

Network Models

Thanks to Jure Leskovec, Stanford and Panayiotis Tsaparas,
Univ. of Ioannina for slides

Agenda

- Erdős-Renyi Random Graph Model
- The Small-World Model
- The Configuration Model
- Power-law distributions
 - Exponential vs Power-law Distributions
 - Scale-free Networks
 - The anatomy of the long-tail
 - Consequence of Power-Law Degrees
- Preferential Attachment Model

Erdős-Renyi Random Graph Model

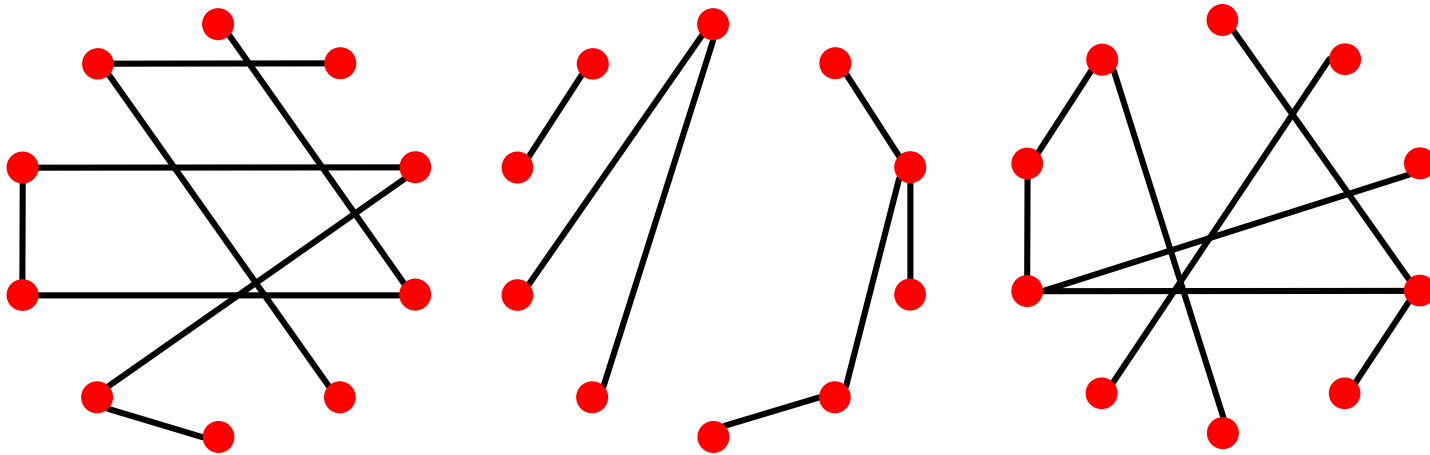
Simplest Model of Graphs

- **Erdős-Renyi Random Graphs** [Erdős-Renyi, '60]
- **Two variants:**
 - $G_{n,p}$: undirected graph on n nodes and each edge (u,v) appears i.i.d. with probability p
 - $G_{n,m}$: undirected graph with n nodes, and m uniformly at random picked edges

What kinds of networks
does such model produce?

Random Graph Model

- n and p do not uniquely determine the graph!
 - The graph is a result of a random process
- We can have many different realizations given the same n and p



$n = 10$
 $p = 1/6$

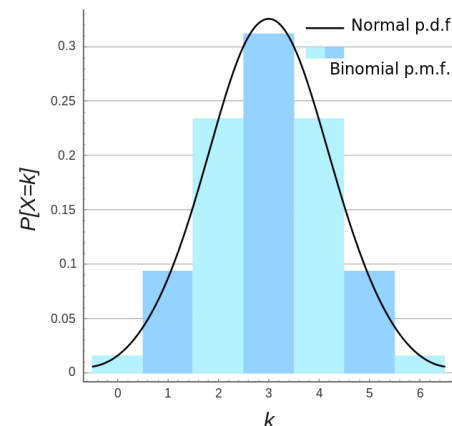
Random Graph Model: Edges

- How likely is a graph on E edges?
- $P(E)$: the probability that a given G_{np} generates a graph on exactly E edges:

$$P(E) = \binom{E_{\max}}{E} p^E (1-p)^{E_{\max}-E}$$

where $E_{\max} = n(n-1)/2$ is the maximum possible number of edges in an undirected graph of n nodes

$P(E)$ is exactly the
Binomial distribution >>>
Number of successes in a sequence of
 $E_{\max}$ independent yes/no experiments



Properties of G_{np}

Degree distribution: $P(k)$

Path length: h

Clustering coefficient: C

What are values of these
properties for G_{np} ?

Node Degrees in a Random Graph

■ What is expected degree of a node?

■ Let X_v be a rnd. var. measuring the degree of node v

■ **We want to know:** $E[X_v] = \sum_{j=0}^{n-1} j P(X_v = j)$

■ **For the calculation we will need: Linearity of expectation**

■ For any random variables $Y_1, Y_2, \dots, Y_k$

■ If $Y = Y_1 + Y_2 + \dots + Y_k$, then $E[Y] = \sum_i E[Y_i]$

■ An easier way:

■ Decompose X_v to $X_v = X_{v,1} + X_{v,2} + \dots + X_{v,n-1}$

■ where $X_{v,u}$ is a $\{0,1\}$ -random variable which tells if edge (v,u) exists or not

$$E[X_v] = \sum_{u=1}^{n-1} E[X_{v,u}] = (n-1)p$$

How to think about this?

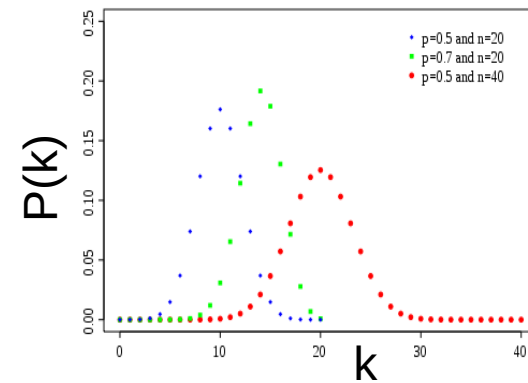
- Prob. of node u linking to node v is p
- u can link (flips a coin) to all other $(n-1)$ nodes
- Thus, the expected degree of node u is: $p(n-1)$

Degree Distribution

- **Fact:** Degree distribution of G_{np} is Binomial.
- Let $P(k)$ denote a fraction of nodes with degree k :

$$P(k) = \binom{n-1}{k} p^k (1-p)^{n-1-k}$$

Select k nodes out of $n-1$ (points to $\binom{n-1}{k}$)
 Probability of having k edges (points to p^k)
 Probability of missing the rest of the $n-1-k$ edges (points to $(1-p)^{n-1-k}$)



Mean, variance of a binomial distribution

$$\bar{k} = p(n-1)$$

$$s^2 = p(1-p)(n-1)$$

$$\frac{s}{\bar{k}} = \frac{1-p}{p} \frac{1}{(n-1)} \frac{1}{p} \gg \frac{1}{(n-1)^{1/2}}$$

By the law of large numbers, as the network size increases, the distribution becomes increasingly narrow—we are increasingly confident that the degree of a node is in the vicinity of $\bar{k}$.

Clustering Coefficient of G_{np}

- **Remember:** $C_i = \frac{2e_i}{k_i(k_i - 1)}$

Where e_i is the number of edges between i 's neighbors

- Edges in G_{np} appear i.i.d. with prob. p

- **So:** $e_i = p \frac{k_i(k_i - 1)}{2}$

Each pair is connected with prob. p

Number of distinct pairs of neighbors of node i of degree k_i

- **Then:** $C_i = \frac{p \cdot k_i(k_i - 1)}{k_i(k_i - 1)} = p = \frac{\bar{k}}{n-1} \approx \frac{\bar{k}}{n}$

Clustering coefficient of a random graph is small.

For a fixed avg. degree (that is $p=1/n$), C decreases with the graph size n .

Network Properties of G_{np}

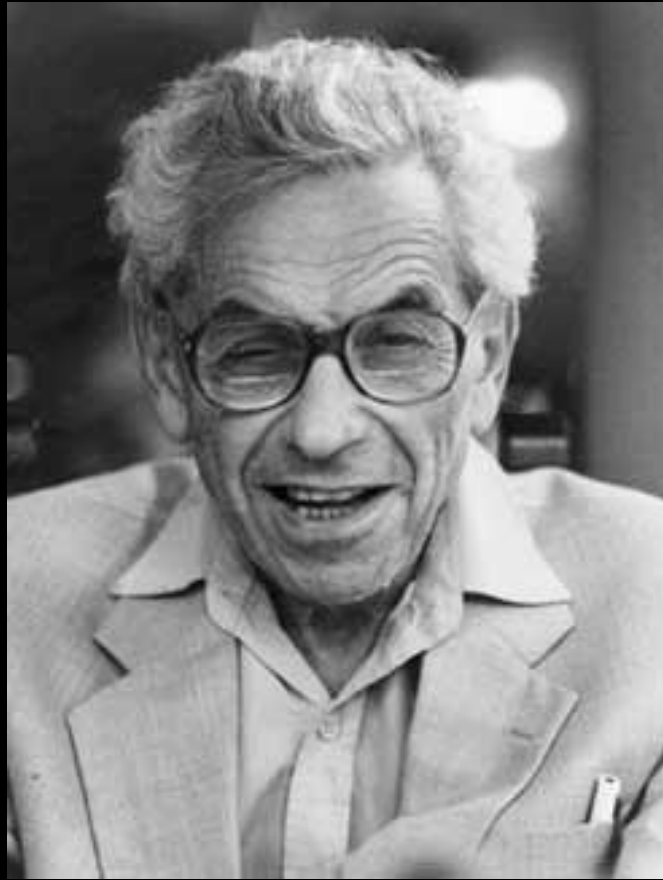
Degree distribution: $P(k) = \binom{n-1}{k} p^k (1-p)^{n-1-k}$

Clustering coefficient: $C = p = \bar{k}/n$

Path length: *next!*

Network Properties of G_{np}

Degree distribution:	$P(k) = \binom{n-1}{k} p^k (1-p)^{n-1-k}$
Clustering coefficient:	$C = p = \bar{k}/n$
Path length:	$O(\log n)$



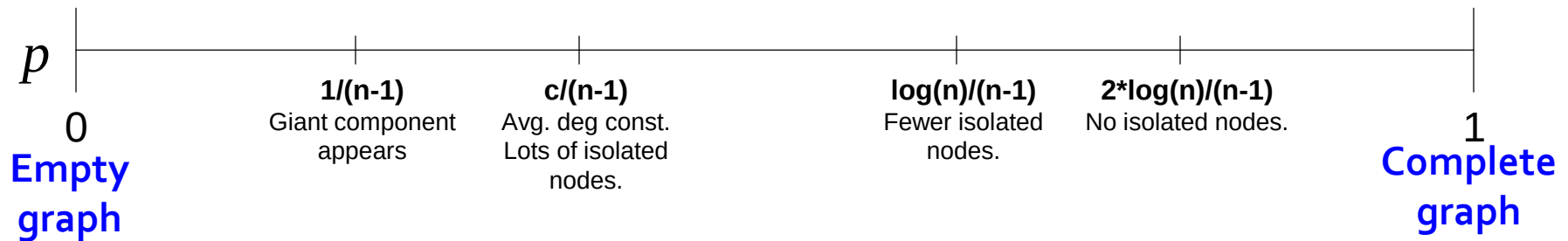
Paul Erdős

G_{np} is so cool!

Let's also look at its evolution

“Evolution” of a Random Graph

■ Graph structure of G_{np} as p changes:

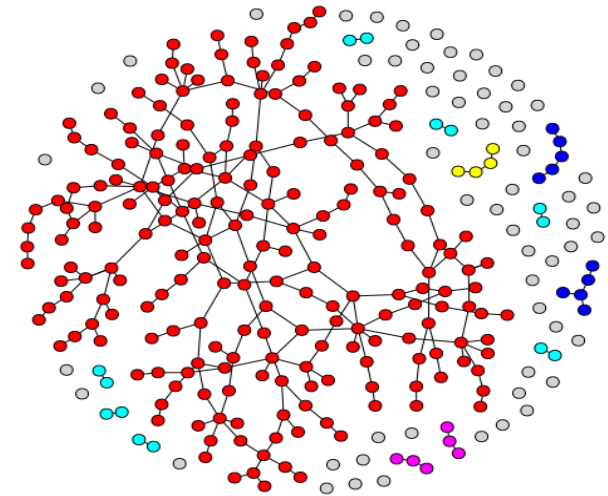
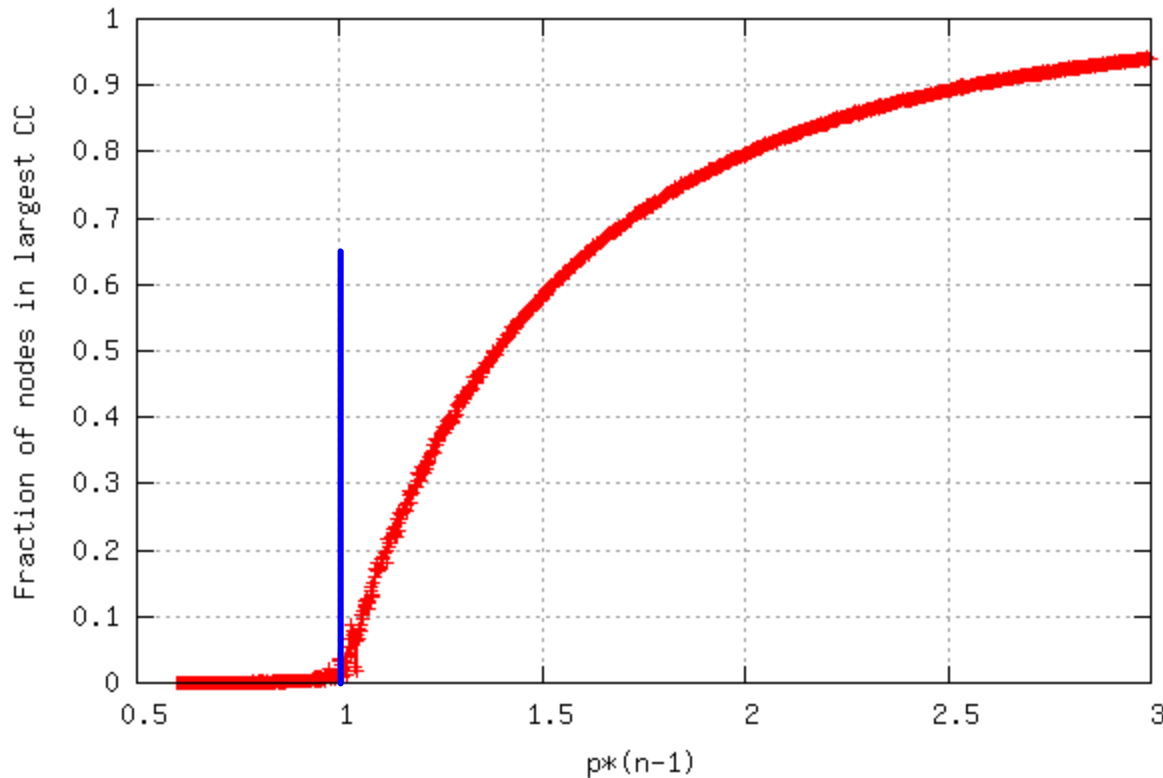


■ Emergence of a Giant Component:

avg. degree $k=2E/n$ or $p=k/(n-1)$

- $k=1-\varepsilon$: all components are of size $\Omega(\log n)$
- $k=1+\varepsilon$: 1 component of size $\Omega(n)$, others have size $\Omega(\log n)$

G_{np} Simulation Experiment



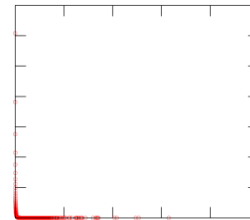
Fraction of nodes in the largest component

- G_{np} , $n=100,000$, $k=p(n-1) = 0.5 \dots 3$

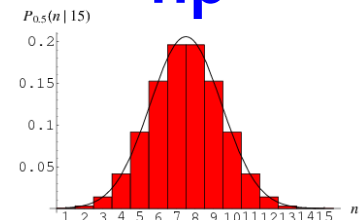
Back to MSN vs. G_{np}

Degree distribution:

MSN



G_{np}



$n=180M$

Path length:

6.6

$O(\log n)$

$h \approx 8.2$



Clustering coefficient: 0.11

$\bar{k} / n$

$C \approx 8 \cdot 10^{-8}$



Connected component: 99%

GCC exists
when $\bar{k} > 1$.

$\bar{k} \approx 14$.



Real Networks vs. G_{np}

- **Are real networks like random graphs?**
 - Average path length: 😊
 - Giant connected component: 😊
 - Clustering Coefficient: 😞
 - Degree Distribution: 😞
- **Problems with the random network model:**
 - Degree distribution differs from that of real networks
 - Giant component in most real networks does NOT emerge through a phase transition
 - No “local” structure – clustering coefficient is too low
- **Most important: Are real networks random?**
 - The answer is simply: **NO!**

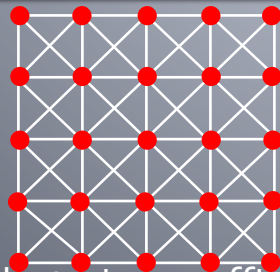
Real Networks vs. G_{np}

- If G_{np} is wrong, why did we spend time on it?
 - It is the reference model for the rest of the class
 - It will help us calculate many quantities, that can then be compared to the real data
 - It will help us understand to what degree is a particular property the result of some random process

So, while G_{np} is WRONG, it will turn out to be extremely USEFUL!

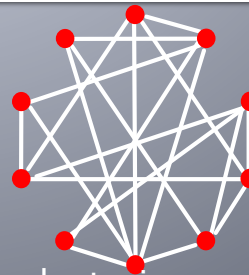
The Small-World Model

Can we have high clustering while also having short paths?



High clustering coefficient,
High diameter

Vs.

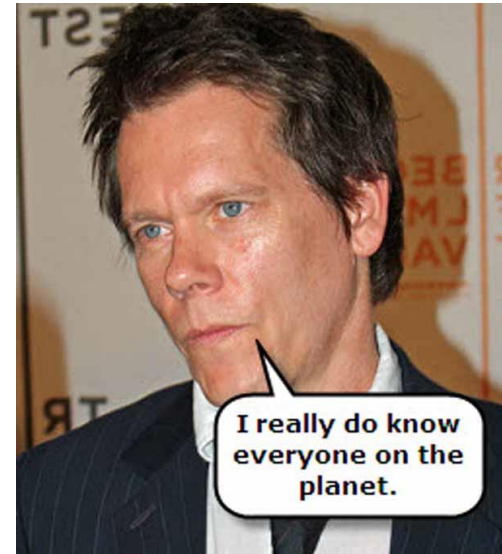


Low clustering coefficient
Low diameter

Six Degrees of Kevin Bacon

Origins of a small-world idea:

- **The Bacon number:**
 - Create a network of Hollywood actors
 - Connect two actors if they co-appeared in the movie
 - **Bacon number:** number of steps to Kevin Bacon
- As of Dec 2007, the highest (finite) Bacon number reported is 8
- Only approx. 12% of all actors cannot be linked to Bacon

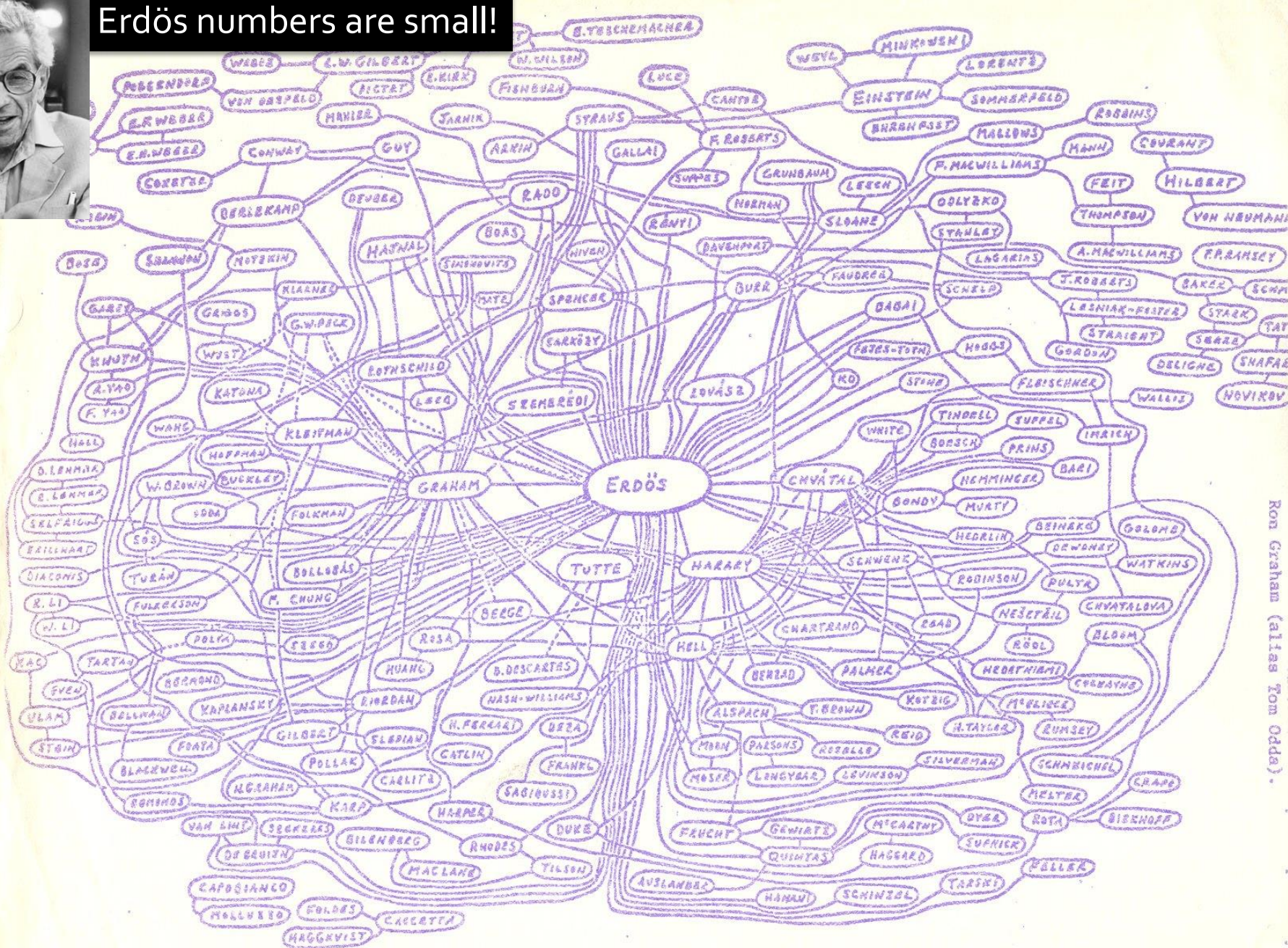


Elvis Presley has a Bacon number of 2.





Erdős numbers are small!



Ron Graham (alias Tom Oda).

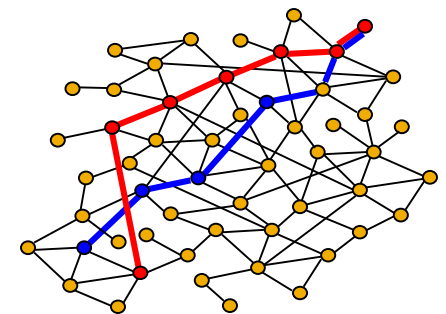


Figure 1
To appear in Topics in Graph Theory (P. Harary, ed.) New York Academy of Sciences (1979).

Find out your Erdos number: <http://www.ams.org/mathscinet/collaborationDistance.html>

The Small-World Experiment

- What is the typical shortest path length between any two people?
 - Experiment on the global friendship network
 - Can't measure, need to probe explicitly
- **Small-world experiment** [Milgram '67]
 - Picked 300 people in Omaha, Nebraska and Wichita, Kansas
 - Ask them to get a letter to a stock-broker in Boston by passing it through friends
- How many steps did it take?

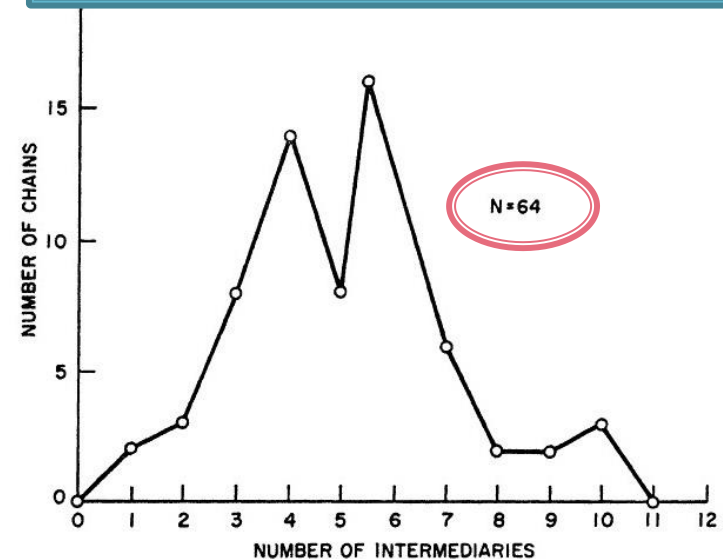


The Small-World Experiment

- **64 chains completed:**
(i.e., 64 letters reached the target)
 - It took 6.2 steps on the average, thus
“6 degrees of separation”

- **Further observations:**
 - People who owned stock had shorter paths to the stockbroker than random people: 5.4 vs. 6.7
 - People from the Boston area have even closer paths: 4.4

Milgram's small world experiment



Milgram: Further Observations

- **Boston vs. occupation networks:**

- **Criticism:**

- **Funneling:**

- 31 of 64 chains passed through 1 of 3 people as their final step → **Not all links/nodes are equal**

- Starting points and the target were non-random

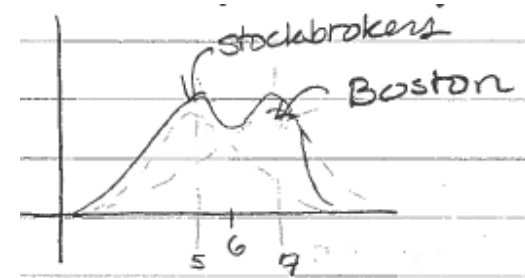
- There are not many samples (only 64)

- People refused to participate (25% for Milgram)

- Not all searches finished (only 64 out of 300)

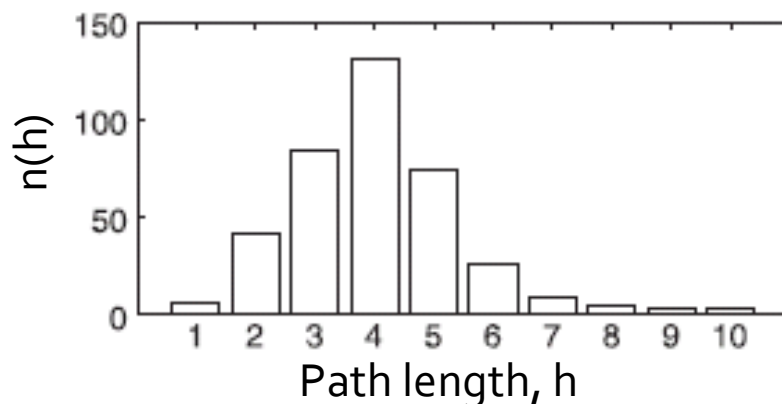
- **Some sort of social search:** People in the experiment follow some strategy instead of forwarding the letter to everyone. **They are not finding the shortest path!**

- People might have used extra information resources



Columbia Small-World Study

- In 2003 Dodds, Muhamad and Watts performed the experiment using e-mail:
 - 18 targets of various backgrounds
 - 24,000 first steps (~1,500 per target)
 - 65% dropout per step
 - 384 chains completed (1.5%)



Avg. chain length = 4.01

Problem: People stop participating

Correction factor: $n^*(h) = \frac{n(h)}{\prod_{i=0}^{h-1} (1 - r_i)}$
 r_i drop-out rate at hop i

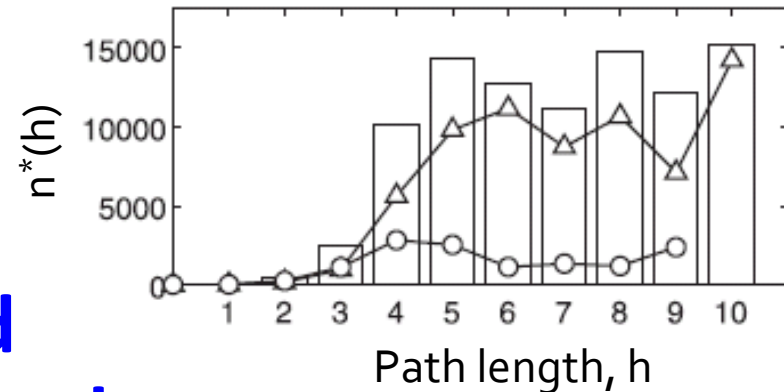
Small-World in Email Study

- **After the correction:**

- Typical path length $h = 7$

- **Some not well understood phenomena in social networks:**

- **Funneling effect:** Some target's friends are more likely to be the final step
 - Conjecture: High reputation/authority
 - **Effects of target's characteristics:** Structurally why are high-status target easier to find
 - Conjecture: Core-periphery network structure



Question

**What is the structure of
a social network?**

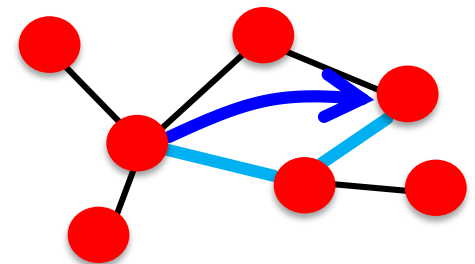
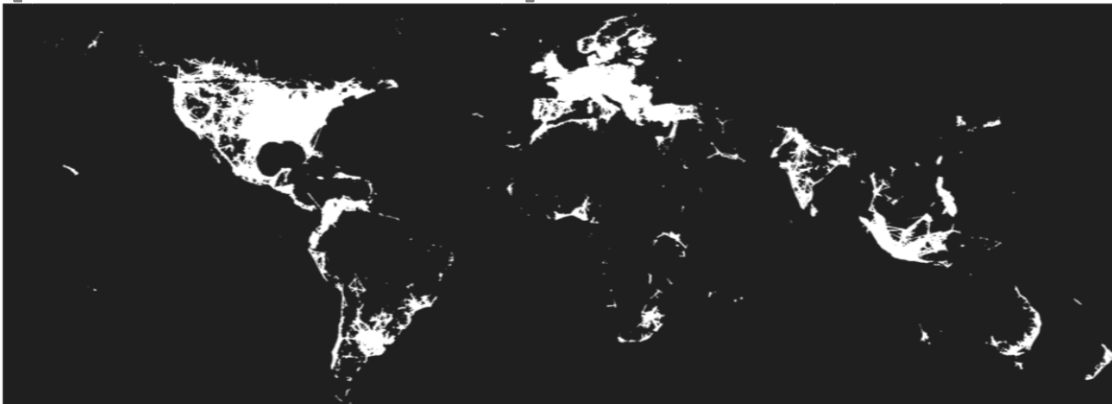
6-Degrees: Should We Be Surprised?

- Assume each human is connected to 100 other people

Then:

- Step 1: reach 100 people
 - Step 2: reach $100 \times 100 = 10,000$ people
 - Step 3: reach $100 \times 100 \times 100 = 1,000,000$ people
 - Step 4: reach $100 \times 100 \times 100 \times 100 = 100\text{M}$ people
 - In 5 steps we can reach 10 billion people
- **What's wrong here?**
- 92% of new FB friendships are to a friend-of-a-friend

[Backstrom-Leskovec '11]



Clustering Implies Edge Locality

- MSN network has 7 orders of magnitude larger clustering than the corresponding G_{np} !
- Other examples:

Actor Collaborations (IMDB): $N = 225,226$ nodes, avg. degree $\bar{k} = 61$

Electrical power grid: $N = 4,941$ nodes, $\bar{k} = 2.67$

Network of neurons: $N = 282$ nodes, $\bar{k} = 14$

Network	h_{actual}	h_{random}	C_{actual}	C_{random}
Film actors	3.65	2.99	0.79	0.00027
Power Grid	18.70	12.40	0.080	0.005
C. elegans	2.65	2.25	0.28	0.05

h ... Average shortest path length

C ... Average clustering coefficient

“actual” ... real network

“random” ... random graph with same avg. degree

The “Controversy”

- **Consequence of expansion:**

- **Short paths: $O(\log n)$**

- This is “best” we can do if we have a constant degree

- But clustering is low!

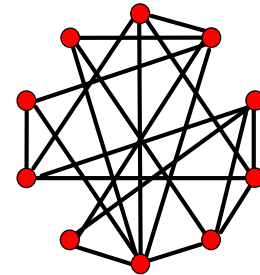
- **But networks have “local” structure:**

- **Triadic closure:**

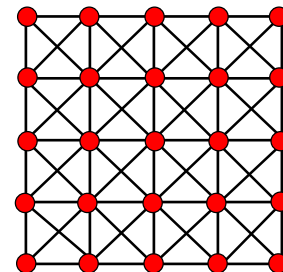
- Friend of a friend is my friend

- High clustering but diameter is also high

- **How can we have both?**



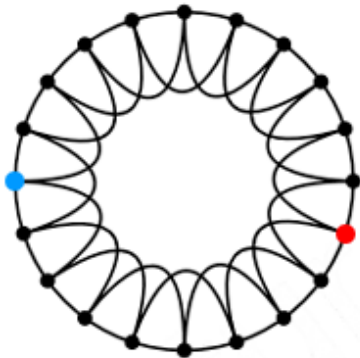
Low diameter
Low clustering coefficient



High clustering coefficient
High diameter

Small-World: How?

- Could a network with high clustering be at the same time a small world?
 - How can we at the same time have **high clustering** and **small diameter**?



High clustering
High diameter



Low clustering
Low diameter

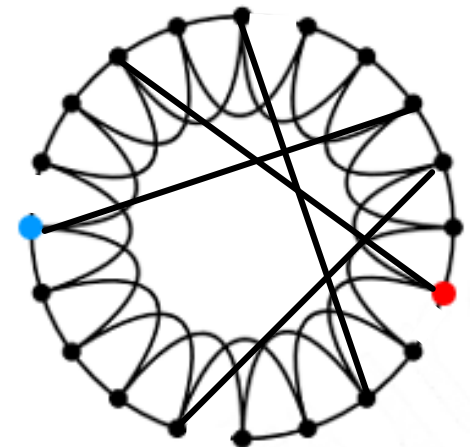
- Clustering implies edge “locality”
- Randomness enables “shortcuts”

Solution: The Small-World Model

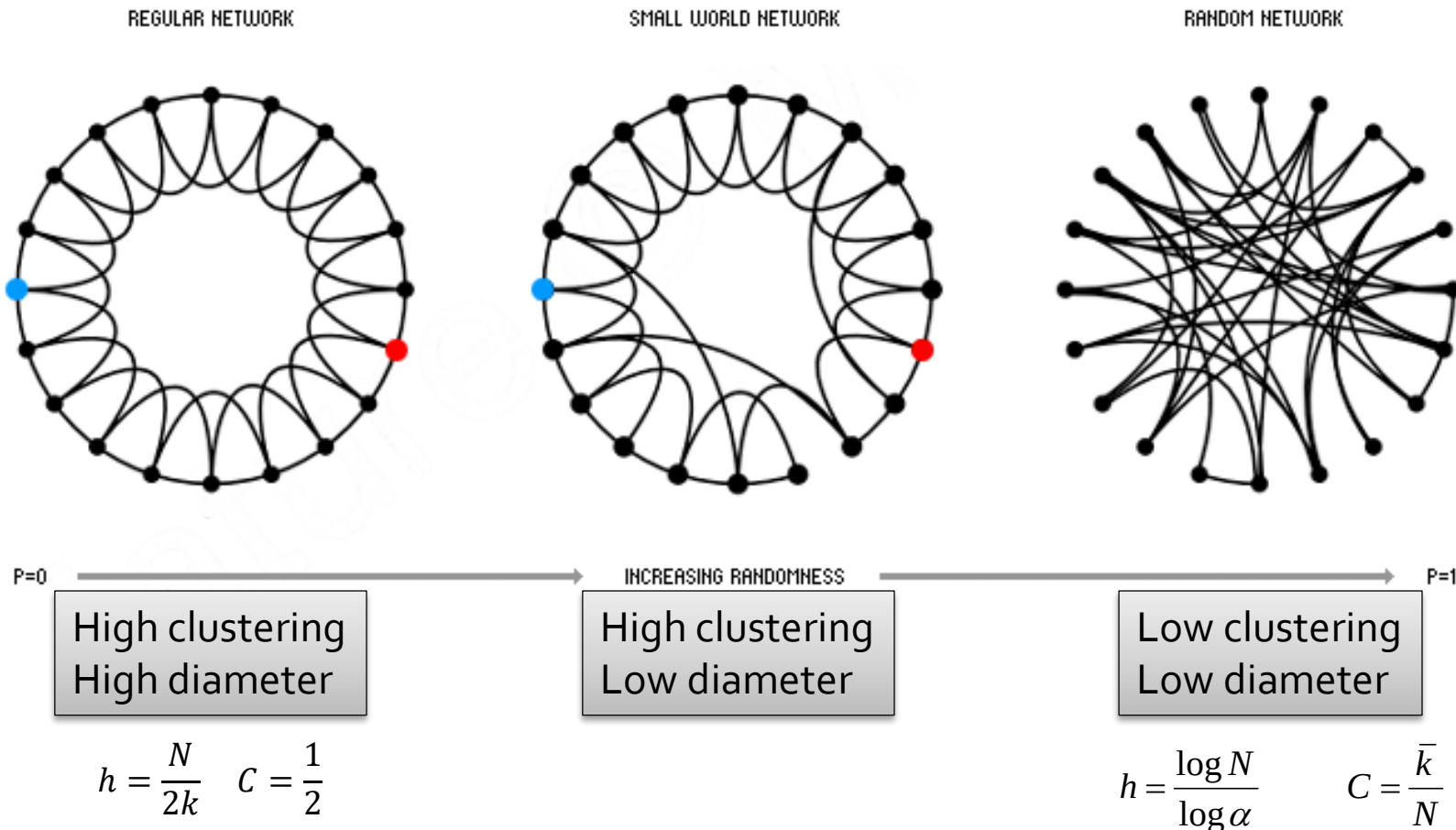
Small-world Model [Watts-Strogatz '98]

Two components to the model:

- **(1)** Start with a **low-dimensional regular lattice**
 - (In our case we use a ring as a lattice)
 - Has high clustering coefficient
- Now introduce randomness (“shortcuts”)
- **(2) Rewire:**
 - Add/remove edges to create shortcuts to join remote parts of the lattice
 - For each edge with prob. p move the other end to a random node

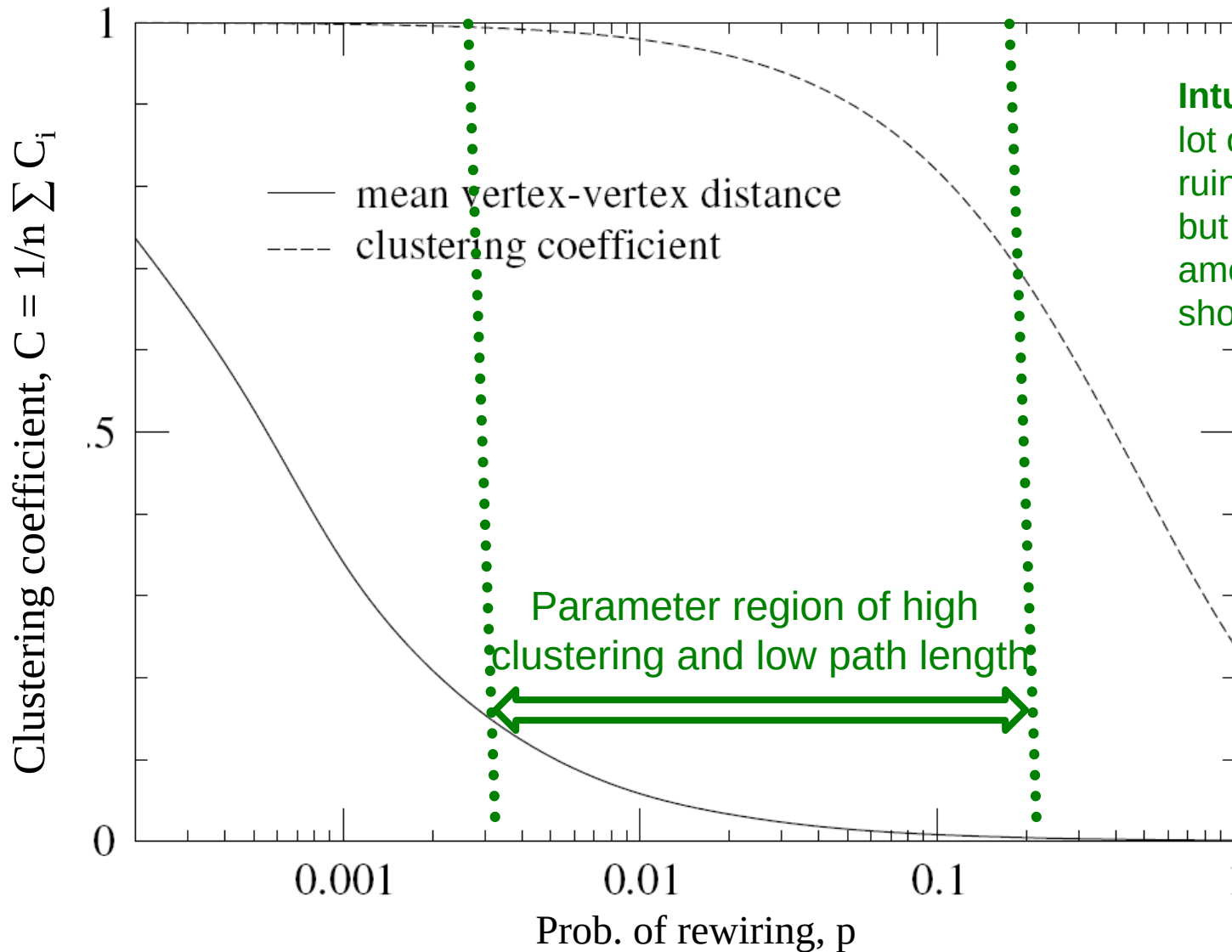


The Small-World Model



Rewiring allows us to “interpolate” between a regular lattice and a random graph

The Small-World Model



Intuition: It takes a lot of randomness to ruin the clustering, but a very small amount to create shortcuts.

Parameter region of high clustering and low path length

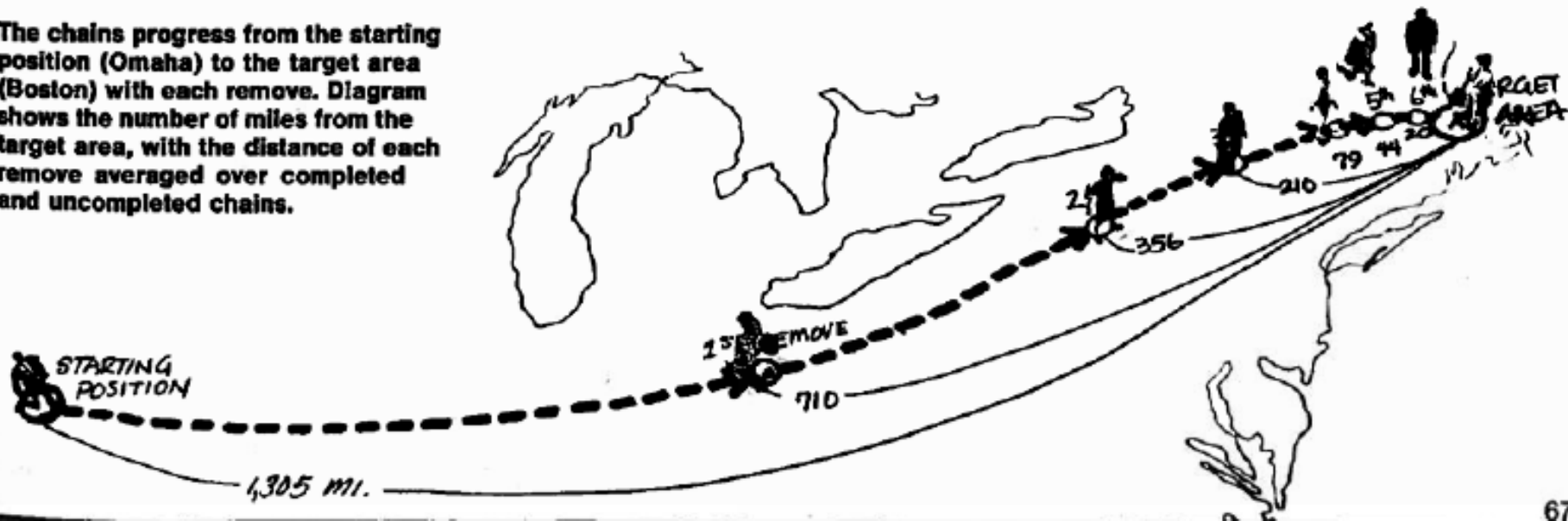
Small-World: Summary

- Could a network with high clustering be at the same time a small world?
 - Yes! You don't need more than a few random links
- **The Watts Strogatz Model:**
 - Provides insight on the interplay between clustering and the small-world
 - Captures the structure of many realistic networks
 - Accounts for the high clustering of real networks
 - Does not lead to the correct degree distribution
 - Does not enable **navigation** (offline lecture)

How to Navigate a Network?

- (offline) What mechanisms do people use to navigate networks and find the target?

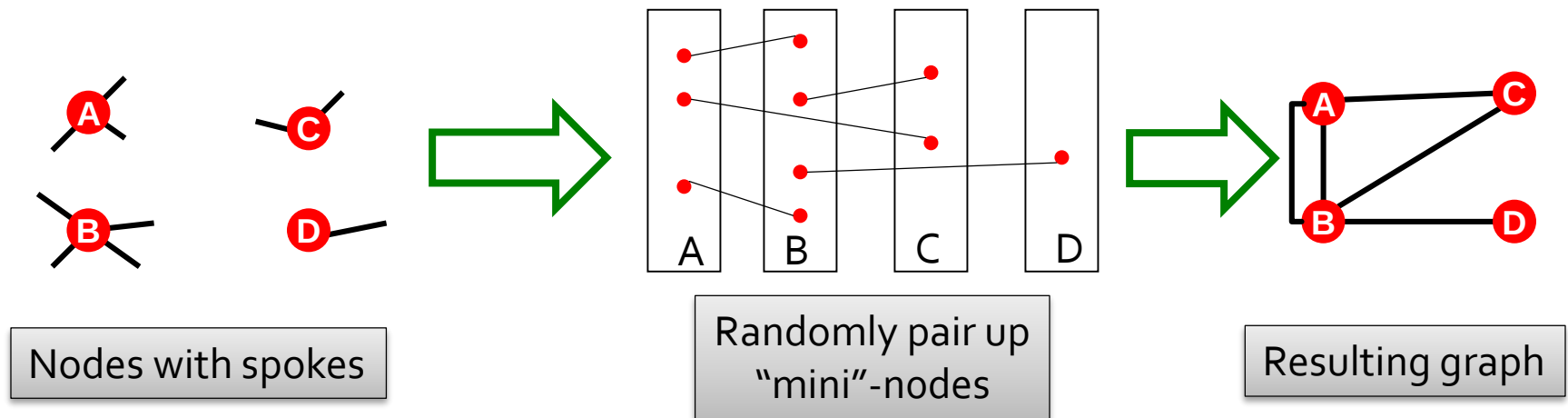
The chains progress from the starting position (Omaha) to the target area (Boston) with each remove. Diagram shows the number of miles from the target area, with the distance of each remove averaged over completed and uncompleted chains.



The Configuration Model

Intermezzo: Configuration Model

- **Goal:** Generate a random graph with a given degree sequence $k_1, k_2, \dots, k_N$
- **Configuration model:**



- **Useful as a “null” model of networks**
 - We can compare the real network G and a “random” G' which has the same degree sequence as G

Another Example

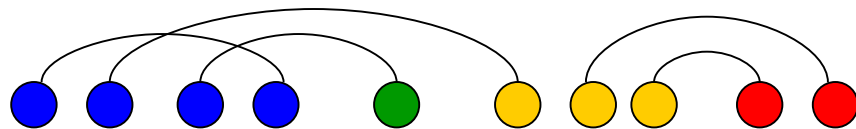
- Suppose that the degree sequence is



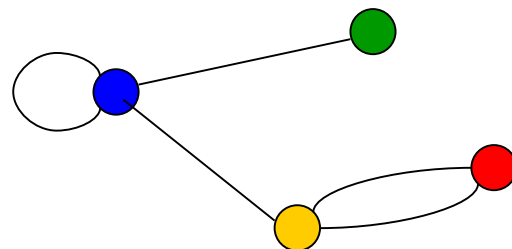
- Create multiple copies of the nodes



- Pair the nodes uniformly at random



- Generate the resulting network



Other Properties

- The **giant component phase transition** for this model happens when

$$\sum_{k=0}^{\infty} k(k-2)p_k = 0$$

p_k : fraction of nodes with degree k

- The **clustering coefficient** is given by

$$C = \frac{1}{n} \frac{(\langle k^2 \rangle - \langle k \rangle)^2}{\langle k \rangle^3}$$

- The **diameter** is logarithmic

Power-Law Degree Distributions

Thanks to Jure Leskovec, Stanford and Panayiotis Tsaparas, Univ. of Ioannina for slides

Agenda

- Power-law distributions
 - Exponential vs Power-law Distributions
 - Scale-free Networks
 - The anatomy of the long-tail
- Mathematics of Power-laws
- Estimating Power-law Exponent Alpha
- Consequence of Power-Law Degrees

Network Formation Processes

What do we observe that needs explaining

- **Small-world model?**

- Diameter
- Clustering coefficient

- **Preferential Attachment:**

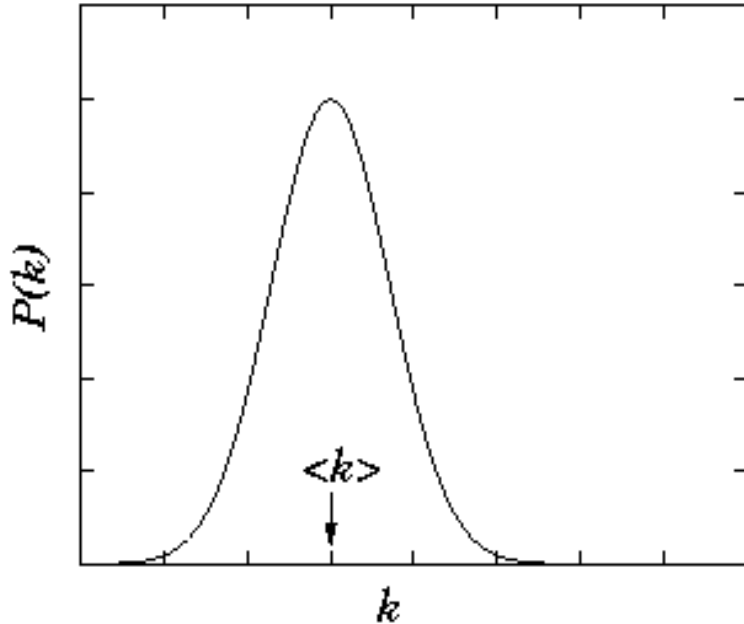
- **Node degree distribution**

- What fraction of nodes has degree k (as a function of k)?
- Prediction from simple random graph models:
 $p(k) = \text{exponential function of } k$
- **Observation: Often a power-law:** $p(k) = k^{-\alpha}$

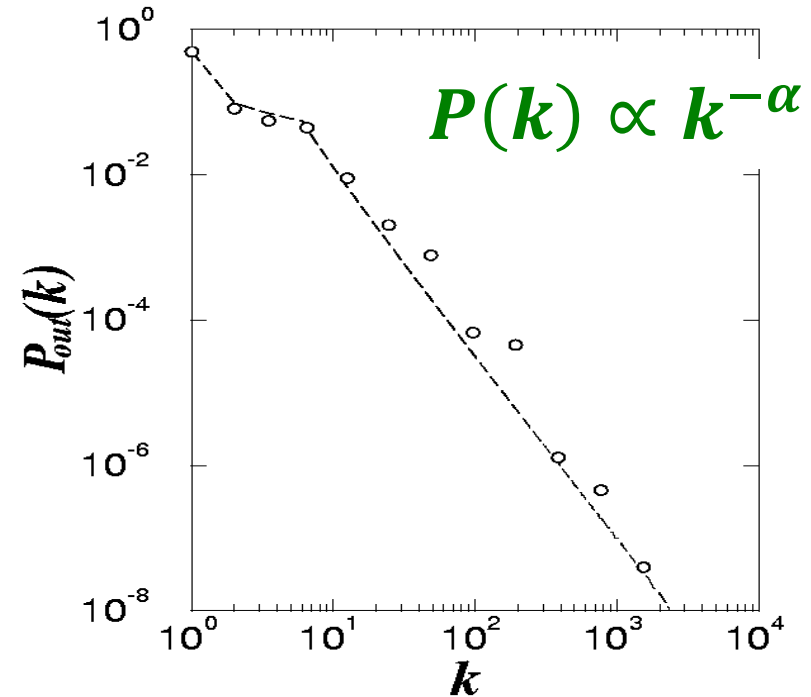


Degree Distributions

Expected based on G_{np}

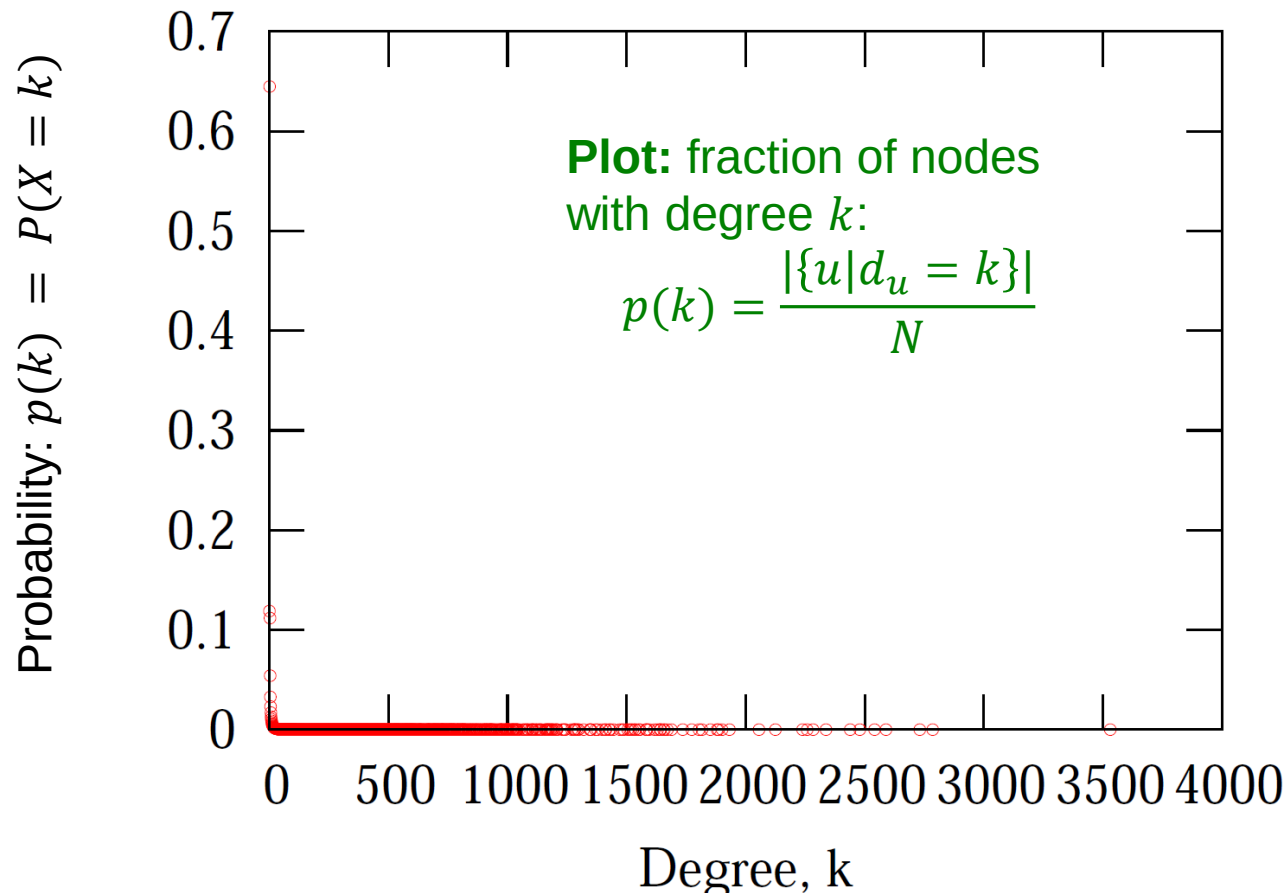


Found in data



Node Degrees in Networks

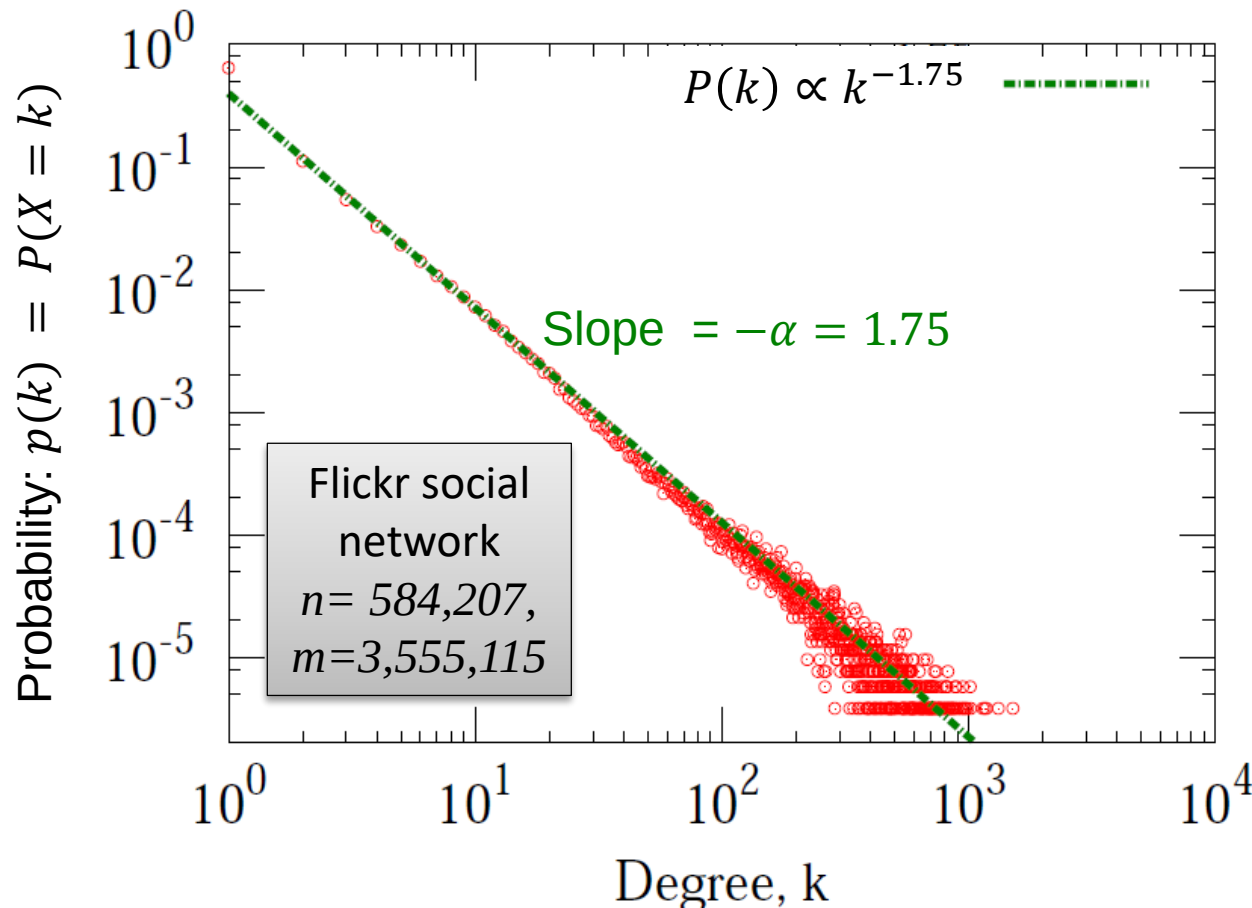
- Take a network, plot a histogram of $P(k)$ vs. k



Flickr social network
 $n = 584,207$,
 $m = 3,555,115$

Node Degrees in Networks

- Plot the same data on *log-log* scale:



How to distinguish:

$P(k) \propto \exp(-k)$ vs.

$P(k) \propto k^{-\alpha}$?

Take logarithms:

if $y = f(x) = e^{-x}$ then

$$\log(y) = -x$$

If $y = x^{-\alpha}$ then

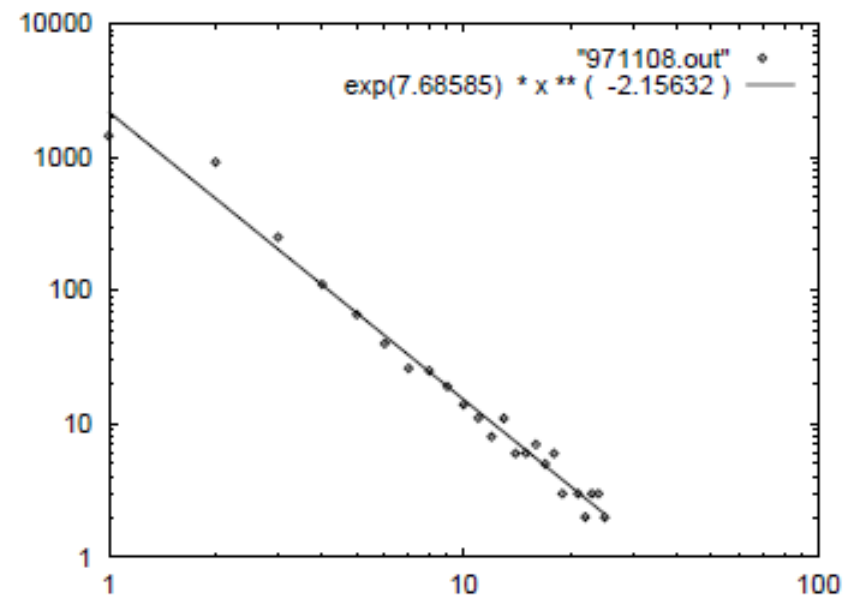
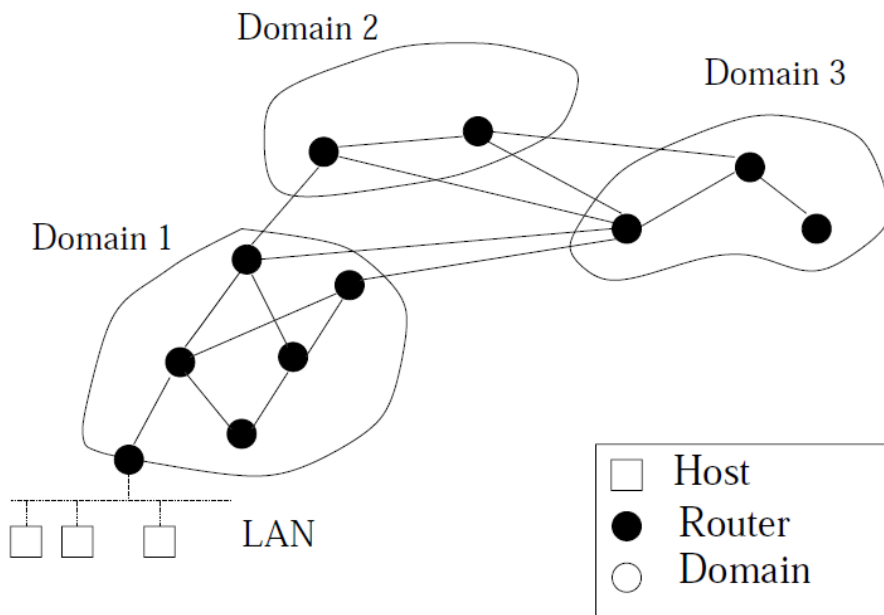
$$\log(y) = -\alpha \log(x)$$

So, on log-log axis
power-law looks like
a straight line of
slope $-\alpha$!

Node Degrees: Faloutsos³

■ Internet Autonomous Systems

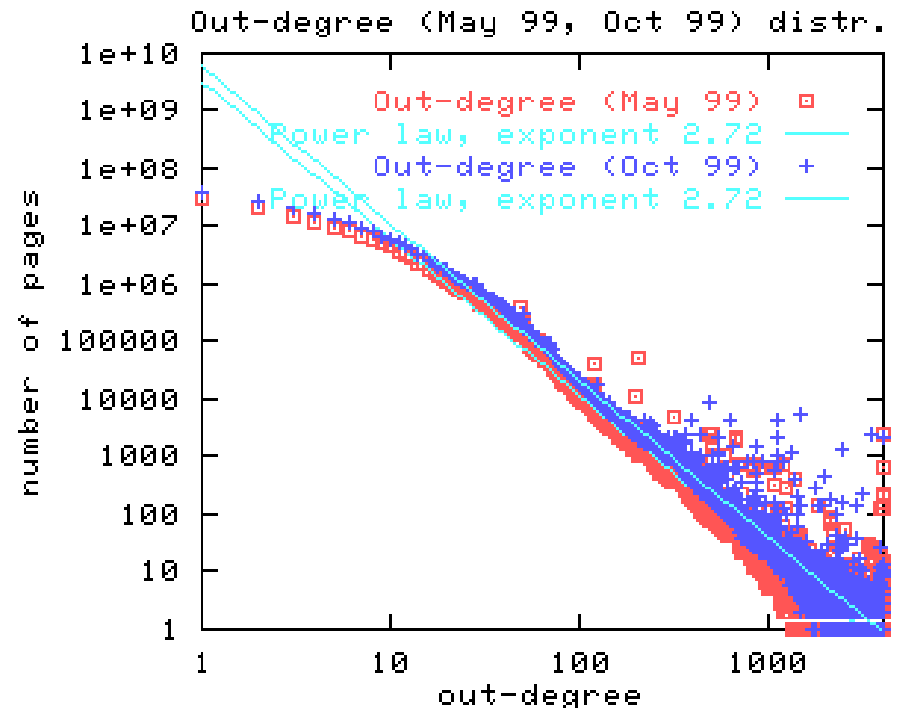
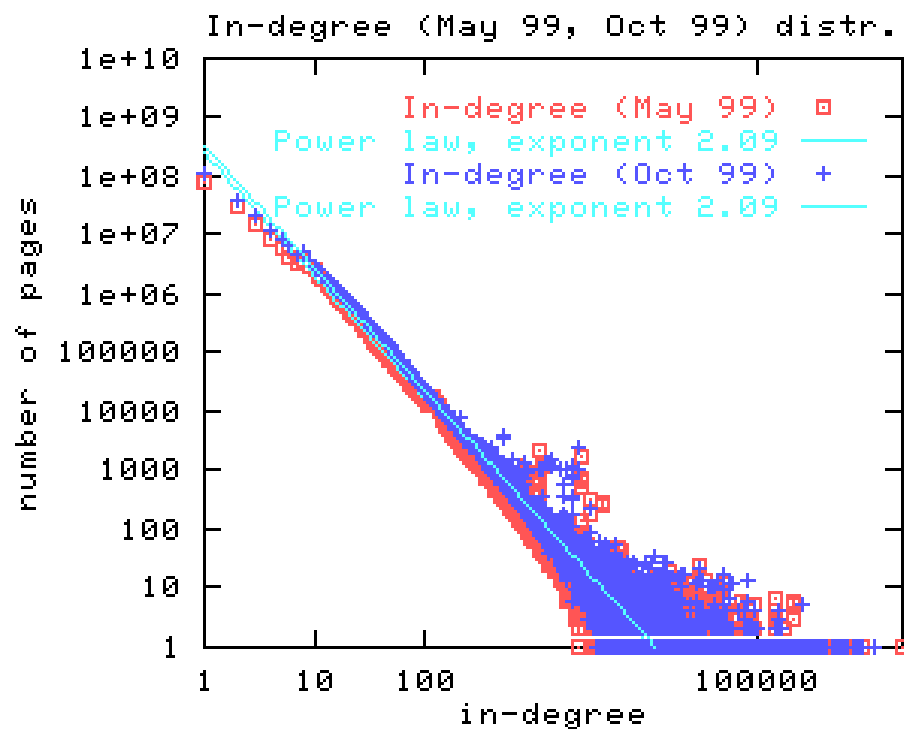
[Faloutsos, Faloutsos and Faloutsos, 1999]



Internet domain topology

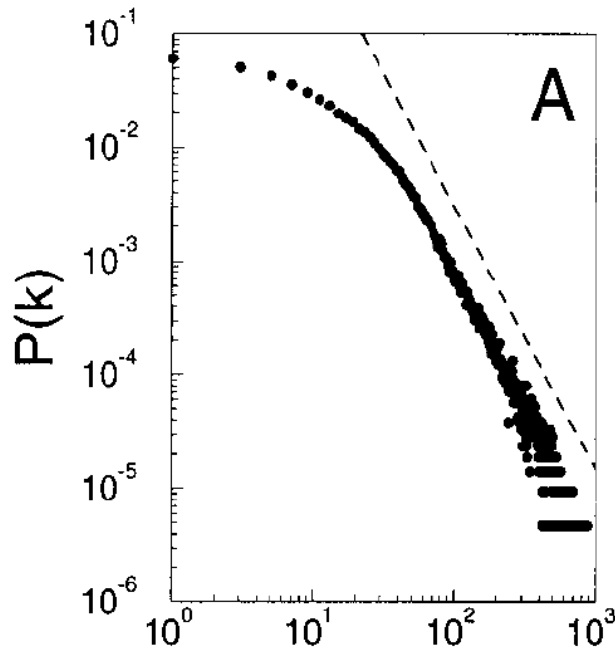
Node Degrees: Web

■ The World Wide Web [Broder et al., 2000]

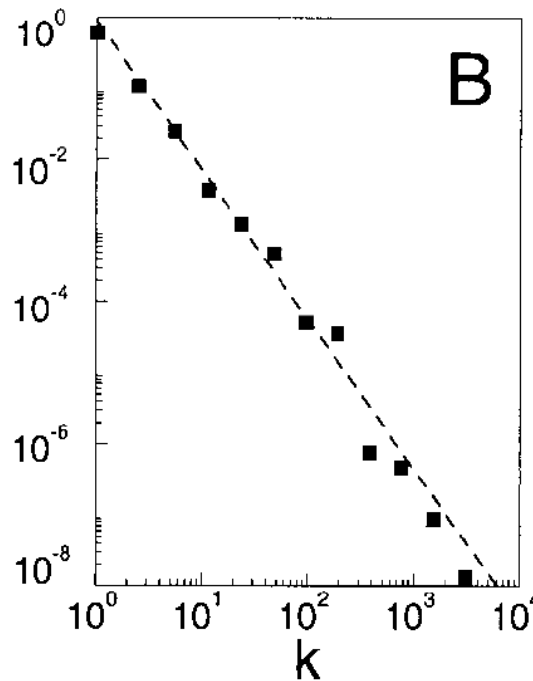


Node Degrees: Barabasi&Albert

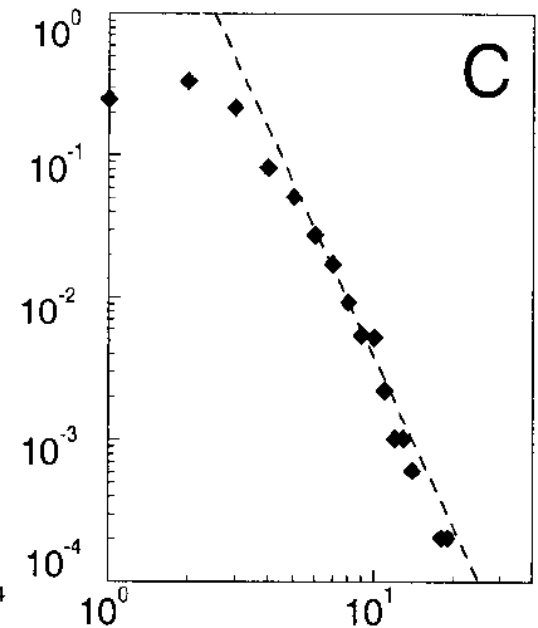
■ Other Networks [Barabasi-Albert, 1999]



Actor collaborations

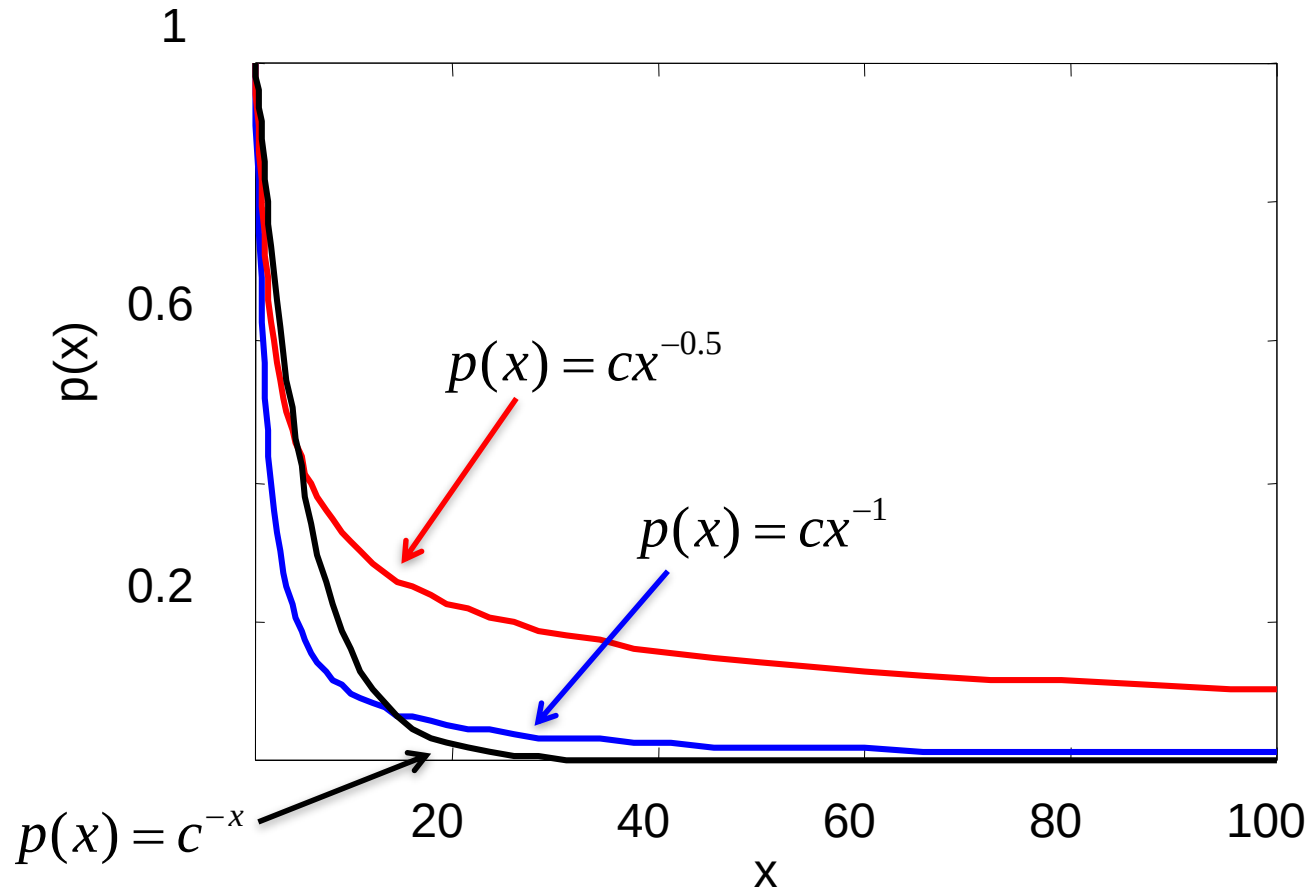


Web graph



Power-grid

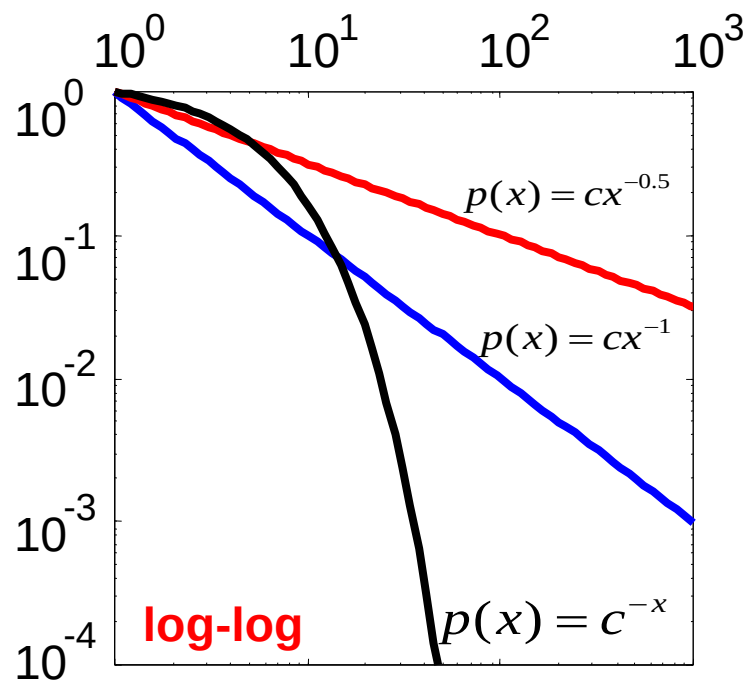
Exponential vs. Power-Law



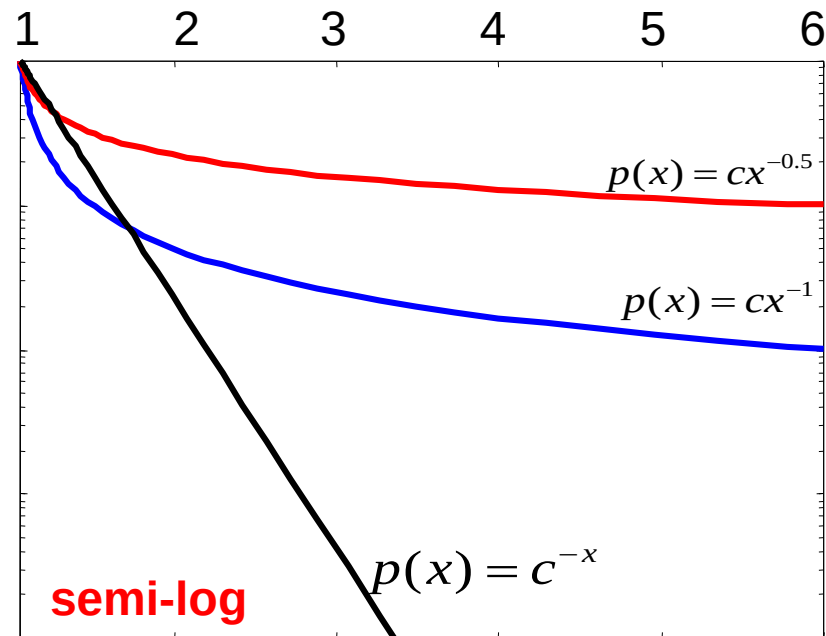
- Above a certain x value, the power law is always higher than the exponential!

Exponential vs. Power-Law

- Power-law vs. Exponential
on log-log and semi-log (log-lin) scales

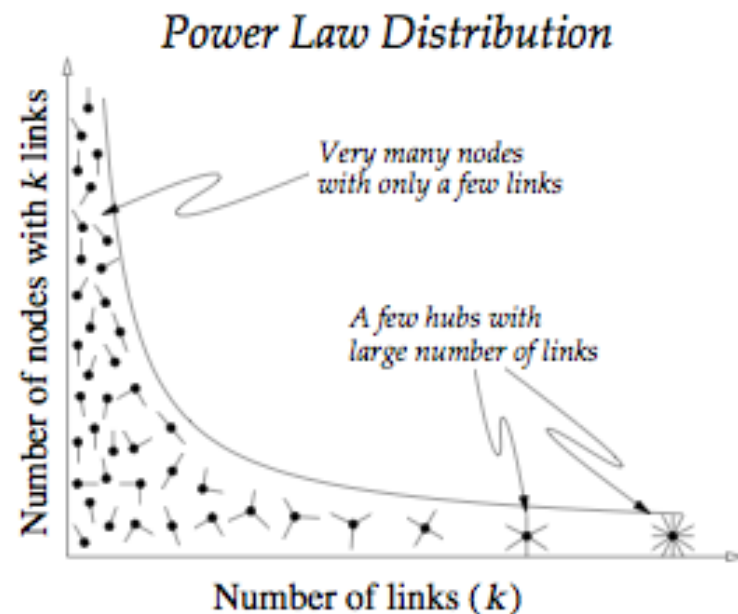
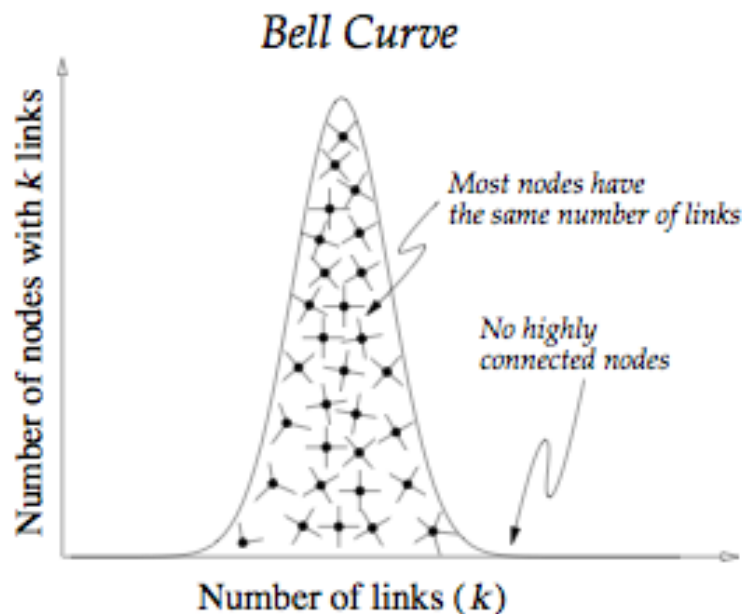


x ... logarithmic axis
y ... logarithmic axis



x ... linear
y ... logarithmic

Exponential vs. Power-Law



Power-Law Degree Exponents

- **Power-law degree exponent is typically $2 < \alpha < 3$**

- **Web graph:**

- $\alpha_{in} = 2.1$, $\alpha_{out} = 2.4$ [Broder et al. 00]

- **Autonomous systems:**

- $\alpha = 2.4$ [Faloutsos³, 99]

- **Actor-collaborations:**

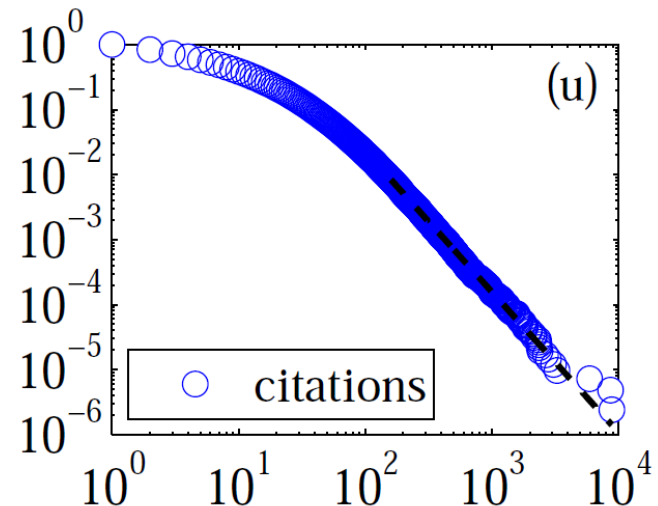
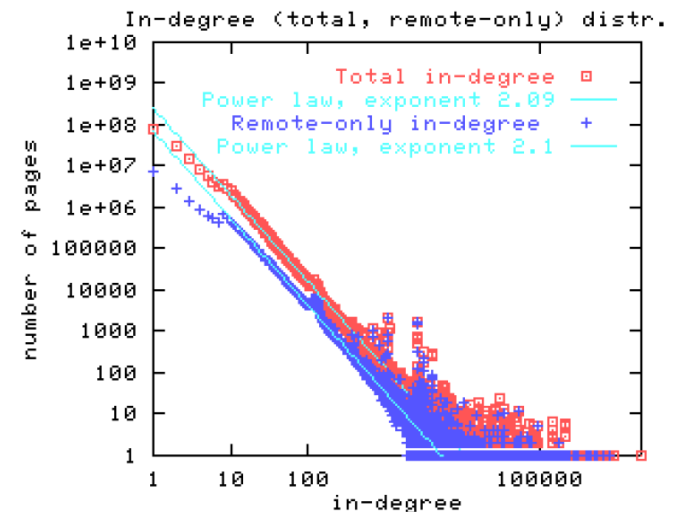
- $\alpha = 2.3$ [Barabasi-Albert 00]

- **Citations to papers:**

- $\alpha \approx 3$ [Redner 98]

- **Online social networks:**

- $\alpha \approx 2$ [Leskovec et al. 07]



Scale-Free Networks

- **Definition:**

Networks with a power-law tail in their degree distribution are called “scale-free networks”

- **Where does the name come from?**

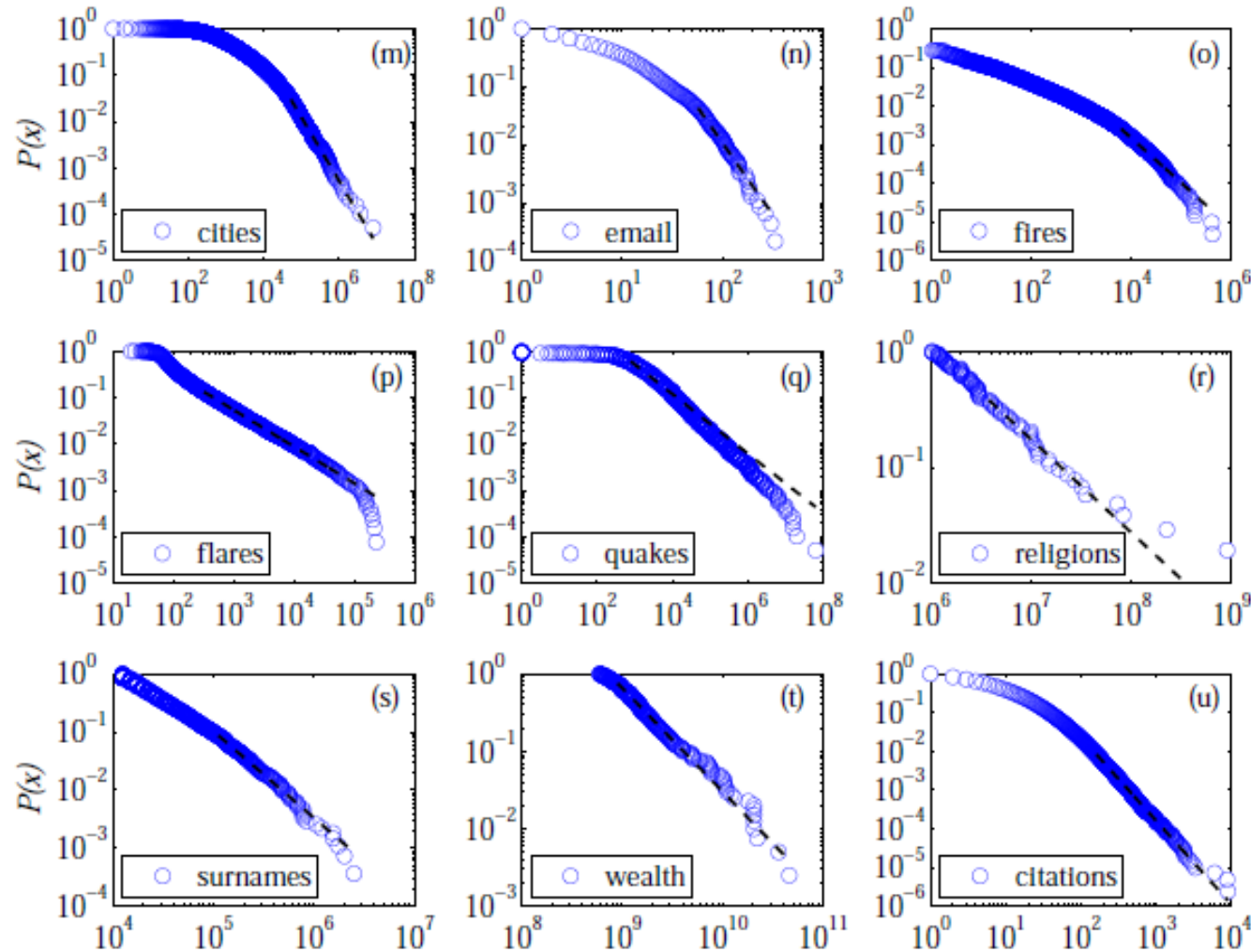
- **Scale invariance:** There is no characteristic scale
- **Scale-free function:** $f(ax) = a^\lambda f(x)$
 - Power-law function: $f(ax) = a^\lambda x^\lambda = a^\lambda f(x)$

Log() or Exp() are not scale free!

$$f(ax) = \log(ax) = \log(a) + \log(x) = \log(a) + f(x)$$

$$f(ax) = \exp(ax) = \exp(x)^a = f(x)^a$$

Power-Laws are Everywhere



Many other quantities follow heavy-tailed distributions

Anatomy of the Long Tail

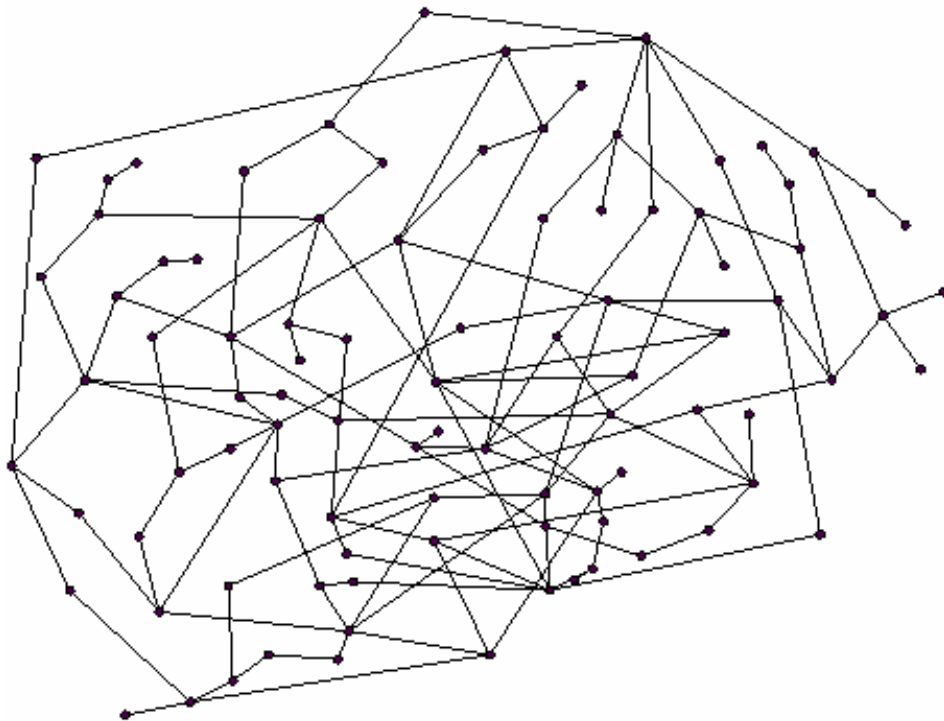
ANATOMY OF THE LONG TAIL

Online services carry far more inventory than traditional retailers. Rhapsody, for example, offers 19 times as many songs as Wal-Mart's stock of 39,000 tunes. The appetite for Rhapsody's more obscure tunes (charted below in yellow) makes up the so-called Long Tail. Meanwhile, even as consumers flock to mainstream books, music, and films (right), there is real demand for niche fare found only online.



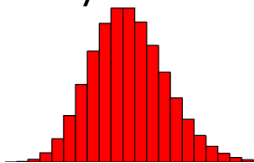
Consequence of Power-Law Degrees

Random vs. Scale-free network

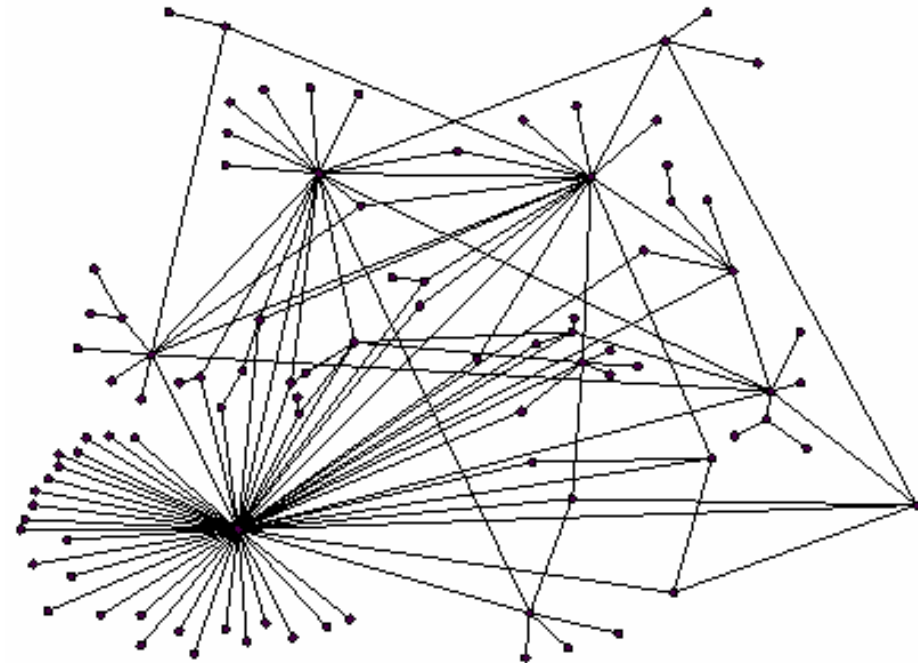


Random network

(Erdos-Renyi random graph)

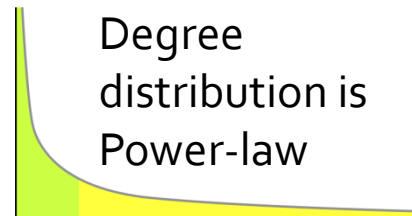


Degree distribution is Binomial



Scale-free (power-law) network

Degree
distribution is
Power-law



Consequence: Network Resilience

- **How does network connectivity change as nodes get removed?**

[Albert et al. 00; Palmer et al. 01]

- **Nodes can be removed:**

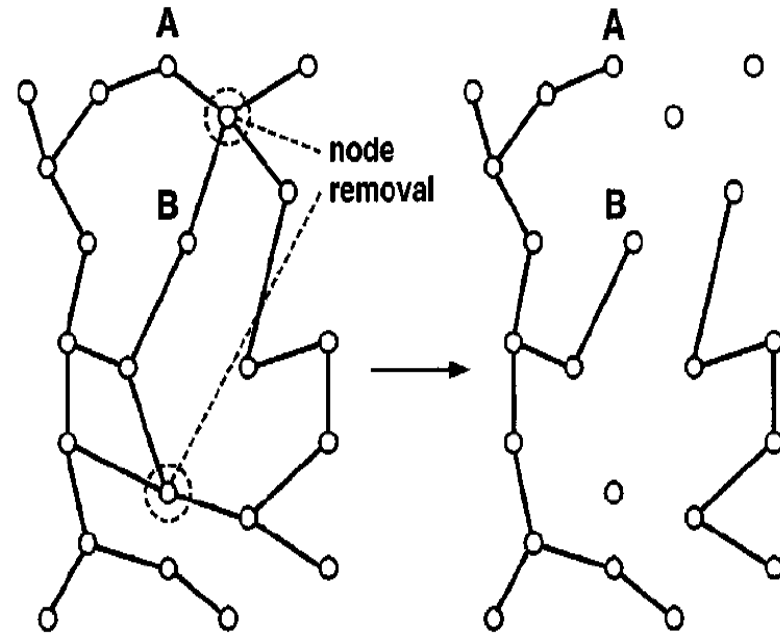
- **Random failure:**

- Remove nodes uniformly at random

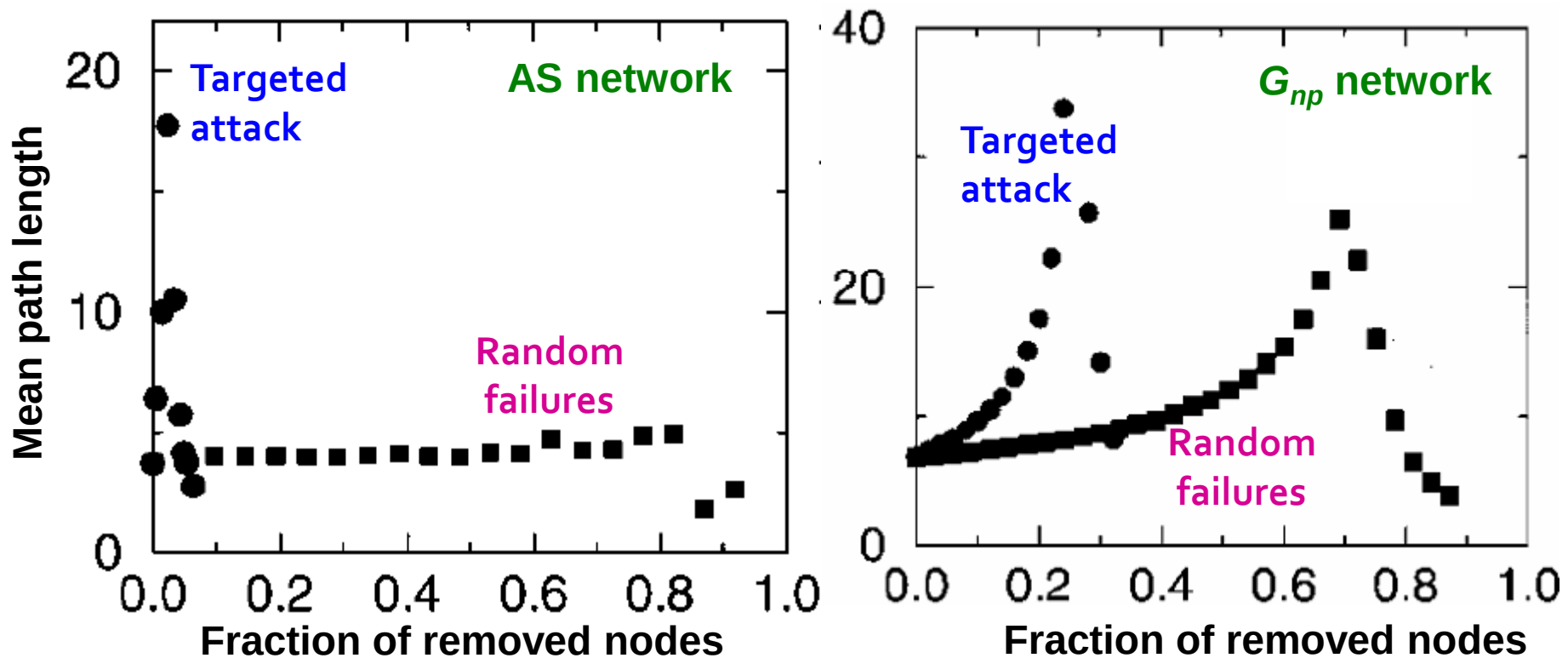
- **Targeted attack:**

- Remove nodes in order of decreasing degree

- This is important for **robustness of the internet** as well as **epidemiology**



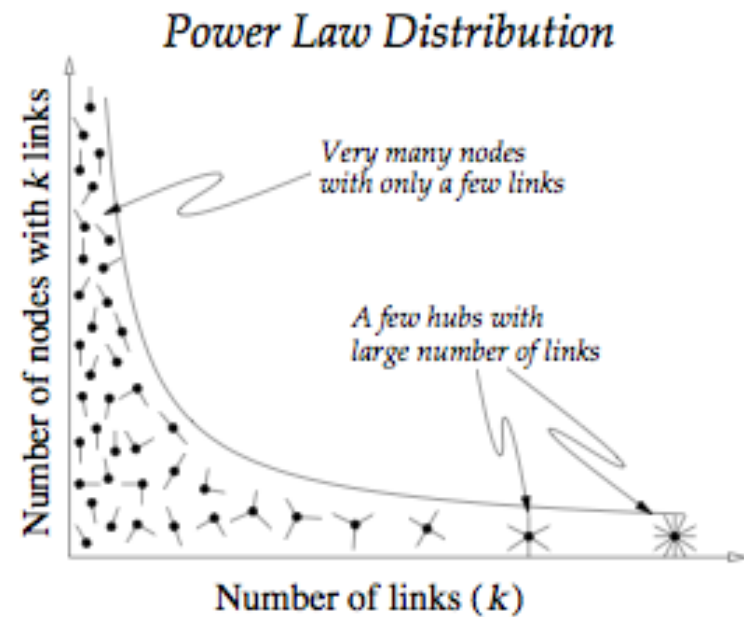
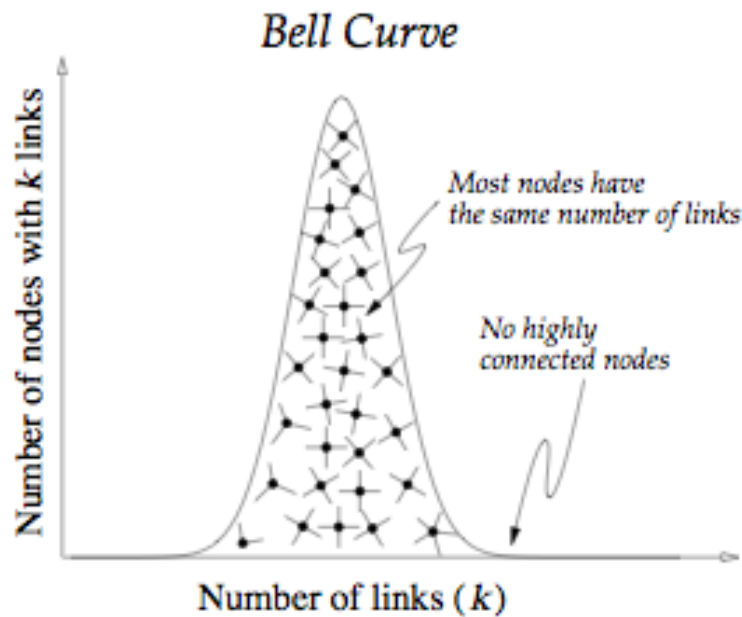
Network Resilience



- **Real networks are resilient to random failures**
- **G_{np} has better resilience to targeted attacks**
 - Need to remove all pages of degree >5 to disconnect the Web
 - But this is a very small fraction of all web pages

Preferential Attachment Model

Exponential vs. Power-Law Tails



Model: G_{np}

?

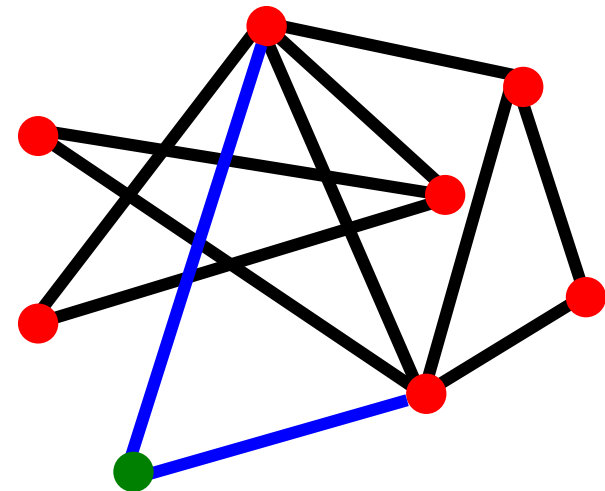
Model: Preferential attachment

■ Preferential attachment:

[de Solla Price '65, Albert-Barabasi '99, Mitzenmacher '03]

- Nodes arrive in order **1,2,...,n**
- At step **j** , let **d_i** be the degree of node **$i < j$**
- A new node **j** arrives and creates **m** out-links
- Prob. of **j** linking to a previous node **i** is **proportional to degree d_i of node i**

$$P(j \rightarrow i) = \frac{d_i}{\sum_k d_k}$$



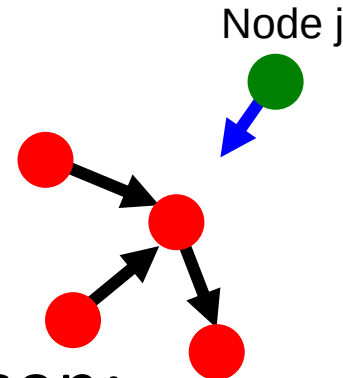
Rich Get Richer

- **New nodes are more likely to link to nodes that already have high degree**
- **Herbert Simon's result:**
 - Power-laws arise from “**Rich get richer**” (cumulative advantage)
- **Examples**
 - **Citations** [de Solla Price '65]: New citations to a paper are proportional to the number it already has
 - **Herding:** If a lot of people cite a paper, then it must be good, and therefore I should cite it too
 - **Sociology:** Matthew effect
 - Eminent scientists often get more credit than a comparatively unknown researcher, even if their work is similar
 - http://en.wikipedia.org/wiki/Matthew_effect

The Exact Model

We will analyze the following model:

- Nodes arrive in order $1, 2, 3, \dots, n$
- When **node j** is created it makes a **single out-link** to an earlier node i chosen:
 - **1)** With prob. p , node j links to i chosen **uniformly at random** (from among all earlier nodes)
 - **2)** With prob. $1 - p$, node j chooses i uniformly at random & links **to a random node l that i points to**
 - **This is same as saying:** With prob. $1 - p$, node j links to node l with prob. proportional to d_l (the in-degree of l)
- **Our graph is directed:** Every node has out-degree 1



The Model Gives Power-Laws

- Claim: The described model generates networks where the fraction of nodes with in-degree k scales as:

$$P(d_i = k) \propto k^{-(1+\frac{1}{q})}$$

where $q=1-p$

So we get power-law
degree distribution
with exponent:

$$\alpha = 1 + \frac{1}{1-p}$$

Preferential attachment: Good news

- Preferential attachment gives power-law degrees!
- Intuitively reasonable process
- Can tune p to get the observed exponent
 - On the web, $P[\text{node has degree } d] \sim d^{-2.1}$
 - $2.1 = 1 + 1/(1-p) \rightarrow \underline{p \sim 0.1}$

Preferential Attachment: Bad News

- Preferential attachment is not so good at predicting network structure
 - Age-degree correlation
 - Solution: Node fitness (virtual degree)
 - Links among high degree nodes:
 - On the web nodes sometime avoid linking to each other
- Further questions:
 - What is a reasonable model for how people sample through network node and link to them?
 - Short random walks

Generating Power-Law Values

- A simple trick to generate values that follow a power-law distribution:
 - Generate values r uniformly at random within the interval $[0,1]$
 - Transform the values using the equation
$$x = x_{min}(1 - r)^{-1/(\alpha-1)}$$
 - Generates values distributed according to **power-law** with exponent α

Many models lead to Power-Laws

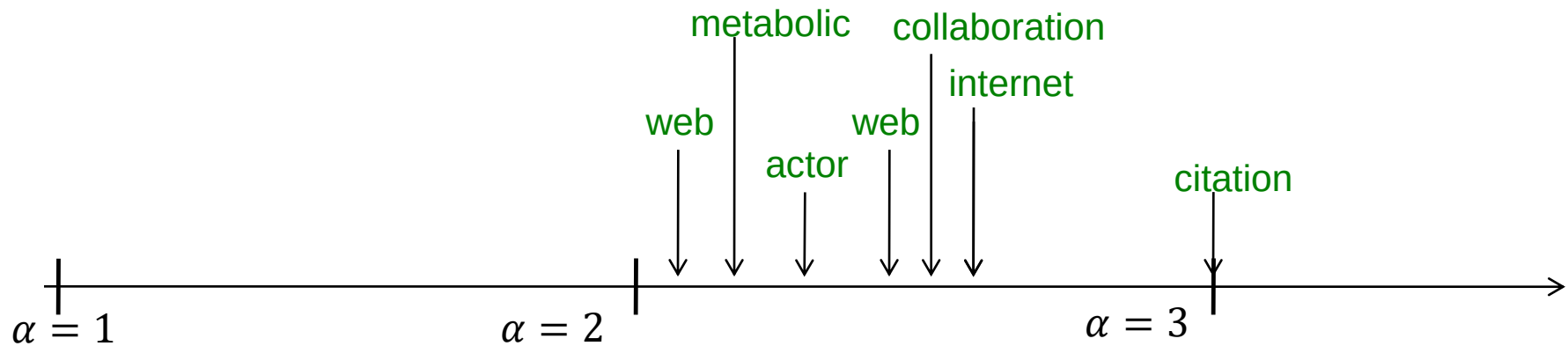
- **Copying mechanism** (directed network)
 - Select a node and an edge of this node
 - Attach to the endpoint of this edge
- **Walking on a network** (directed network)
 - The new node connects to a node, then to every first, second, ... neighbor of this node
- **Attaching to edges**
 - Select an edge and attach to both endpoints of this edge
- **Node duplication**
 - Duplicate a node with all its edges
 - Randomly prune edges of new node

Distances in Preferential Attachment

Ultra small world	$\bar{h} = \left\{ \begin{array}{l} \text{const} \\ \frac{\log \log n}{\log(\alpha-1)} \end{array} \right.$	$\alpha = 2$	Size of the biggest hub is of order $O(N)$. Most nodes can be connected within two steps, thus the average path length will be independent of the network size.
		$2 < \alpha < 3$	The average path length increases slower than logarithmically. In G_{np} all nodes have comparable degree, thus most paths will have comparable length. In a scale-free network vast majority of the path go through the few high degree hubs, reducing the distances between nodes.
Small world	$\bar{h} = \left\{ \begin{array}{l} \frac{\log n}{\log \log n} \\ \log n \end{array} \right.$	$\alpha = 3$	Some models produce $\alpha = 3$. This was first derived by Bollobas et al. for the network diameter in the context of a dynamical model, but it holds for the average path length as well.
		$\alpha > 3$	The second moment of the distribution is finite, thus in many ways the network behaves as a random network. Hence the average path length follows the result that we derived for the random network model earlier.
		Avg. path length	Degree exponent

Summary: Scale-Free Networks

Extra!



Second moment $\langle k^2 \rangle$ diverges

$\langle k^2 \rangle$ finite

Average $\langle k \rangle$ diverges

Average $\langle k \rangle$ finite

Ultra small world behavior

Small world

Regime full of anomalies...

The scale-free behavior is relevant

Behaves like a random network