)}$.
• $\therefore F_{\pi}(x) = xe^{-\langle k \rangle (1-F_{\pi}(x))}$

We're first after S₁ = 1 − F_π(1) so set x = 1 and replace F_π(1) by 1 − S₁:

$$1-S_1=e^{-\langle k\rangle S_1}$$

Or: $\langle k
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Just as we found with our dirty trick

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- Next: find average size of finite components $\langle n \rangle$.
- Using standard G.F. result: $\langle n \rangle = F'_{\pi}(1)$.
- Try to avoid finding $F_{\pi}(x)$...
- Starting from $F_{\pi}(x) = xF_P(F_{\rho}(x))$, we differentiate:

 $F'_{\pi}(x) = F_{P}\left(F_{\rho}(x)\right) + xF'_{\rho}(x)F'_{P}\left(F_{\rho}(x)\right)$

• While $F_{\rho}(x) = xF_R(F_{\rho}(x))$ gives

 $F'_{\rho}(x) = F_R(F_{\rho}(x)) + xF'_{\rho}(x)F'_R(F_{\rho}(x))$

- Now set x = 1 in both equations.
- We solve the second equation for F'_ρ(1) (we must already have F_ρ(1)).
- ▶ Plug $F'_{\rho}(1)$ and $F_{\rho}(1)$ into first equation to find $F'_{\pi}(1)$.

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- ▶ Plug $F'_{\rho}(1)$ and $F_{\rho}(1)$ into first equation to find $F'_{\pi}(1)$.

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- Using standard G.F. result: $\langle n \rangle = F'_{\pi}(1)$.
- Try to avoid finding $F_{\pi}(x)$...
- Starting from $F_{\pi}(x) = xF_{P}(F_{\rho}(x))$, we differentiate:

$$F'_{\pi}(x) = F_{\mathcal{P}}\left(F_{\rho}(x)\right) + xF'_{\rho}(x)F'_{\mathcal{P}}\left(F_{\rho}(x)\right)$$

• While
$$F_{\rho}(x) = xF_{R}(F_{\rho}(x))$$
 gives

$$F_{
ho}'(x)=F_{R}\left(F_{
ho}(x)
ight)+xF_{
ho}'(x)F_{R}'\left(F_{
ho}(x)
ight)$$

- Now set x = 1 in both equations.
- We solve the second equation for F'_ρ(1) (we must already have F_ρ(1)).
- ▶ Plug $F'_{\rho}(1)$ and $F_{\rho}(1)$ into first equation to find $F'_{\pi}(1)$.

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References

- Next: find average size of finite components $\langle n \rangle$.
- Using standard G.F. result: $\langle n \rangle = F'_{\pi}(1)$.
- Try to avoid finding $F_{\pi}(x)$...
- Starting from $F_{\pi}(x) = xF_{P}(F_{\rho}(x))$, we differentiate:

$$F'_{\pi}(x) = F_{\mathcal{P}}\left(F_{\rho}(x)\right) + xF'_{\rho}(x)F'_{\mathcal{P}}\left(F_{\rho}(x)\right)$$

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Example: Standard random graphs.

• Use fact that $F_P = F_R$ and $F_{\pi} = F_{\rho}$.

Two differentiated equations reduce to only one:

 $F'_{\pi}(x) = F_{P}(F_{\pi}(x)) + xF'_{\pi}(x)F'_{P}(F_{\pi}(x))$

Rearrange:
$$F'_{\pi}(x) = rac{F_{P}(F_{\pi}(x))}{1 - xF'_{P}(F_{\pi}(x))}$$

- Simplify denominator using $F'_P(x) = \langle k \rangle F_P(x)$
- ► Replace $F_P(F_\pi(x))$ using $F_\pi(x) = xF_P(F_\pi(x))$.
- Set x = 1 and replace $F_{\pi}(1)$ with $1 S_1$.

End result:
$$\langle n \rangle = F'_{\pi}(1) = \frac{(1-S_1)}{1-\langle k \rangle(1-S_1)}$$

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- Replace $F_P(F_{\pi}(x))$ using $F_{\pi}(x) = xF_P(F_{\pi}(x))$.
- Set x = 1 and replace $F_{\pi}(1)$ with $1 S_1$.

End result: $\langle n \rangle = F'_{\pi}(1) = \frac{(1-S_1)}{1-\langle k \rangle(1-S_1)}$

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argest component

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Our result for standard random networks:

$$\langle n \rangle = F'_{\pi}(1) = rac{(1-S_1)}{1-\langle k \rangle(1-S_1)}$$

- Recall that (k) = 1 is the critical value of average degree for standard random networks.
- Look at what happens when we increase (k) to 1 from below.
- We have $S_1 = 0$ for all $\langle k \rangle < 1$ so



- This blows up as $\langle k \rangle \rightarrow 1$.
- ► Reason: we have a power law distribution of component sizes at ⟨k⟩ = 1.
- Typical critical point behavior....

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Typical critical point behavior....

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• Limits of $\langle k \rangle = 0$ and ∞ make sense for

$$\langle n \rangle = F'_{\pi}(1) = \frac{(1-S_1)}{1-\langle k \rangle(1-S_1)}$$

• As
$$\langle k \rangle \rightarrow 0$$
, $S_1 = 0$, and $\langle n \rangle \rightarrow 1$

- All nodes are isolated.
- As $\langle k \rangle \to \infty$, $S_1 \to 1$ and $\langle n \rangle \to 0$.
- ▶ No nodes are outside of the giant component.

Extra on largest component size:

- For $\langle k \rangle = 1$, $S_1 \sim N^{2/3}$.
- For $\langle k \rangle < 1$, $S_1 \sim \log N$.

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