

Theoretical Network Models

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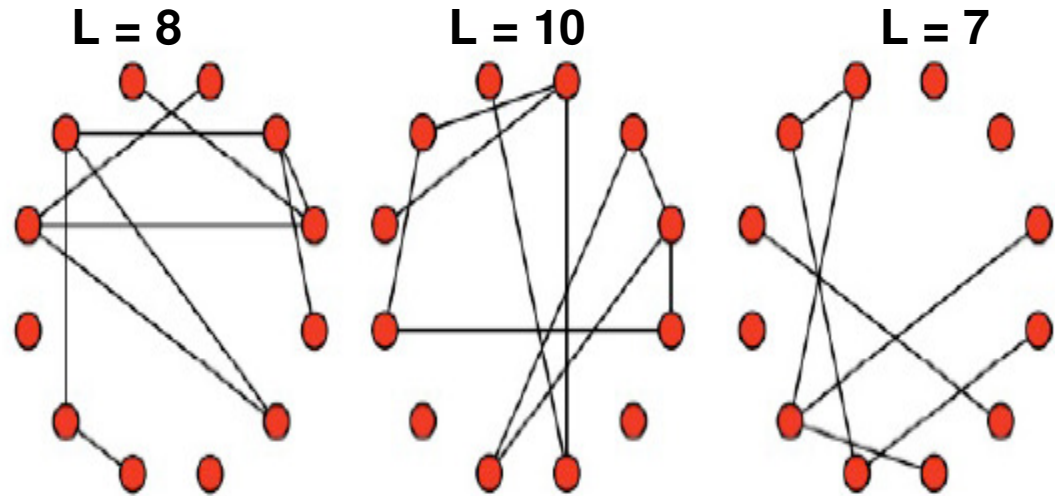
- In this module, we will see the theoretical models using which one could generate complex networks resembling those of real-world networks.
- The theoretical models we will see are as follows
 - Random Networks
 - Erdos Renyi Model (ER Model)
 - Scale-Free Networks
 - Barabasi Albert Model (BA Model)
 - Bianconi-Barabasi (BB Model)
 - Small-World Networks
 - Watts-Strogatz Model (WS Model)
- We will see the generation of the networks based on the above models and analyze their characteristics.

Random Networks

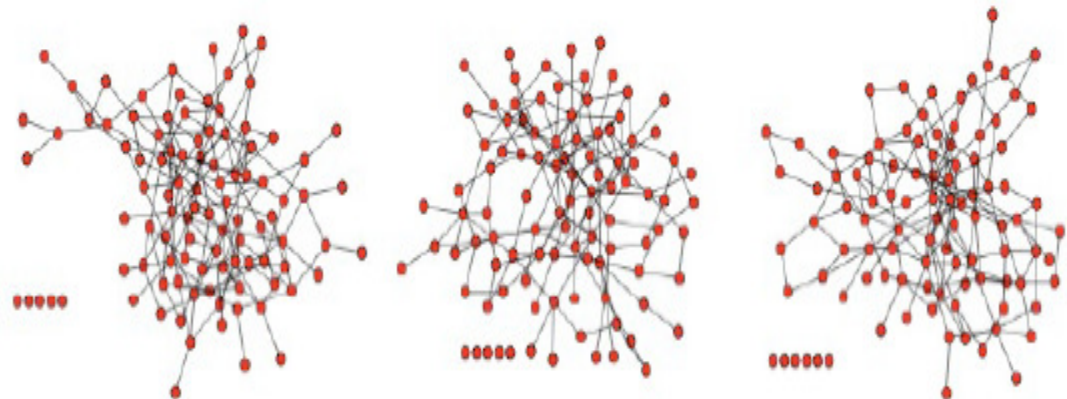
- A random network is the one in which there is a certain probability for a link between any two nodes in the network.
- Erdos-Renyi Model (ER) Model
 - The probability for a link between any two nodes is the same.
 - Called the $G(N, p)$ model where N is the number of nodes and 'p' is the probability for a link between any two nodes
 - Highly theoretical model and it is primarily used to determine whether the links in a real-world network are formed due to random interactions of nodes or due to the preference of nodes to communicate or attach to certain nodes.

ER Model

- Step 1: Start with N isolated nodes
- Step 2: For a particular node pair (u, v) , generate a random number r . If $r \leq p$, then, add the link (u, v) to the network.
- Repeat Step 2 for each of the $N(N-1)/2$ node pairs.
- Each random network we generate with the same parameters (N, p) will look slightly different.
 - The number of links L is likely to be different.



$N = 12$ nodes, $p = 1/6$

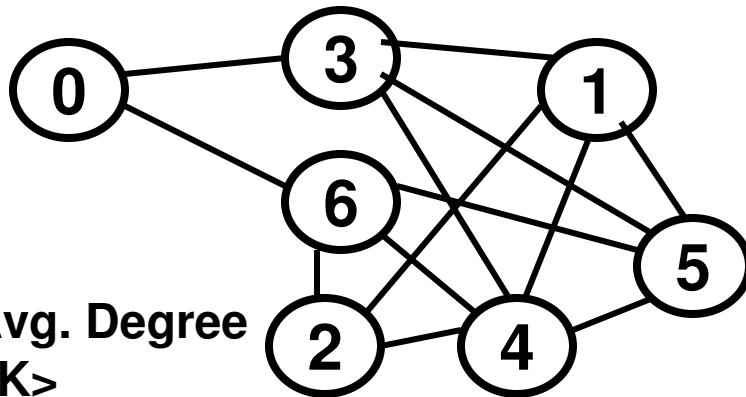


$N = 100$ nodes, $p = 1/6$

Source: Figure 3.3a: Barabasi

Generation of ER-Random Network

Let plink = 0.524



Avg. Degree
<K>

$$= (2 + 4 + 3 + 4 + 5 + 4 + 4) / 7$$

$$= 3.71$$

Index	Pairs	Random Val	Edge
1	0, 1	0.6335	N
2	0, 2	0.7478	N
3	0, 3	0.1721	Y
4	0, 4	0.9234	N
5	0, 5	0.8563	N
6	0, 6	0.3141	Y
7	1, 2	0.1594	Y
8	1, 3	0.2945	Y
9	1, 4	0.2227	Y
10	1, 5	0.0343	Y
11	1, 6	0.7621	N
12	2, 3	0.8595	N
13	2, 4	0.3091	Y
14	2, 5	0.5312	N
15	2, 6	0.1834	Y
16	3, 4	0.4194	Y
17	3, 5	0.2549	Y
18	3, 6	0.6974	N
19	4, 5	0.0968	Y
20	4, 6	0.4486	Y
21	5, 6	0.2983	Y

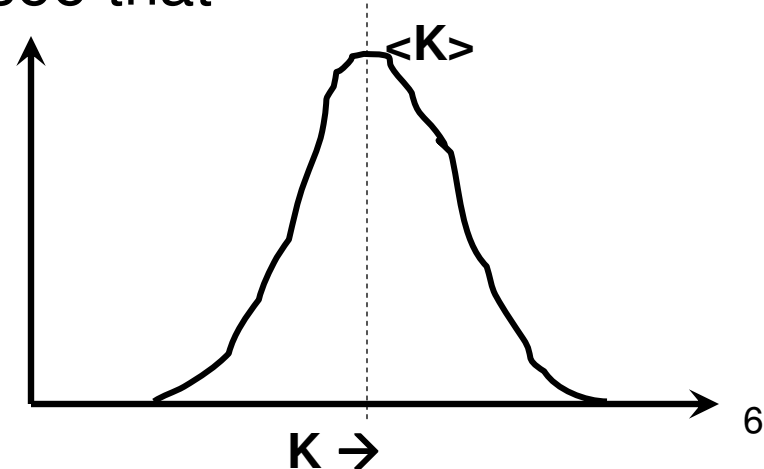
ER Model: Poisson Degree Distribution

- In a network of N nodes, the maximum number of links for a node with its neighbors is $N-1$ and each of these links can occur with a probability p .
 - Average degree of a node $\langle K \rangle = (N-1)p$
 - Standard deviation for the degree of a node $\sigma_k = \text{sqrt}(\langle K \rangle)$
- There could be a maximum $N(N-1)/2$ links in a random network of N nodes and each of these links can occur with a probability p .
 - Average number of links $\langle L \rangle = \{N(N-1)/2\} * p$
- From the above, we can easily see that

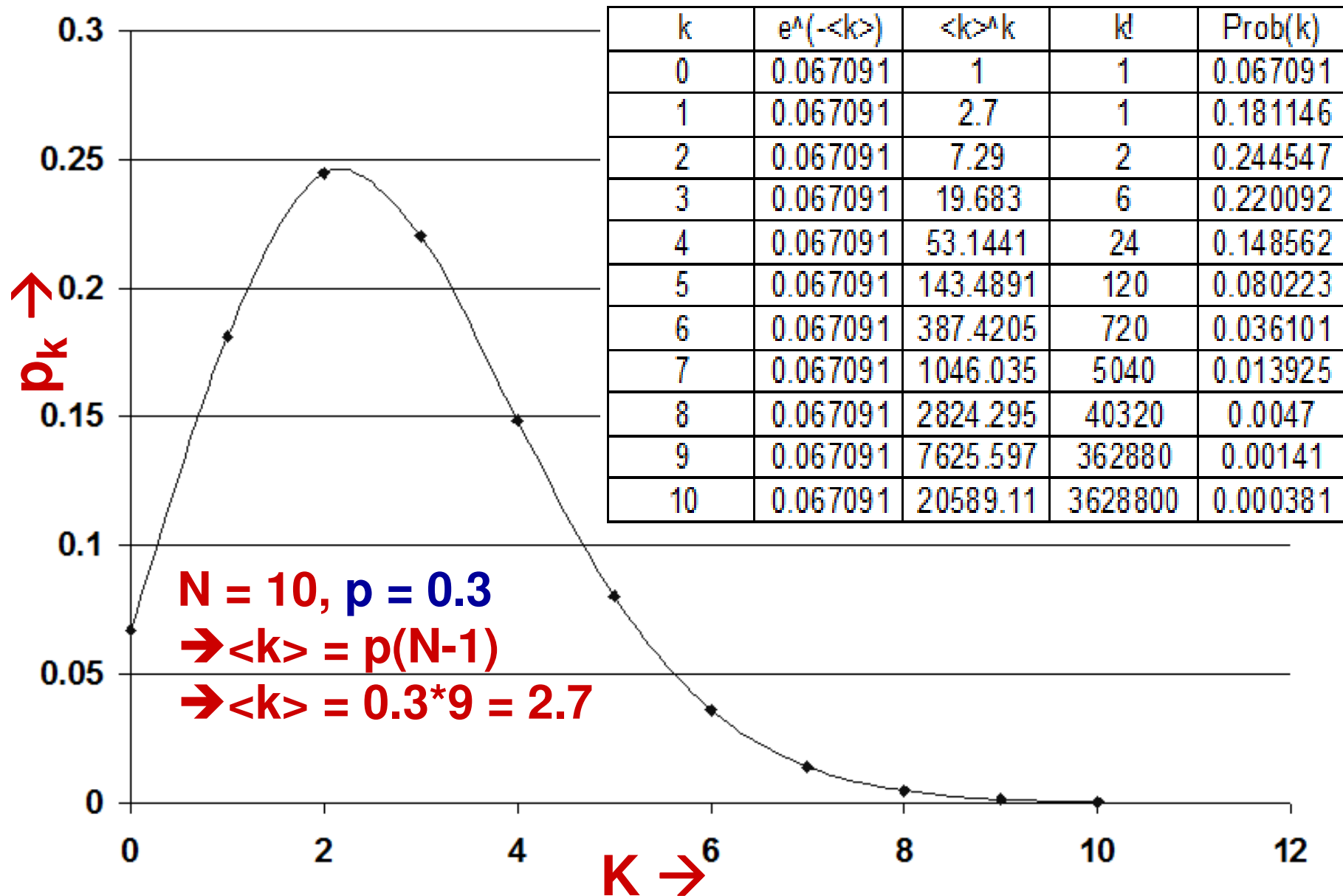
$$\langle K \rangle = 2 * \langle L \rangle / N$$

Poisson degree distribution

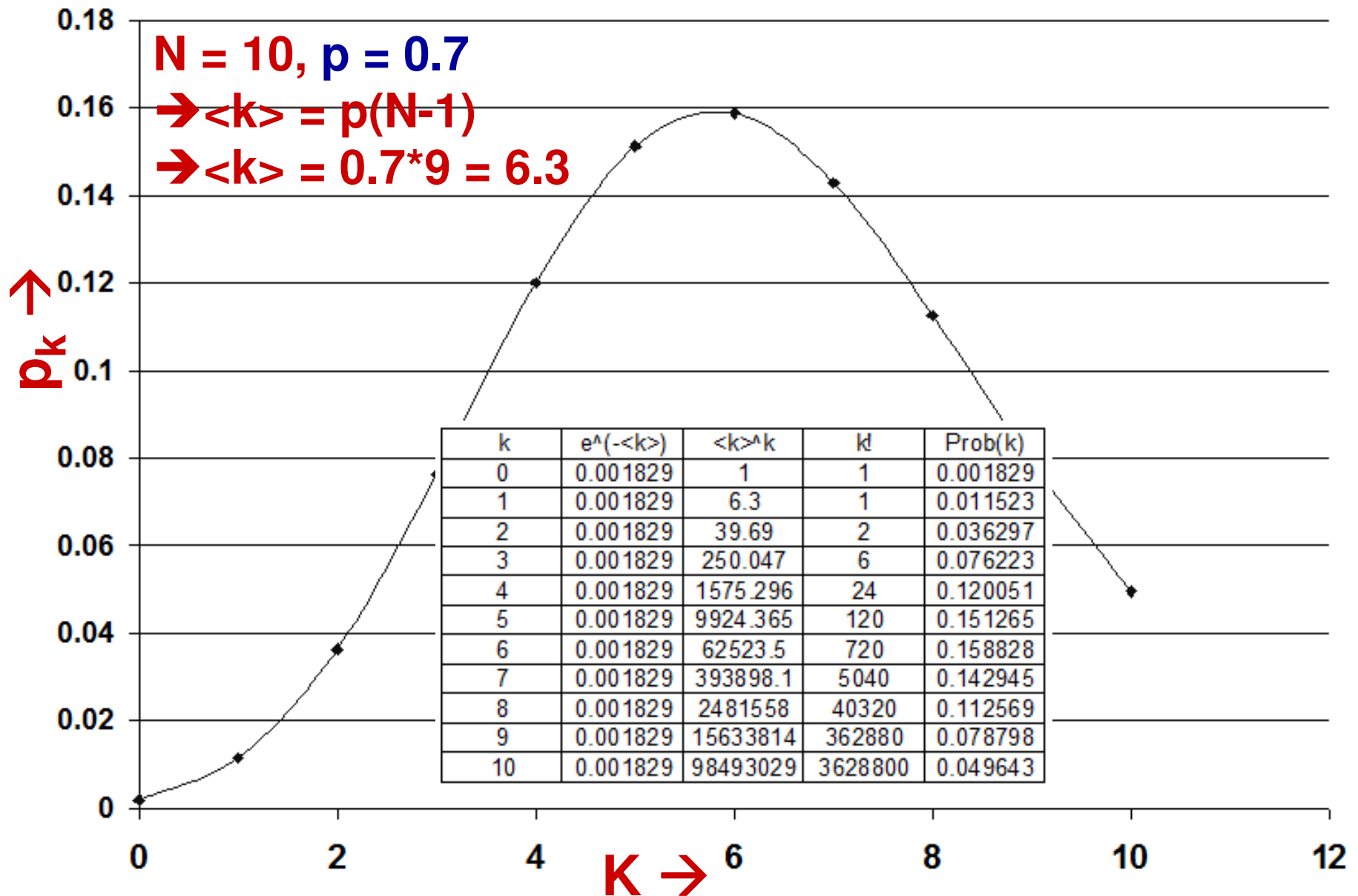
$$p_k = e^{-\langle k \rangle} \frac{\langle k \rangle^k}{k!}$$



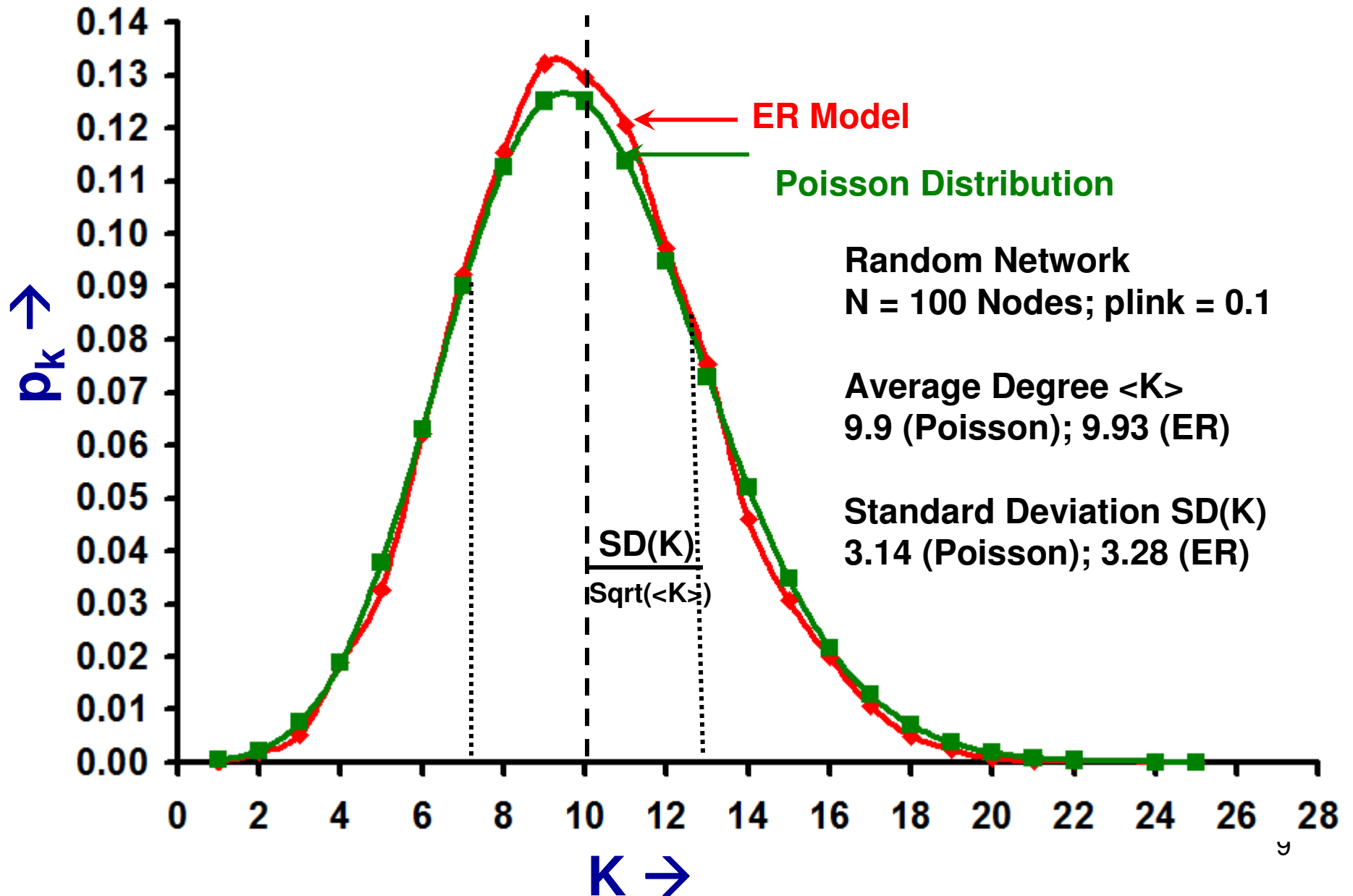
Generating a Poisson Degree Distribution



Generating a Poisson Degree Distribution



Degree Distribution: ER Model vs. Poisson

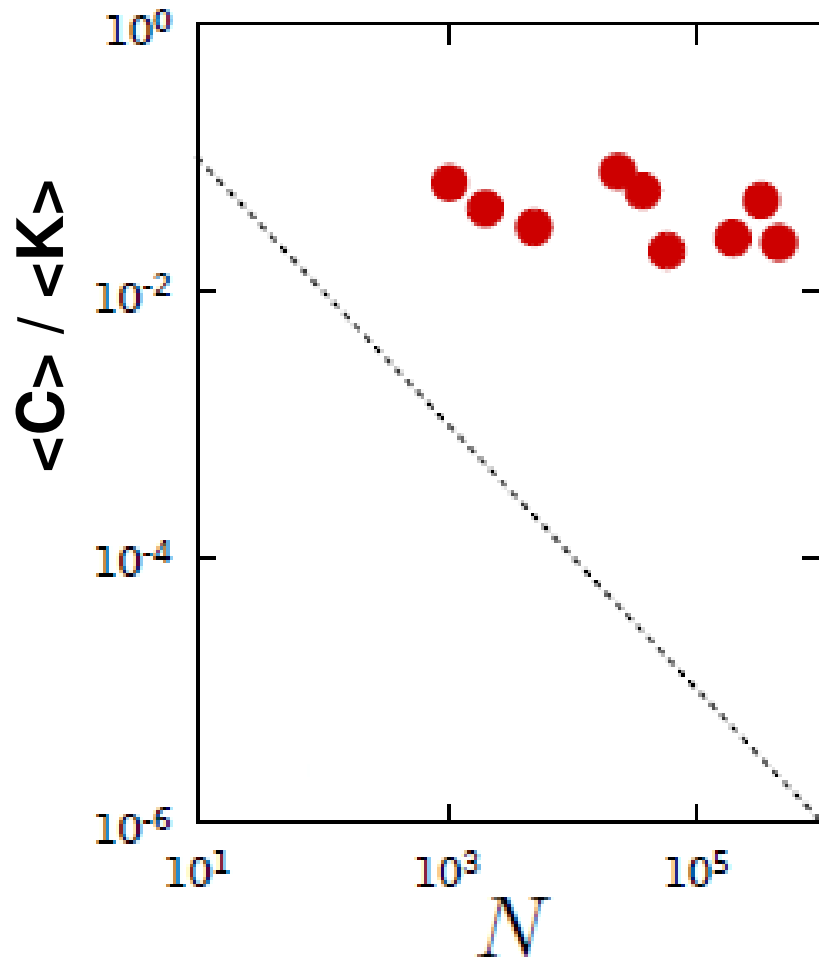


Clustering Coefficient

- Local Clustering Coefficient of a node is the probability that any two neighbors of the node have a link between them.
- According to the ER $G(N, p)$ model, p is the probability for a link between any two nodes.
- Hence, for a random network evolved under the ER $G(N, p)$ model, the local clustering coefficient for any node is expected to be close to the parameter p , probability for a link between any two nodes.
- Average Clustering Coefficient $\langle C \rangle = p \sim \langle K \rangle / N$
 - $(N-1) \sim N$ for large networks.

Networks	Actual	Random: ER- $G(N, p)$
Prison		
Friendships	0.31	0.0134
Co-authorships		
Math	0.15	0.00002
Biology	0.09	0.00001
Economy	0.19	0.00002
WWW		
Web links	0.11	0.002

Clustering Coefficients for Real Networks



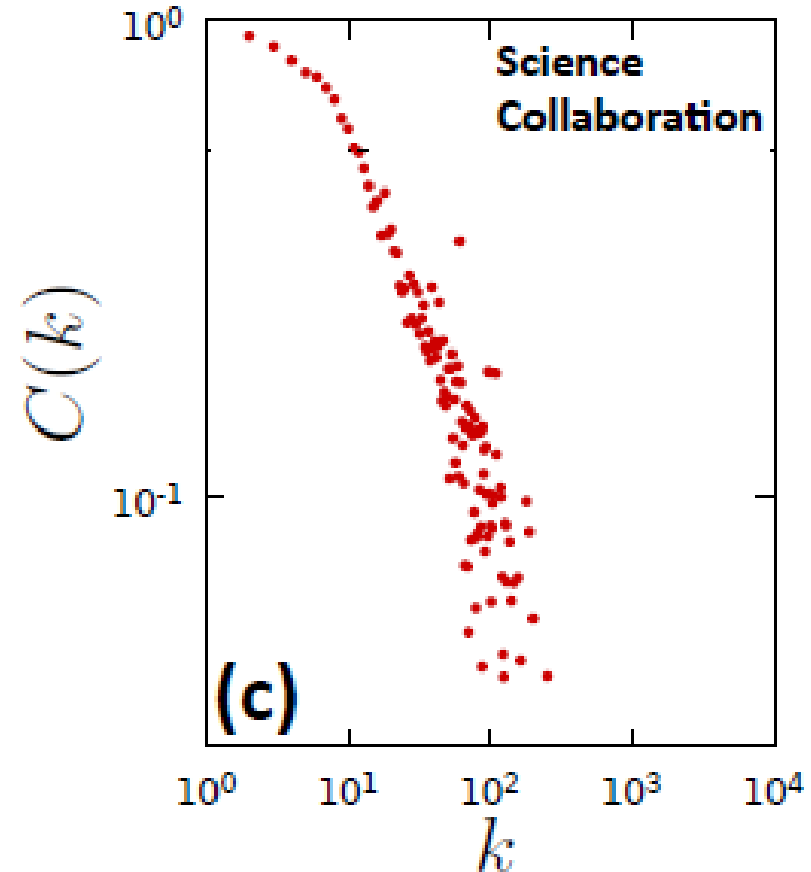
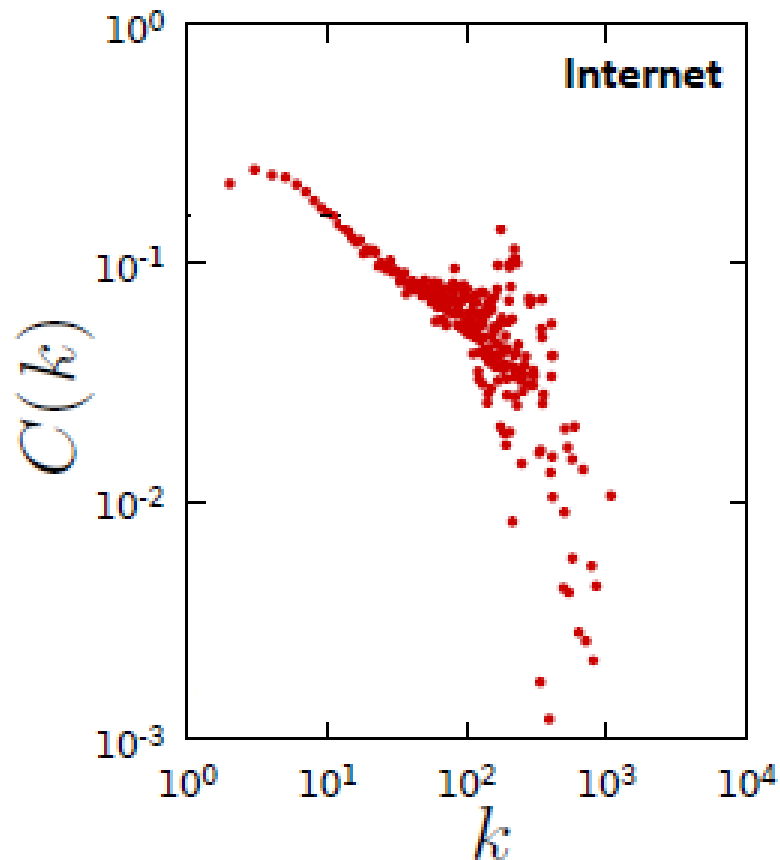
Each circle corresponds to a real network.

Directed networks were made undirected to calculate C .

For ER-random networks, the average clustering coefficient decreases as $1/N$. In contrast, for real networks, $\langle C \rangle$ has only a weak dependence on N .

Real networks have a much higher Clustering coefficient than expected for a ER-random network of similar N and L .

Clustering for Real Networks



$C(k)$ is measured by averaging the local clustering coefficient of all nodes with the same degree k .

According to the ER-Random Network theory model, $C(k)$ is independent of the individual node degrees. However, we find that $C(k)$ decreases as k increases.

Nodes with fewer neighbors have larger local clustering coefficients and vice-versa.

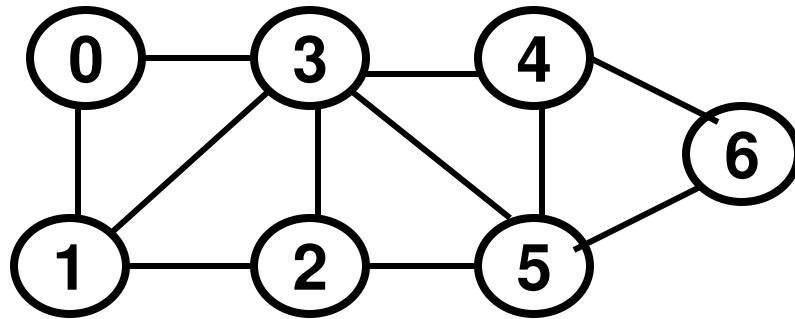
Real Networks are not ER-Random

- Degree distribution:
 - ER-Random networks –Poisson distribution, esp. for $k \ll N$.
 - Highly connected nodes (hubs) are effectively forbidden.
 - Real networks: More highly connected nodes, compared to that predicted with random model.
- Connectedness:
 - ER-Random networks: One single giant component exists only if $\langle k \rangle > \ln N$ (i.e., $p > (\ln N)/N$)
 - Real networks: One single giant component exists for several networks with $\langle k \rangle < \ln N$.
- Average Path Length (small world property):
 - For both ER-random and real networks, the average path length scales as $\ln N / \ln \langle k \rangle$.
- Clustering coefficient:
 - ER-Random model: Local clustering coefficient is independent of the node's degree and $\langle C \rangle$ depends on the system size as $1/N$.
 - Real networks: $\langle C \rangle$ decreases with increase in node degrees and is largely independent of the system size.

Real Networks are not ER-Random

- Except for the small world property (avg. path length $\sim \ln N / \ln \langle K \rangle$), the properties observed for real-world networks are not matching with that observed for ER-random networks.
- Then why study random graph theory (ER-model)?
- If a certain property is observed for real-world networks, we can refer to the random graph theory and analyze whether the property is observed by chance (like the small world property).
- If the property observed does not coincide with that of the random networks (like the local clustering coefficient), we need to further analyze the real-world network for the existence of the property because it did not just happen by chance.
- Establish useful benchmarks (e.g., diameter, degree distribution)

Generation of ER-Random Network



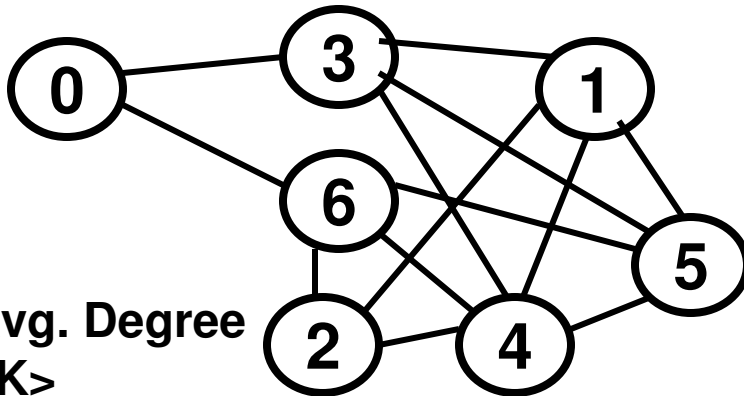
Avg. Degree $\langle K \rangle$

$$= (2 + 3 + 3 + 5 + 3 + 4 + 2) / 7$$

$$= 3.14$$

ER Model plink = $\langle K \rangle / (N-1)$

$$\text{plink} = 3.14 / 6 = 0.524$$



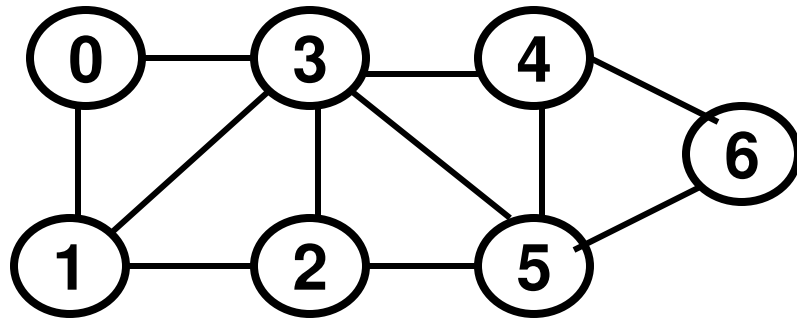
Avg. Degree $\langle K \rangle$

$$= (2 + 4 + 3 + 4 + 5 + 4 + 4) / 7$$

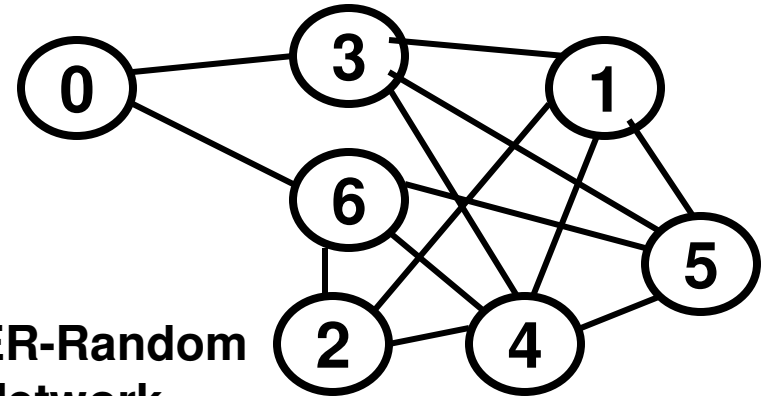
$$= 3.71$$

Index	Pairs	Random Val	Edge
1	0, 1	0.6335	N
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Degree vs LCC Analysis



Given Network



ER-Random Network

Degree #Nodes Prob.

2	2	$2/7 = 0.286$
3	3	$3/7 = 0.428$
4	1	$1/7 = 0.143$
5	1	$1/7 = 0.143$

Degree #Nodes Prob.

2	1	$1/7 = 0.143$
3	1	$1/7 = 0.143$
4	4	$4/7 = 0.571$
5	1	$1/7 = 0.143$

Degree Nodes LCC Avg <LCC>

2	0, 6	1, 1	1.0
3	1, 2, 4	2/3, 2/3, 2/3	0.67
4	5	3/6	0.5
5	3	4/10	0.4

Degree Nodes LCC Avg <LCC>

2	0	0.0	0.0
3	2	2/3	0.67
4	1, 3, 5, 6	4/6, 3/6	0.542
		4/6, 2/6	
5	4	6/10	0.6

Randomness Index of a Real-World Net

Given Network

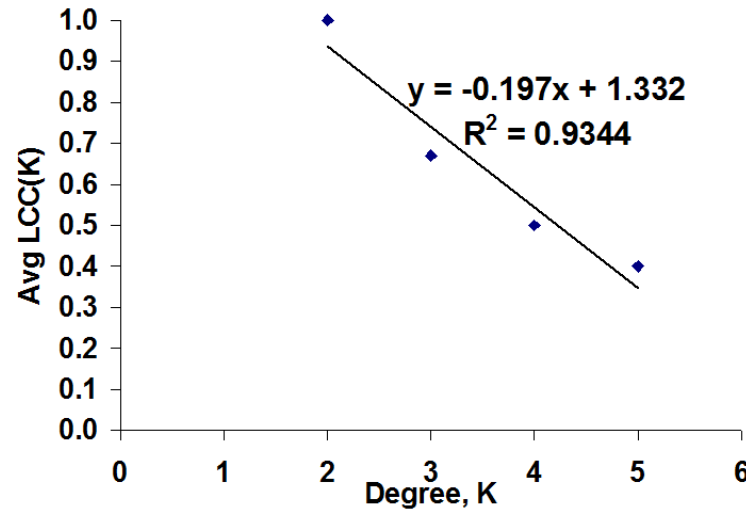
Degree	Avg <LCC>
2	1.0
3	0.67
4	0.5
5	0.4

Randomness Index of a given network
 = (sign of the slope) Sqrt(R^2)

The closer it is to 1, more random the network is;
 The closer it is to -1, less random the network is

ER-Random Network

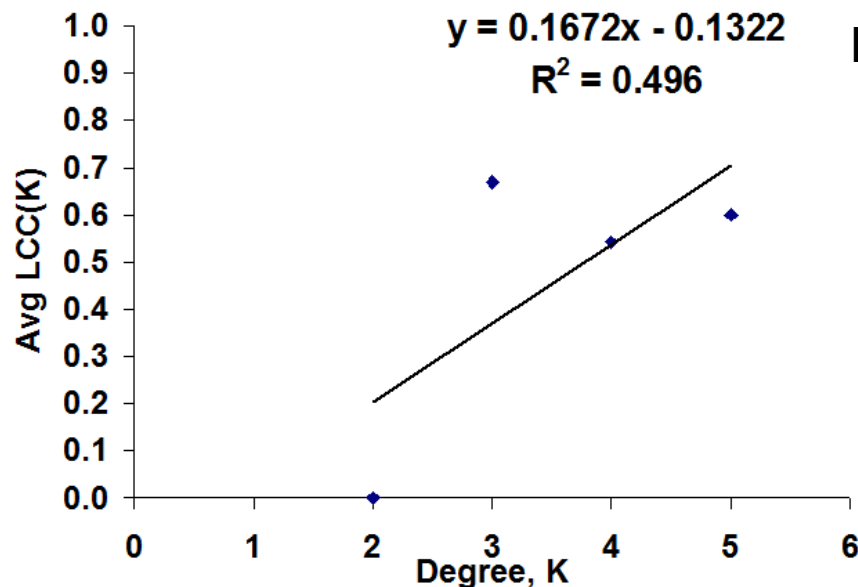
Degree	Avg <LCC>
2	0.0
3	0.67
4	0.542
5	0.6



$$R^2 = 0.9344$$

K and Avg LCC(K) exhibit a strong (-ve) correlation

$$\begin{aligned} \text{Randomness Index} &= -\sqrt{0.9344} \\ &= -0.9667 \end{aligned}$$



$$R^2 = 0.4960$$

K and Avg LCC(K) exhibit a weak (+ve) correlation

$$\begin{aligned} \text{Randomness Index} &= +\sqrt{0.4960} \\ &= +0.7043 \end{aligned}$$

Problem Example 1

- Consider a random network generated according to the $G(N, p)$ model where the total number of nodes is 12 and the probability that there are links between any two nodes is 0.20. Determine the following:
 - The average number of links in the network
 - The average node degree
 - The standard deviation of the node degree
 - The average path length (distance between any two nodes in the network)
 - The average local clustering coefficient for any node in the network.
 - The expected local clustering coefficient for a node that has exactly 5 neighbors.

Problem Example 1: Solution

- There are $N = 12$ nodes
- Prob[link between any two nodes] = $p = 0.2$

Max. possible number of links between any two nodes is $(N)(N-1)/2 = (12*11/2) = 66$

(2) The average number of links in the network = $p * N(N-1)/2$
 $= 0.2 * 66 = 13.2$

(3) Average node degree = $p*(N-1) = 0.2 * 11 = 2.2$

(4) Standard deviation of node degree = $\text{sqrt}(\langle K \rangle)$
 $= \text{sqrt}(2.2) = 1.48$

(5) Average path length = $\ln N / \ln \langle k \rangle = \ln(12) / \ln(2.2) = 3.15$

(6) Avg. Local clustering coefficient for any node in the network = $p = 0.2$.

(7) The expected local clustering coefficient for a node in a random network is independent of its number of neighbors. Hence, the answer is 0.2

Scale-Free Networks

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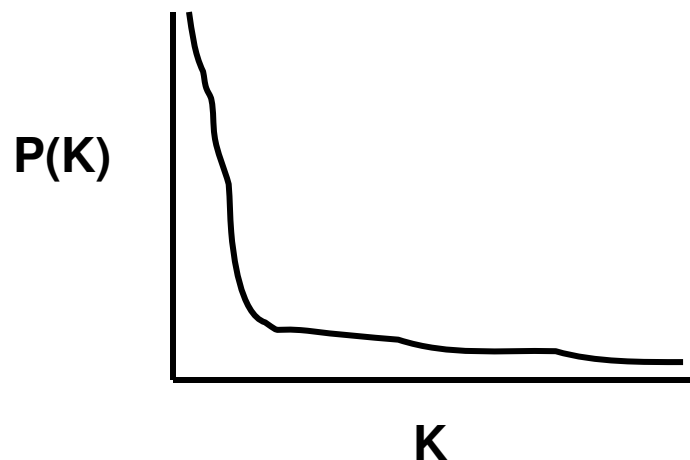
Scale-Free Networks

- Scale-free networks follows a Power-law distribution.
- $P(k) \sim k^{-\gamma}$, where γ is the degree exponent (> 1)
- $P(k) = Ck^{-\gamma}$, where C is the proportionality constant

Assuming the degree distribution is discrete

$$C = \frac{1}{\sum_{k=1}^{\infty} k^{-\gamma}} = \frac{1}{\zeta(\gamma)}$$
$$\zeta(\gamma) = \sum_{k=1}^{\infty} k^{-\gamma}$$

$\zeta(\gamma)$ is called the Riemann-Zeta Function



Proportionality Constant (Discrete)

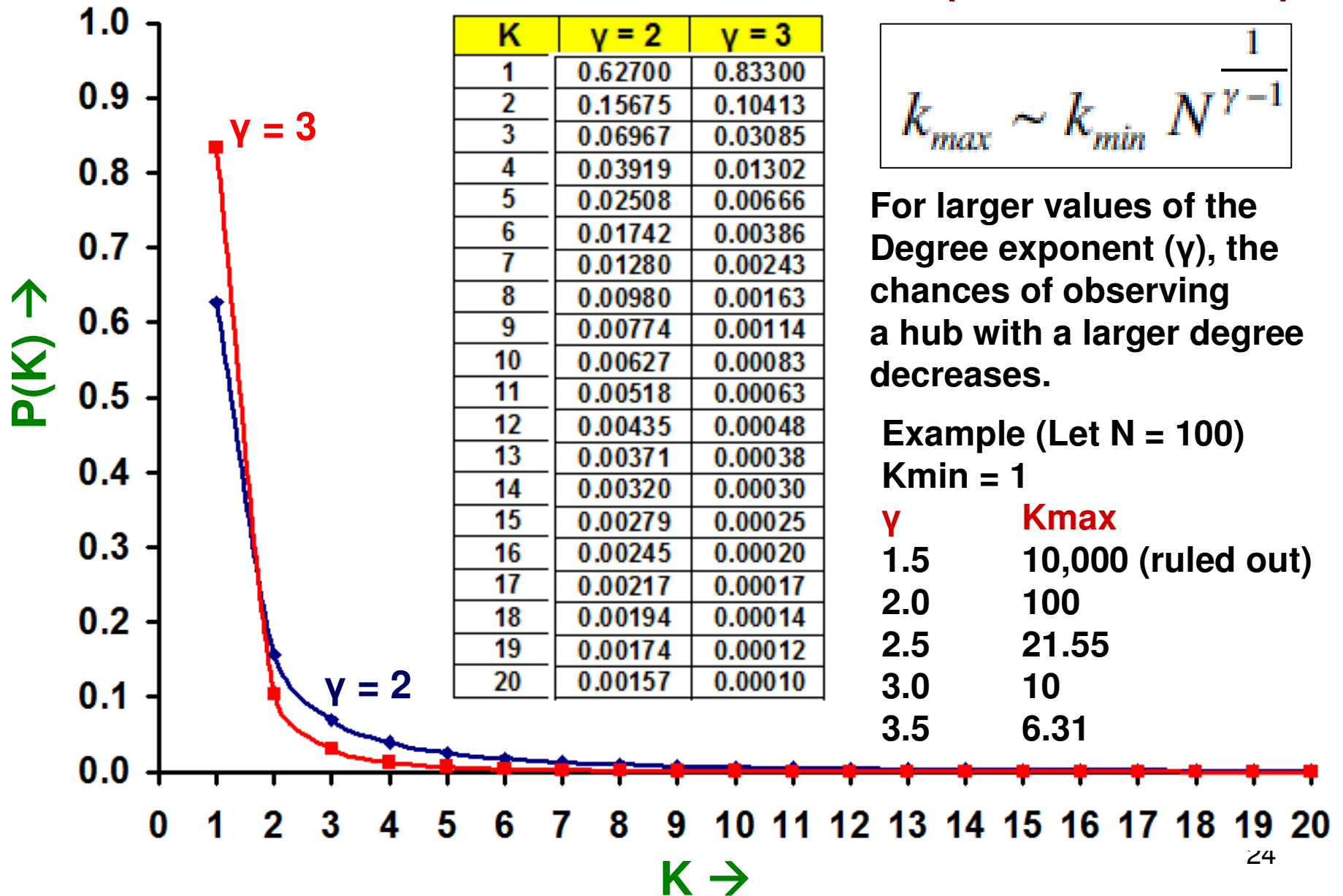
γ

k	1.9	2	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	3	3.1
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	0.268	0.250	0.233	0.218	0.203	0.189	0.177	0.165	0.154	0.144	0.134	0.125	0.117
3	0.124	0.111	0.100	0.089	0.080	0.072	0.064	0.057	0.051	0.046	0.041	0.037	0.033
4	0.072	0.063	0.054	0.047	0.041	0.036	0.031	0.027	0.024	0.021	0.018	0.016	0.014
5	0.047	0.040	0.034	0.029	0.025	0.021	0.018	0.015	0.013	0.011	0.009	0.008	0.007
6	0.033	0.028	0.023	0.019	0.016	0.014	0.011	0.009	0.008	0.007	0.006	0.005	0.004
7	0.025	0.020	0.017	0.014	0.011	0.009	0.008	0.006	0.005	0.004	0.004	0.003	0.002
8	0.019	0.016	0.013	0.010	0.008	0.007	0.006	0.004	0.004	0.003	0.002	0.002	0.002
9	0.015	0.012	0.010	0.008	0.006	0.005	0.004	0.003	0.003	0.002	0.002	0.001	0.001
10	0.013	0.010	0.008	0.006	0.005	0.004	0.003	0.003	0.002	0.002	0.001	0.001	0.001
11	0.011	0.008	0.007	0.005	0.004	0.003	0.002	0.002	0.002	0.001	0.001	0.001	0.001
12	0.009	0.007	0.005	0.004	0.003	0.003	0.002	0.002	0.001	0.001	0.001	0.001	0.000
13	0.008	0.006	0.005	0.004	0.003	0.002	0.002	0.001	0.001	0.001	0.001	0.000	0.000
14	0.007	0.005	0.004	0.003	0.002	0.002	0.001	0.001	0.001	0.001	0.000	0.000	0.000
15	0.006	0.004	0.003	0.003	0.002	0.002	0.001	0.001	0.001	0.001	0.000	0.000	0.000
16	0.005	0.004	0.003	0.002	0.002	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000
17	0.005	0.003	0.003	0.002	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000
18	0.004	0.003	0.002	0.002	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000
19	0.004	0.003	0.002	0.002	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
20	0.003	0.003	0.002	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
Sum	1.676	1.596	1.527	1.468	1.417	1.373	1.334	1.301	1.271	1.245	1.221	1.201	1.183
C (1/Sum)	0.596	0.627	0.655	0.681	0.706	0.728	0.749	0.769	0.787	0.803	0.819	0.833	0.846

$k^{-\gamma}$

C 22

Power-Law Distribution (Discrete)



$$k_{max} \sim k_{min} N^{\frac{1}{\gamma-1}}$$

For larger values of the Degree exponent (γ), the chances of observing a hub with a larger degree decreases.

Example (Let $N = 100$)

$K_{min} = 1$

γ	K_{max}
1.5	10,000 (ruled out)
2.0	100
2.5	21.55
3.0	10
3.5	6.31

Power Law (Discrete): Avg. Degree

	1.9	2	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	3	3.1
1	0.596	0.627	0.655	0.681	0.706	0.728	0.749	0.769	0.787	0.803	0.819	0.833	0.846
2	0.319	0.314	0.306	0.296	0.287	0.276	0.265	0.254	0.242	0.231	0.219	0.208	0.197
3	0.222	0.209	0.196	0.182	0.169	0.156	0.144	0.133	0.122	0.111	0.102	0.093	0.084
4	0.171	0.157	0.143	0.129	0.116	0.105	0.094	0.084	0.075	0.066	0.059	0.052	0.046
5	0.140	0.125	0.112	0.099	0.087	0.076	0.067	0.059	0.051	0.044	0.038	0.033	0.029
6	0.119	0.105	0.091	0.079	0.069	0.059	0.051	0.044	0.037	0.032	0.027	0.023	0.020
7	0.103	0.090	0.077	0.066	0.056	0.048	0.040	0.034	0.029	0.024	0.020	0.017	0.014
8	0.092	0.078	0.067	0.056	0.047	0.040	0.033	0.028	0.023	0.019	0.016	0.013	0.011
9	0.082	0.070	0.058	0.049	0.041	0.034	0.028	0.023	0.019	0.015	0.013	0.010	0.008
10	0.075	0.063	0.052	0.043	0.035	0.029	0.024	0.019	0.016	0.013	0.010	0.008	0.007
11	0.069	0.057	0.047	0.038	0.031	0.025	0.021	0.017	0.013	0.011	0.009	0.007	0.006
12	0.064	0.052	0.043	0.035	0.028	0.022	0.018	0.014	0.012	0.009	0.007	0.006	0.005
13	0.059	0.048	0.039	0.031	0.025	0.020	0.016	0.013	0.010	0.008	0.006	0.005	0.004
14	0.055	0.045	0.036	0.029	0.023	0.018	0.014	0.011	0.009	0.007	0.005	0.004	0.003
15	0.052	0.042	0.033	0.026	0.021	0.016	0.013	0.010	0.008	0.006	0.005	0.004	0.003
16	0.049	0.039	0.031	0.024	0.019	0.015	0.012	0.009	0.007	0.005	0.004	0.003	0.003
17	0.047	0.037	0.029	0.023	0.018	0.014	0.011	0.008	0.006	0.005	0.004	0.003	0.002
18	0.044	0.035	0.027	0.021	0.016	0.013	0.010	0.008	0.006	0.004	0.003	0.003	0.002
19	0.042	0.033	0.026	0.020	0.015	0.012	0.009	0.007	0.005	0.004	0.003	0.002	0.002
20	0.040	0.031	0.024	0.019	0.014	0.011	0.008	0.006	0.005	0.004	0.003	0.002	0.002
$\langle K \rangle$	2.441	2.256	2.090	1.947	1.825	1.717	1.626	1.548	1.481	1.422	1.373	1.330	1.292

Why Power-Law is said to be scale-free?

- Kurtosis is a measure of how “heavy-tailed” a distribution is.
- A probability distribution is generally said to be scale-free (i.e., heavy-tailed) if its kurtosis is quite high (typically larger than 3).
- Scale-free distributions also have a standard deviation that is comparable or even larger than the mean.

$$Kurtosis[K] = \frac{E[K - \langle K \rangle]^4}{\left(E[K - \langle K \rangle]^2 \right)^2}$$

*K is the degree;
<K> is the mean degree*

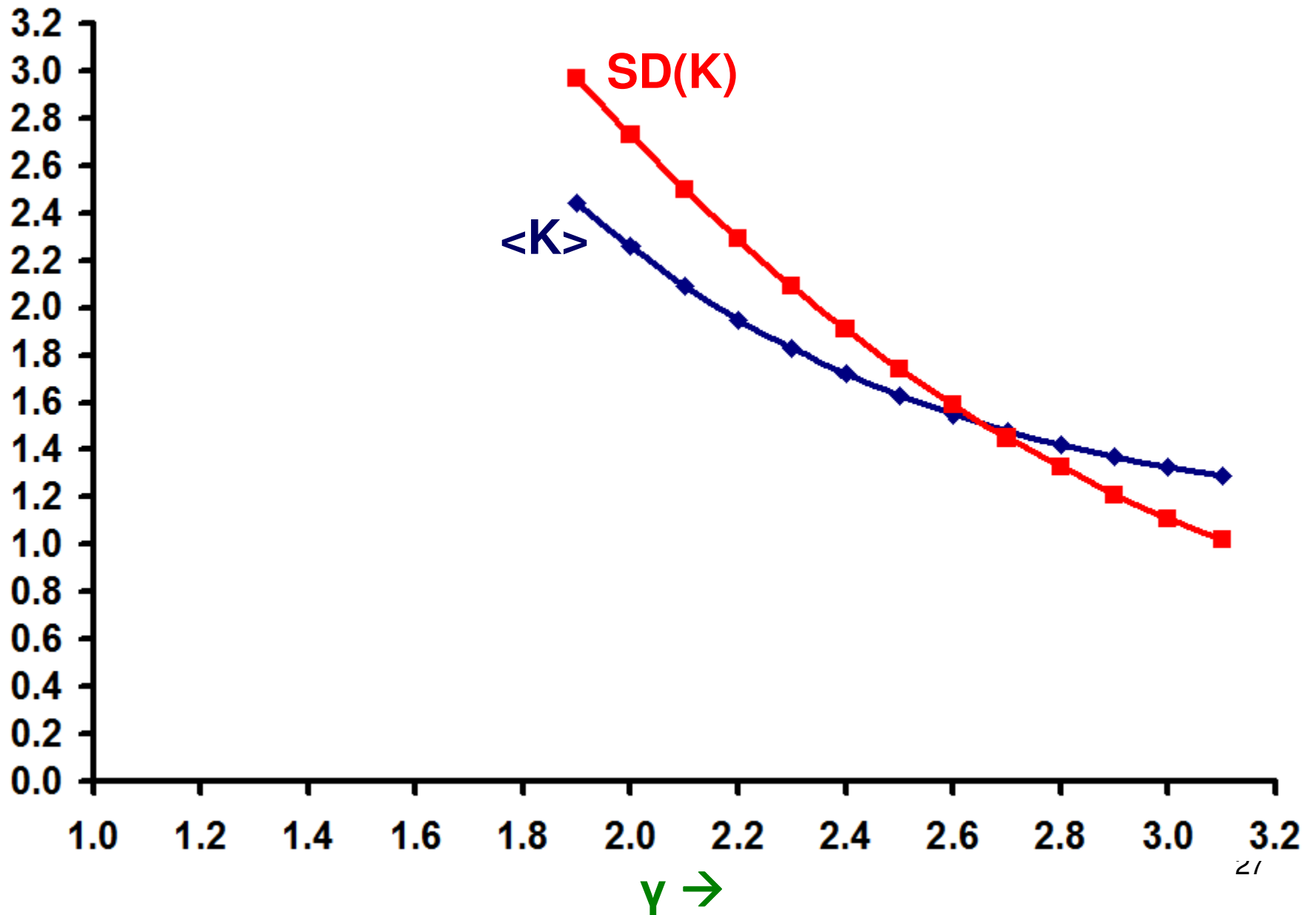
$$\text{Standard Deviation, SD (K)} = \sqrt{\frac{1}{N} \sum_{K; P(K) > 0} (K - \langle K \rangle)^2}$$

$$\text{SD(K)} = \sqrt{\sum_K P(K) * (K - \langle K \rangle)^2}$$

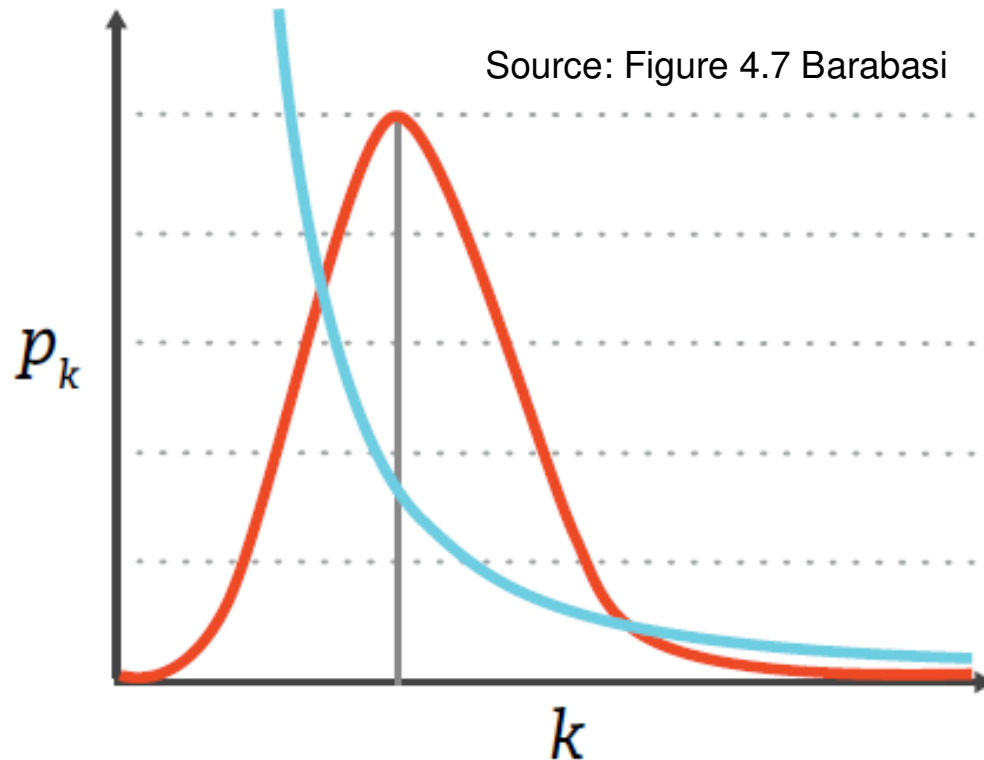
$$\text{Kurtosis(K)} = \frac{\sum_K P(K) * (K - \langle K \rangle)^4}{SD^4}$$

The Kurtosis and SD formula are applied for all values (# samples: N) of K for which there is a non-zero probability of finding a vertex with the particular degree

Power-Law (Discrete): Degree (Avg. and SD)



Scale-free networks lack an intrinsic scale



Random network

Randomly chosen node: $k = \langle k \rangle \pm \langle k \rangle^{1/2}$
Scale: $\langle k \rangle$

Scale-free network

Randomly chosen node: $k = \langle k \rangle \pm \infty$
 $\langle k \rangle$ is meaningless as 'scale'

- For any bounded distribution (e.g. a Poisson or a Gaussian distribution) the degree of a randomly chosen node will be in the vicinity of $\langle k \rangle$. Hence $\langle k \rangle$ serves as the network's scale.
- In a scale-free network the second moment diverges, hence the degree of a randomly chosen node can be arbitrarily different from $\langle k \rangle$. Thus, a scale-free network lacks an intrinsic scale (and hence gets its name).

Example 1: Power-law

- Consider a network modeled using the power-law, $P(K) = CK^{-\gamma}$. Determine the power-law exponent γ and the constant C if the network has approximately 4% of nodes with degree 4 and 10% of nodes with degree 3.

- Solution:

- $P(K) = CK^{-\gamma} \rightarrow \ln P(K) = \ln C + (-\gamma)\ln K$

- Given that $P(3) = 0.10$ and $P(4) = 0.04$

$$\ln(0.10) = \ln C + (-\gamma)\ln(3) \rightarrow -2.303 = \ln C + (-\gamma)*1.098$$

$$\ln(0.04) = \ln C + (-\gamma)\ln(4) \rightarrow -3.219 = \ln C + (-\gamma)*1.386$$

Solving for γ , we get $\gamma = (3.219 - 2.303)/(1.386 - 1.098) = 3.18$

Substituting for **$\gamma = 3.18$** in the Power-law equation for one of the two degrees, we get $C = P(4) / 4^{-\gamma} = 0.04 / 4^{-3.18}$

We get **$C = 3.286$**

Example 2: Analyzing a Degree Distribution for Scale-Free Property

Given the following adjacency list for the vertices, determine whether the Degree distribution could be classified to exhibit “scale-free” property.

0 1
0 2
0 3
0 4
0 5
0 7
0 8
1 3
1 5
1 6
1 9
3 4
4 6
4 7
5 9
7 8

0 → 1, 2, 3, 4, 5, 7, 8
1 → 0, 3, 5, 6, 9
2 → 0
3 → 0, 1, 4
4 → 0, 3, 6, 7
5 → 0, 1, 9
6 → 1, 4
7 → 0, 4, 8
8 → 0, 7
9 → 1, 5

ID	Degree
0	7
1	5
2	1
3	3
4	4
5	3
6	2
7	3
8	2
9	2

Degree	#Nodes	P(K)
1	1	1/10 = 0.1
2	3	3/10 = 0.3
3	3	3/10 = 0.3
4	1	1/10 = 0.1
5	1	1/10 = 0.1
7	1	1/10 = 0.1

Avg. Degree = $\sum_k K * P(K)$

Avg. Degree, <K>
 = (1)(0.1) + (2)(0.3) + (3)(0.3)
 + (4)(0.1) + (5)(0.1) + (7)(0.1)
 = 3.2

Example 2(1): Analyzing a Degree Distribution for Scale-Free Property

$$\langle K \rangle = 3.2$$

Degree (K)	P(K)	$(K - \langle K \rangle)^2$	$(K - \langle K \rangle)^4$	$P(K) * (K - \langle K \rangle)^2$	$P(K) * (K - \langle K \rangle)^4$
1	0.1	4.84	23.43	0.484	2.343
2	0.3	1.44	2.07	0.432	0.621
3	0.3	0.04	0.0016	0.012	0.00048
4	0.1	0.64	0.4096	0.064	0.04096
5	0.1	3.24	10.498	0.324	1.0498
7	0.1	14.44	208.51	1.444	20.851

$$SD(K) = \sqrt{\sum_K P(K) * (K - \langle K \rangle)^2} = \sqrt{2.76} = \underline{1.661}$$

$$\sum_K P(K) * (K - \langle K \rangle)^4 = 24.906$$

Since the Kurtosis (K) = 3.27 is greater than 3, we say the Degree distribution is heavy-tailed.

$$Kurtosis(K) = \frac{\sum_K P(K) * (K - \langle K \rangle)^4}{SD^4} = \frac{24.906}{(1.661)^4} = \underline{3.27}$$

Example 3: Analyzing a Degree Distribution for Scale-Free Property

Given the following adjacency list for the vertices, determine whether the Degree distribution could be classified to exhibit “scale-free” property.

0 1
 0 2
 0 3
 0 4
 0 5
 1 2
 1 4
 1 6
 1 9
 2 3
 2 8
 3 6
 3 8
 4 5
 4 7
 4 9
 5 7

0 → 1, 2, 3, 4, 5
 1 → 0, 2, 4, 6, 9
 2 → 0, 1, 3, 8
 3 → 0, 2, 6, 8
 4 → 0, 1, 5, 7, 9
 5 → 0, 4, 7
 6 → 1, 3
 7 → 4, 5
 8 → 2, 3
 9 → 1, 4

ID	Degree
0	5
1	5
2	4
3	4
4	5
5	3
6	2
7	2
8	2
9	2

Degree	#Nodes	P(K)
2	4	4/10 = 0.4
3	1	1/10 = 0.1
4	2	2/10 = 0.2
5	3	3/10 = 0.3

Avg. Degree = $\sum_k K * P(K)$

Avg. Degree, <K>
 = (2)(0.4) + (3)(0.1) + (4)(0.2)
 + (5)(0.3) = 3.4

Example 3(1): Analyzing a Degree Distribution for Scale-Free Property

$$\langle K \rangle = 3.4$$

Degree (K)	P(K)	$(K - \langle K \rangle)^2$	$(K - \langle K \rangle)^4$	$P(K) * (K - \langle K \rangle)^2$	$P(K) * (K - \langle K \rangle)^4$
2	0.4	1.96	3.842	0.784	1.5368
3	0.1	0.16	0.0256	0.016	0.00256
4	0.2	0.36	0.1296	0.072	0.02592
5	0.3	2.56	6.5536	0.768	1.9661

$$SD(K) = \sqrt{\sum_K P(K) * (K - \langle K \rangle)^2} = \sqrt{1.64} = \underline{1.281}$$

$$\sum_K P(K) * (K - \langle K \rangle)^4 = 3.5313$$

Since the Kurtosis (K) = 1.31
Is lower than 3, we say the
Degree distribution is NOT
heavy-tailed.

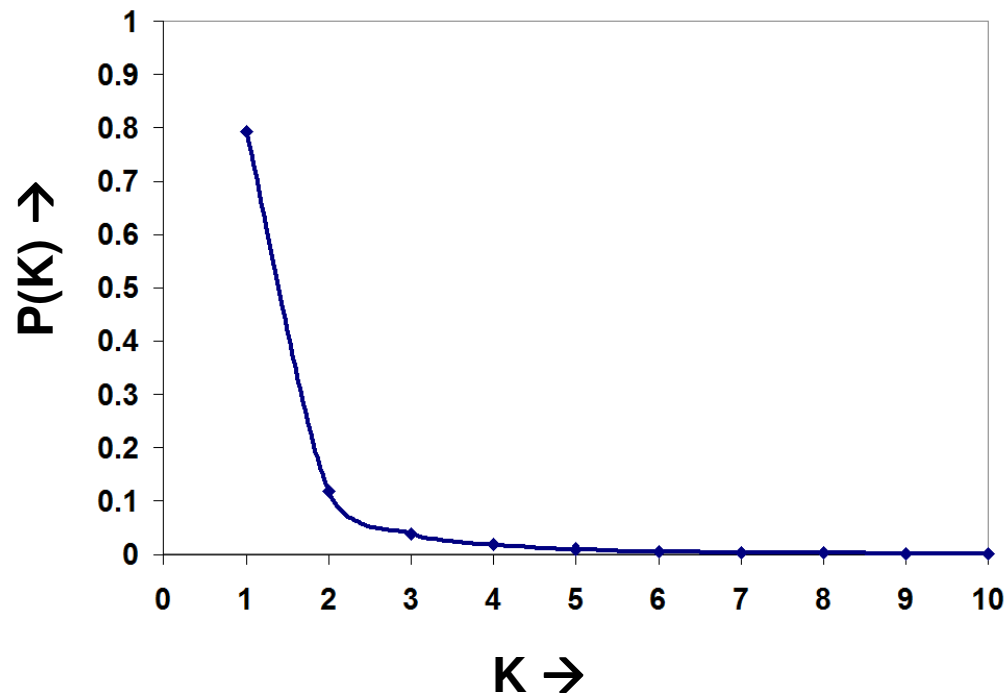
$$Kurtosis(K) = \frac{\sum_K P(K) * (K - \langle K \rangle)^4}{SD^4} = \frac{3.5313}{(1.281)^4} = \underline{1.31}$$

Example 4: Predicting the Nature of Degree Distribution

Given the following probability degree distribution:

- 1) Draw a plot of the degree distribution and determine if the degree distribution follows a power-law or Poisson?
- 2) Determine the parameters of the degree distribution you decided.

K	P(K)
1	0.794
2	0.119
3	0.039
4	0.018
5	0.010
6	0.006
7	0.004
8	0.003
9	0.002
10	0.001



It looks clearly like a power-law distribution.

Example 4(1): Predicting the Nature of Degree Distribution

$$P(K) = C \cdot K^{-\gamma}$$

$\ln P(K) = \ln C + (-\gamma \cdot \ln K)$: Compared to $Y = (\text{slope}) \cdot X + \text{constant}$;
 slope = $-\gamma$; constant = $\ln C$;

We will use curve (line) fitting in Excel to find the slope and constant

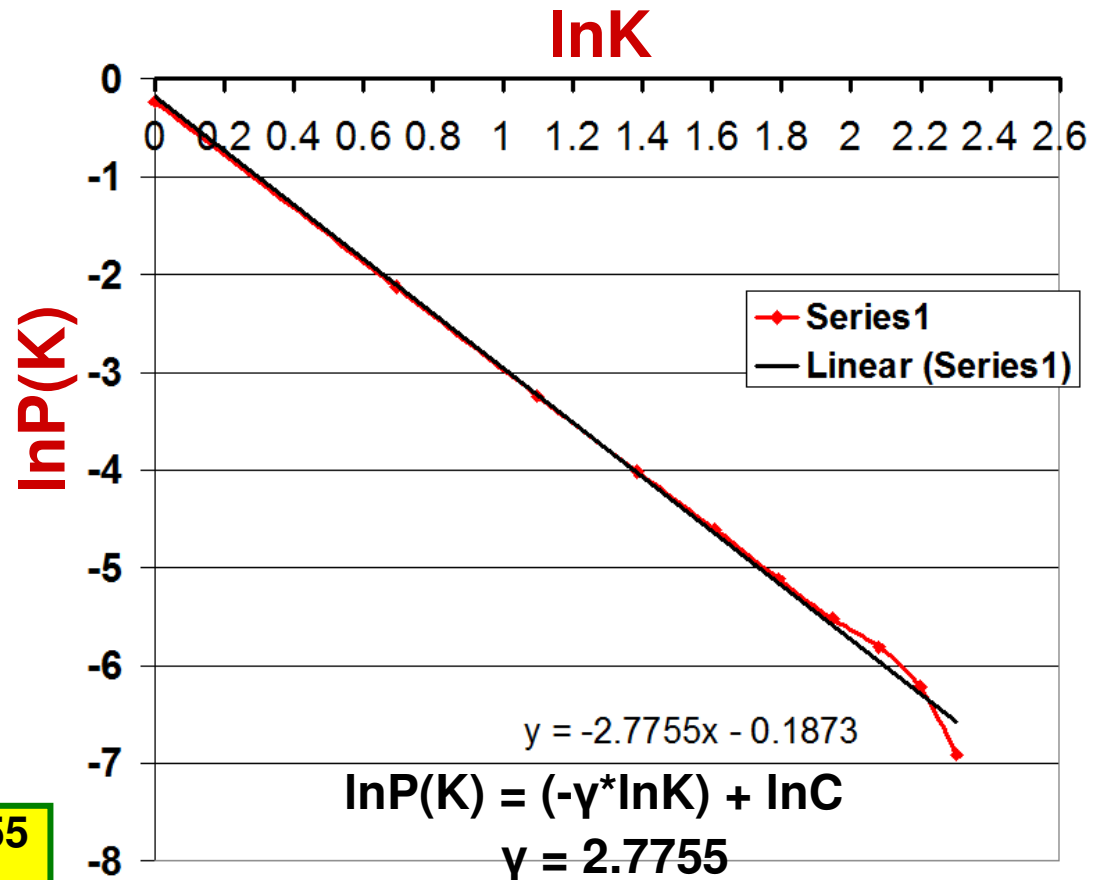
K	P(K)	lnK	lnP(K)
1	0.794	0	-0.23
2	0.119	0.69	-2.13
3	0.039	1.10	-3.24
4	0.018	1.39	-4.02
5	0.010	1.61	-4.61
6	0.006	1.79	-5.12
7	0.004	1.95	-5.52
8	0.003	2.08	-5.81
9	0.002	2.20	-6.21
10	0.001	2.30	-6.91

Constant = $\ln C = -0.1873$

$C = e^{-0.1873} = 2.718^{-0.1873}$

$C = 0.829$

$P(K) = 0.829 \cdot K^{-2.7755}$

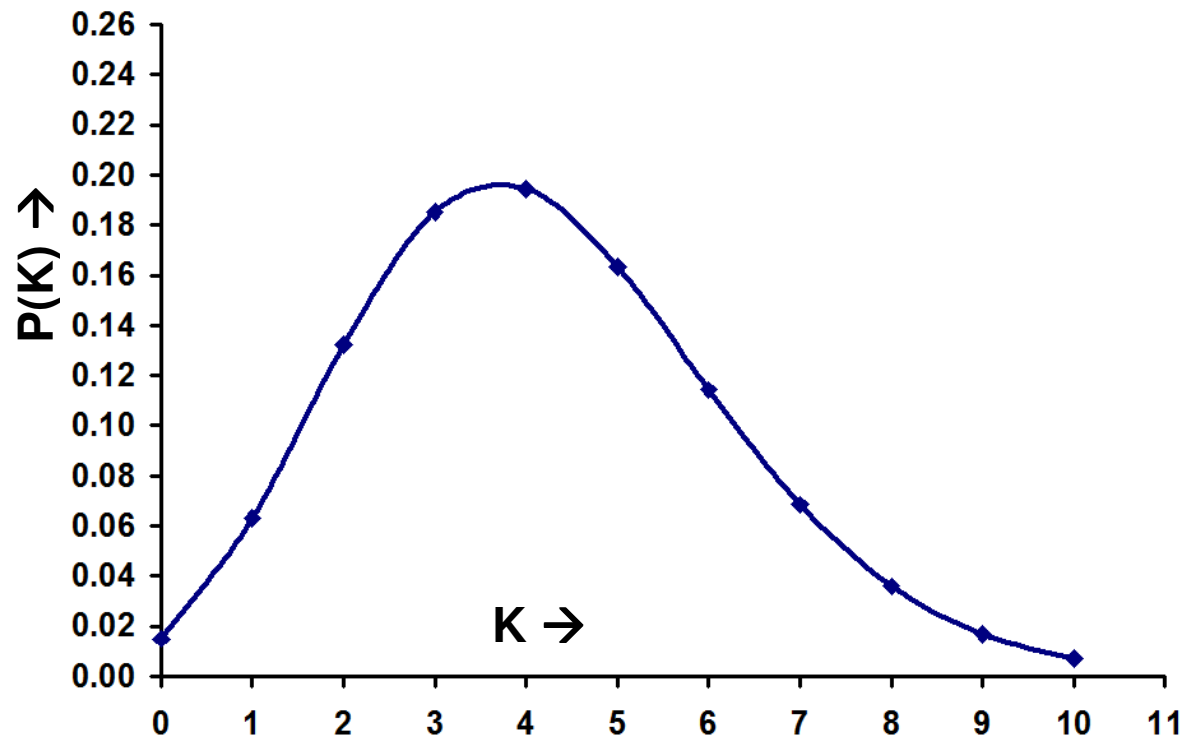


Example 5: Predicting the Nature of Degree Distribution

Given the following probability degree distribution:

- 1) Draw a plot of the degree distribution and determine if the degree distribution follows a power-law or Poisson?
- 2) Determine the parameters of the degree distribution you decided.

K	P(K)
0	0.015
1	0.163
2	0.132
3	0.185
4	0.194
5	0.163
6	0.114
7	0.068
8	0.036
9	0.017
10	0.007



It looks clearly like a Poisson distribution.

K	P(K)	K*P(K)	(K-<K>)^2	(K-<K>)^4	P(K)*(K-<K>)^2	P(K)*(K-<K>)^4
0	0.015	0.000	17.256	297.760	0.259	4.466
1	0.063	0.063	9.948	98.957	0.627	6.233
2	0.132	0.265	4.640	21.527	0.614	2.848
3	0.185	0.556	1.332	1.773	0.247	0.328
4	0.194	0.778	0.024	0.001	0.005	0.000
5	0.163	0.817	0.716	0.512	0.117	0.084
6	0.114	0.686	3.408	11.613	0.390	1.328
7	0.069	0.480	8.100	65.605	0.556	4.501
8	0.036	0.288	14.792	218.795	0.533	7.880
9	0.017	0.151	23.484	551.485	0.395	9.269
10	0.007	0.071	34.176	1167.980	0.241	8.245
SUM	1	4.154			3.981	45.181

$$\text{Avg. Degree } \langle K \rangle = \sum_k K * P(K) = 4.154$$

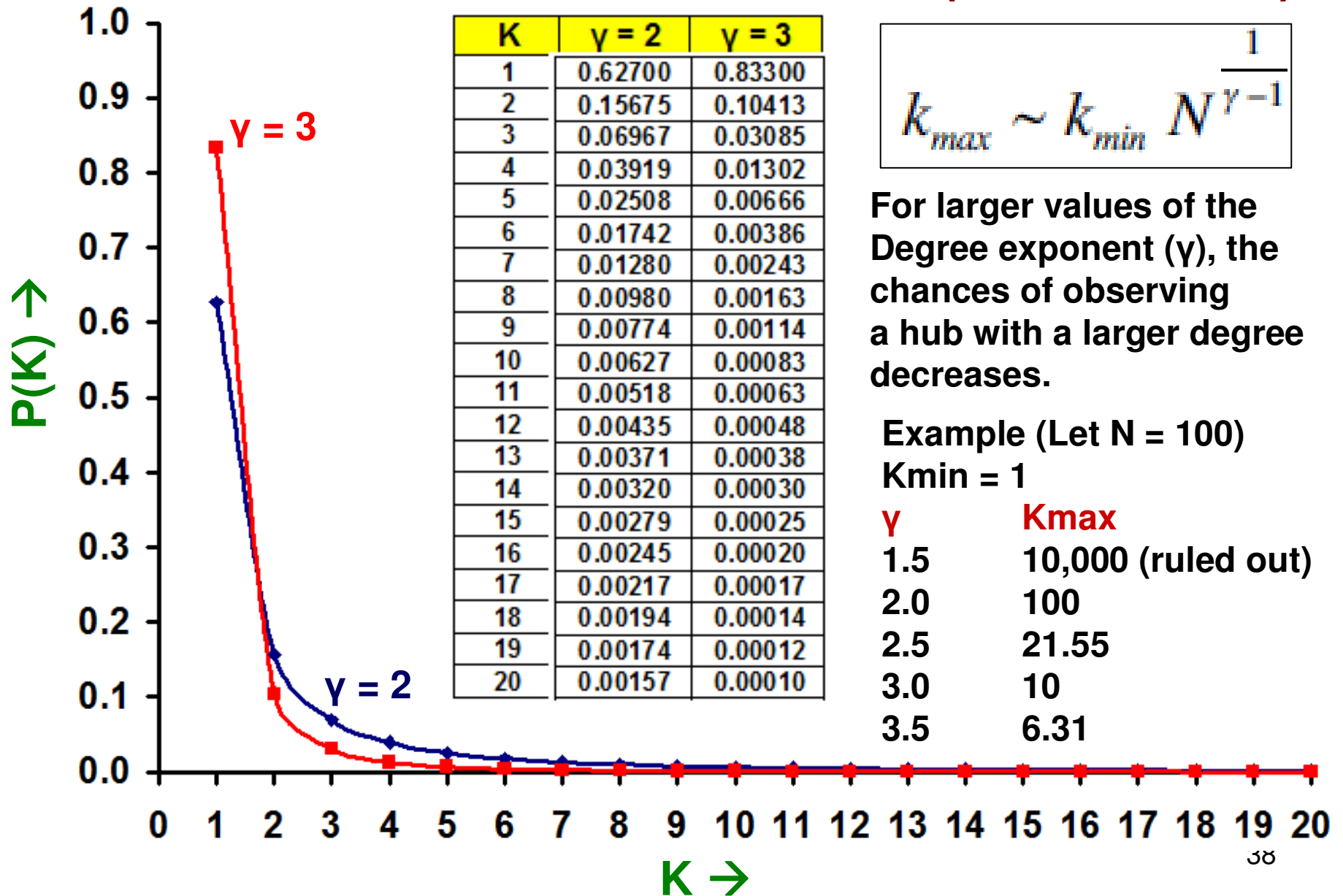
$$\text{SD}(K) = \sqrt{\sum_K P(K) * (K - \langle K \rangle)^2} = \sqrt{3.981} = \underline{1.995}$$

$$\text{Kurtosis}(K) = \frac{\sum_K P(K) * (K - \langle K \rangle)^4}{\text{SD}^4} = \frac{45.181}{(1.995)^4} = \underline{2.852}$$

Kurtosis of Poisson distribution is expected to be close to 3

Kurtosis of Heavy-tailed Power-law distribution is expected to be (much) larger than 3.

Power-Law Distribution (Discrete)



$$k_{max} \sim k_{min} N^{\frac{1}{\gamma-1}}$$

For larger values of the Degree exponent (γ), the chances of observing a hub with a larger degree decreases.

Example (Let N = 100)

Kmin = 1

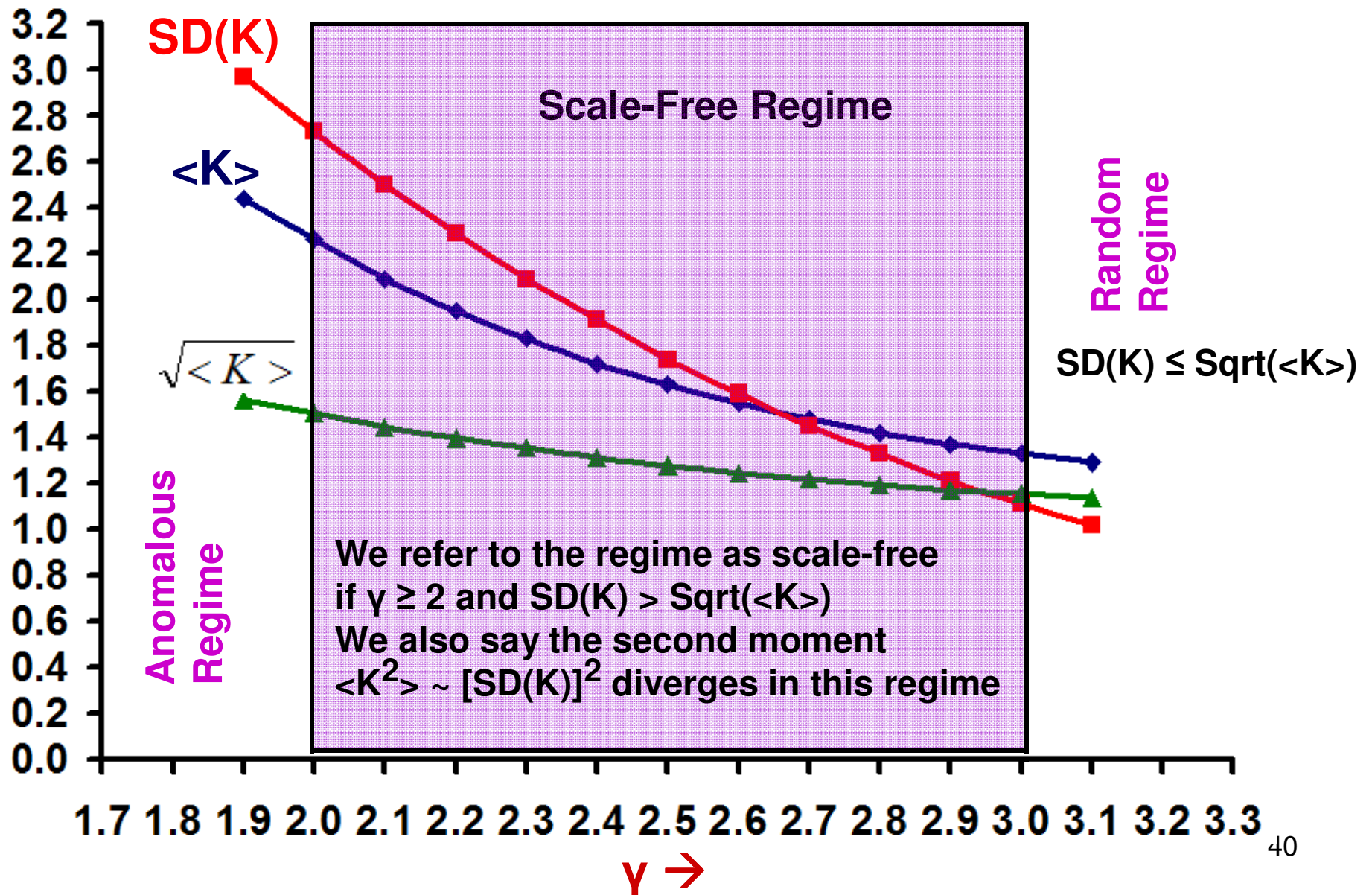
γ	Kmax
1.5	10,000 (ruled out)
2.0	100
2.5	21.55
3.0	10
3.5	6.31

Average Distance: Power-Law

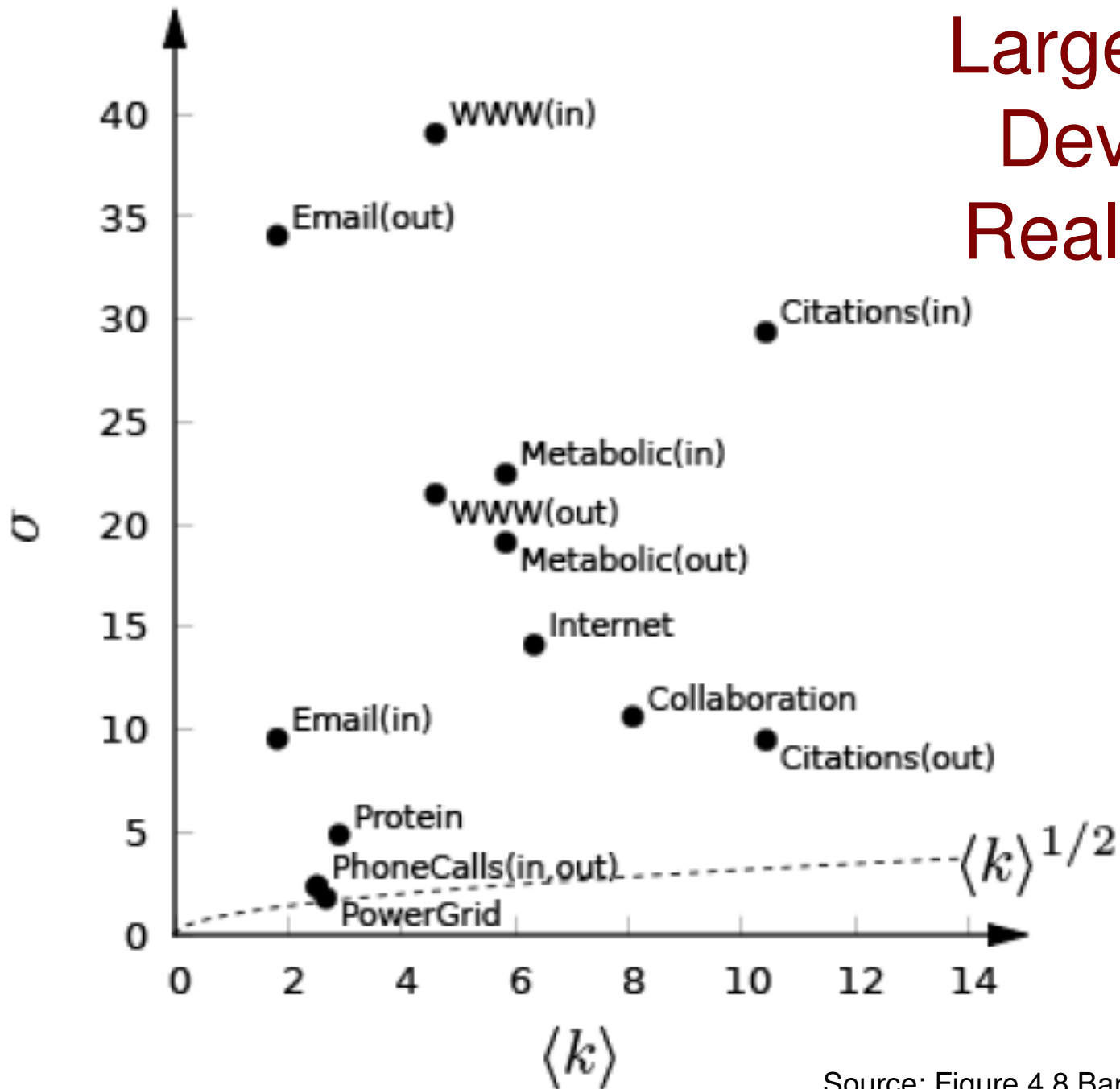
$d \sim$	const.	if $\gamma = 2$,	Anomalous regime: Hub and spoke configuration; average distance independent of N.
	$\frac{\ln \ln N}{\ln(\gamma - 1)}$	if $2 < \gamma < 3$,	Ultra small world regime Hubs still reduce the path length
	$\frac{\ln N}{\ln \ln N}$	if $\gamma = 3$,	the $\ln N$ dependence on N (as in random networks) starts
	$\ln N$	if $\gamma > 3$.	Small world property: Hubs are not sufficiently large and numerous to have impact on path length

The scale-free property shrinks the average path lengths as well as changes the dependence of $\langle d \rangle$ on the system size. The smaller γ , the shorter are the distances between the nodes.

Network Regimes based on SD(K)



Large Standard Deviation for Real Networks



Source: Figure 4.8 Barabasi

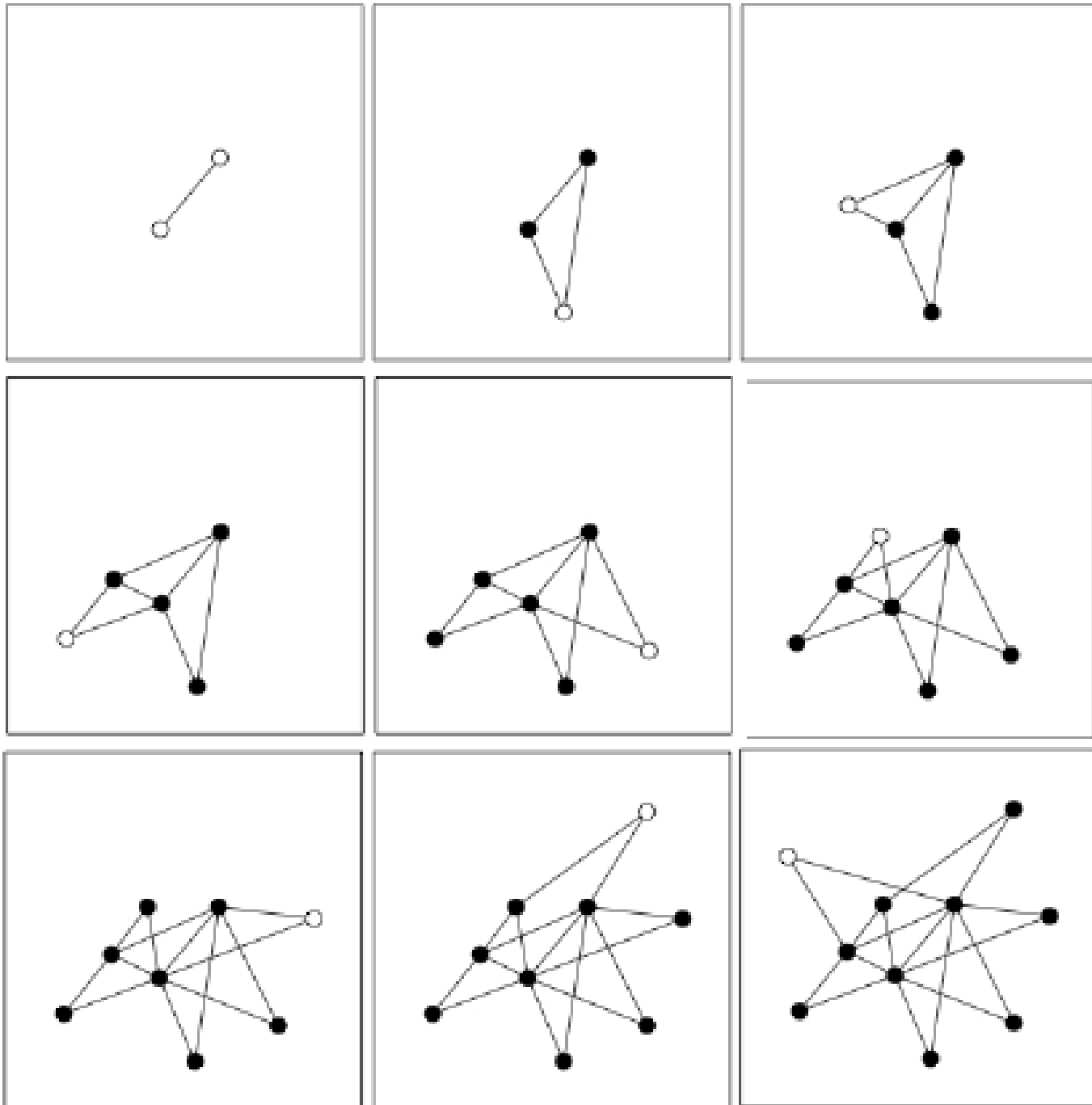
Barabasi Albert (BA) Model

- BA model is a model for generating networks with power-law degree distribution.
- The model is defined as follows:
 - We start with m_0 nodes, the links between which are chosen arbitrarily, as long as each node has at least one link.
 - The network develops as per the following growth and preferential attachment properties:
 - Growth: At each time step, we add a new node with m ($\leq m_0$) links that connect the new node to m nodes already in the network.
 - Preferential Attachment: The probability $\pi(k)$ that one of the links of the new node connects to node i depends on the degree k_i of node i as:

a node with larger degree has good chances of getting connected to even more nodes.

$$\pi(k_i) = \frac{k_i}{\sum_j k_j}$$

BA Model Example ($m = 2$)



Source: Figure 5.4
Barabasi

BA Model: Time-dependent Degree of a Node

- In the BA model, a node has a chance to increase its degree each time a new node enters the network.
- Let k_i be a time-dependent continuous real variable (k_i is the degree of node i that enters the network at time t_i)
- The degree of node i at any time instant $t \geq t_i$ is given by:

$$k_i(t) = m \left(\frac{t}{t_i} \right)^\beta$$

where $\beta = 1/2$ is called the network's dynamical exponent.

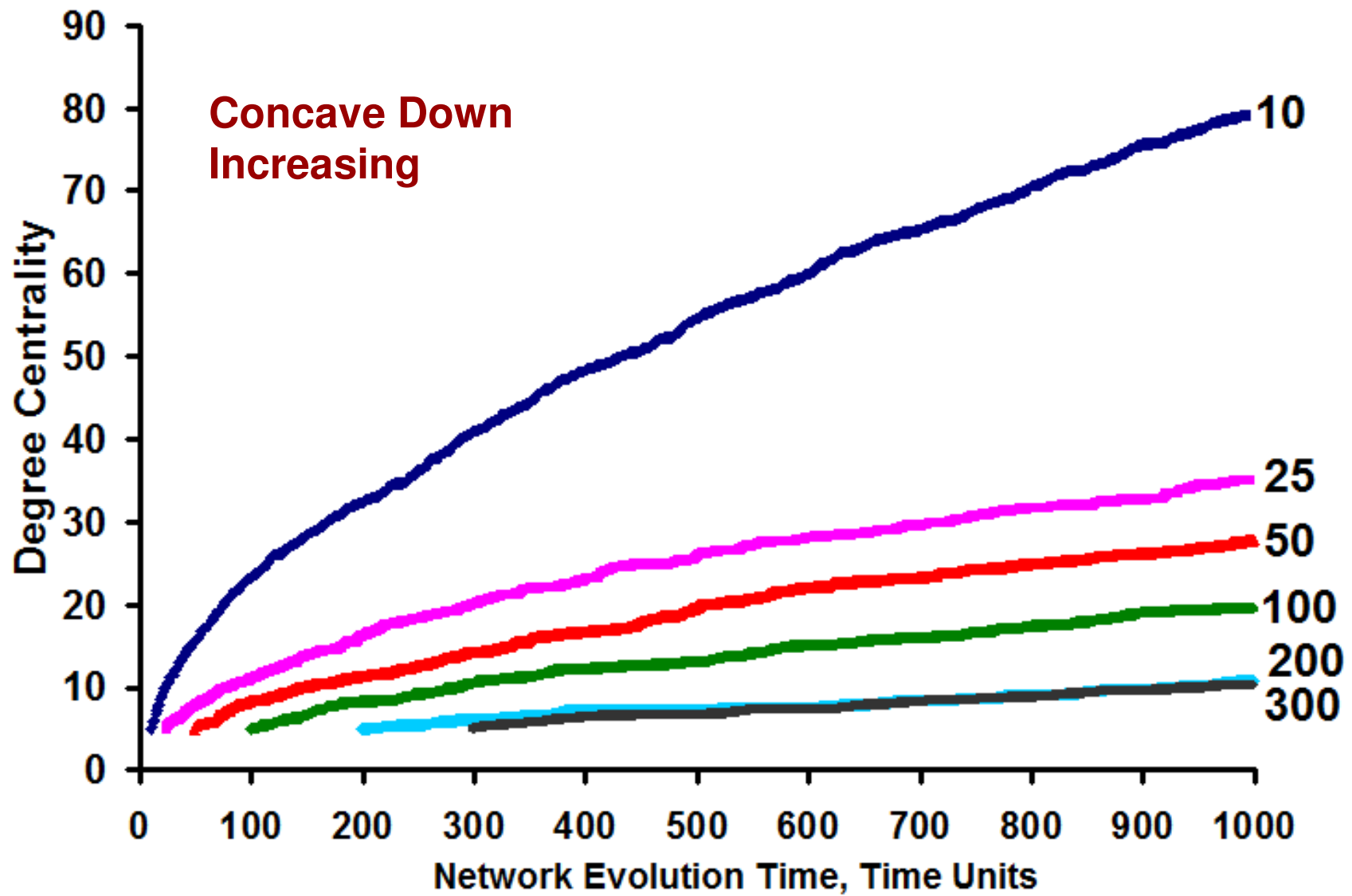
Observations:

- 1) The degree of each node increases following the above power law.
 - 2) Each new node has more nodes to link than the previous nodes.
- In other words, with time, each node competes for links with an increasing pool of nodes.

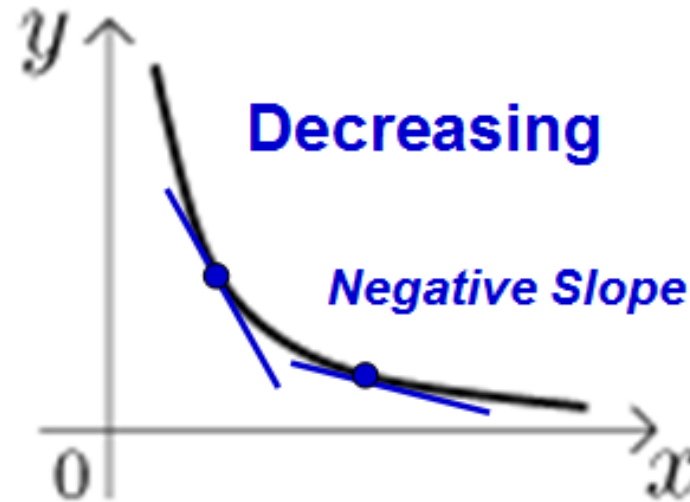
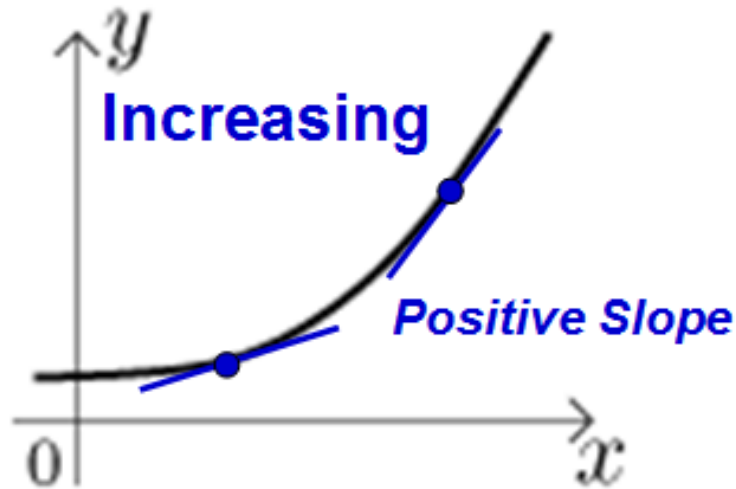
Time Dependent Degree of a Node

- The earlier node i was added, the higher is its degree $k_i(t)$.
 - Hence, hubs are large not because they grow faster, but because they arrived earlier.
 - The growth in the degrees is sub linear ($\beta < 1$).
- The rate at which node i acquires new links is given by the derivative:
$$\frac{dk_i(t)}{dt} = \frac{m}{2} \frac{1}{\sqrt{t_i t}}$$
- Indicating that older nodes acquire more links in a unit time (as they have smaller t_i), as well as that the rate at which a node acquires links decreases with time as $t^{-1/2}$. Hence, less and less links go to a node with time.
- Thus, the BA model offers a dynamical description of a network's evolution: in real networks, nodes arrive one after the other, connecting to the earlier nodes.
 - This sets up a competition for links during which the older nodes have an advantage over the younger nodes, eventually turning into hubs.

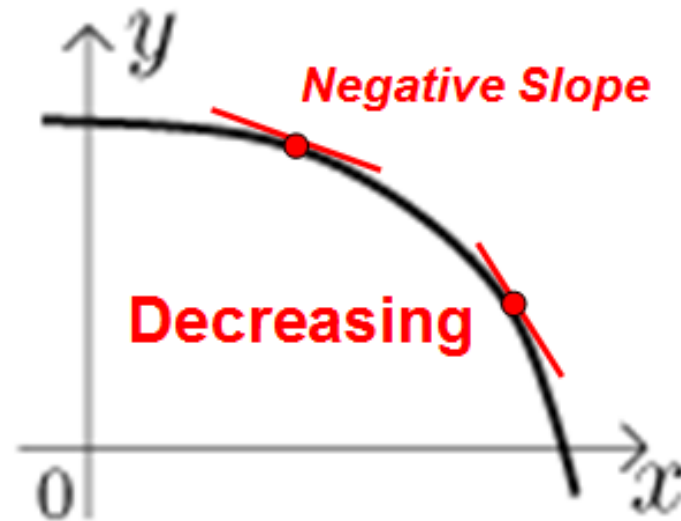
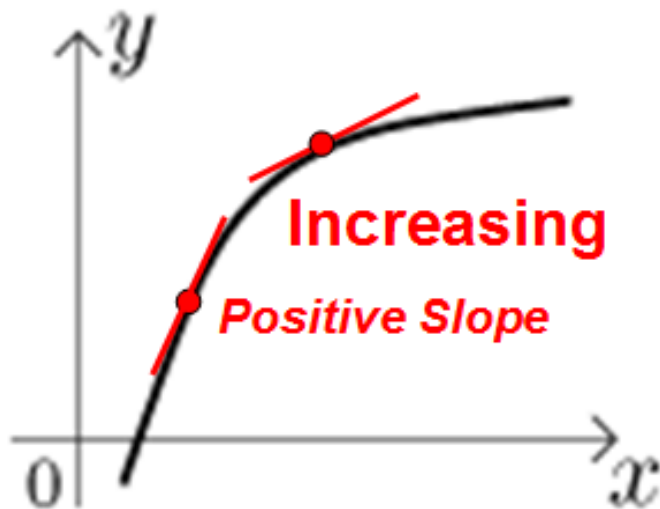
Time-Dependent Variation of Degree Centrality



Nature of Functions

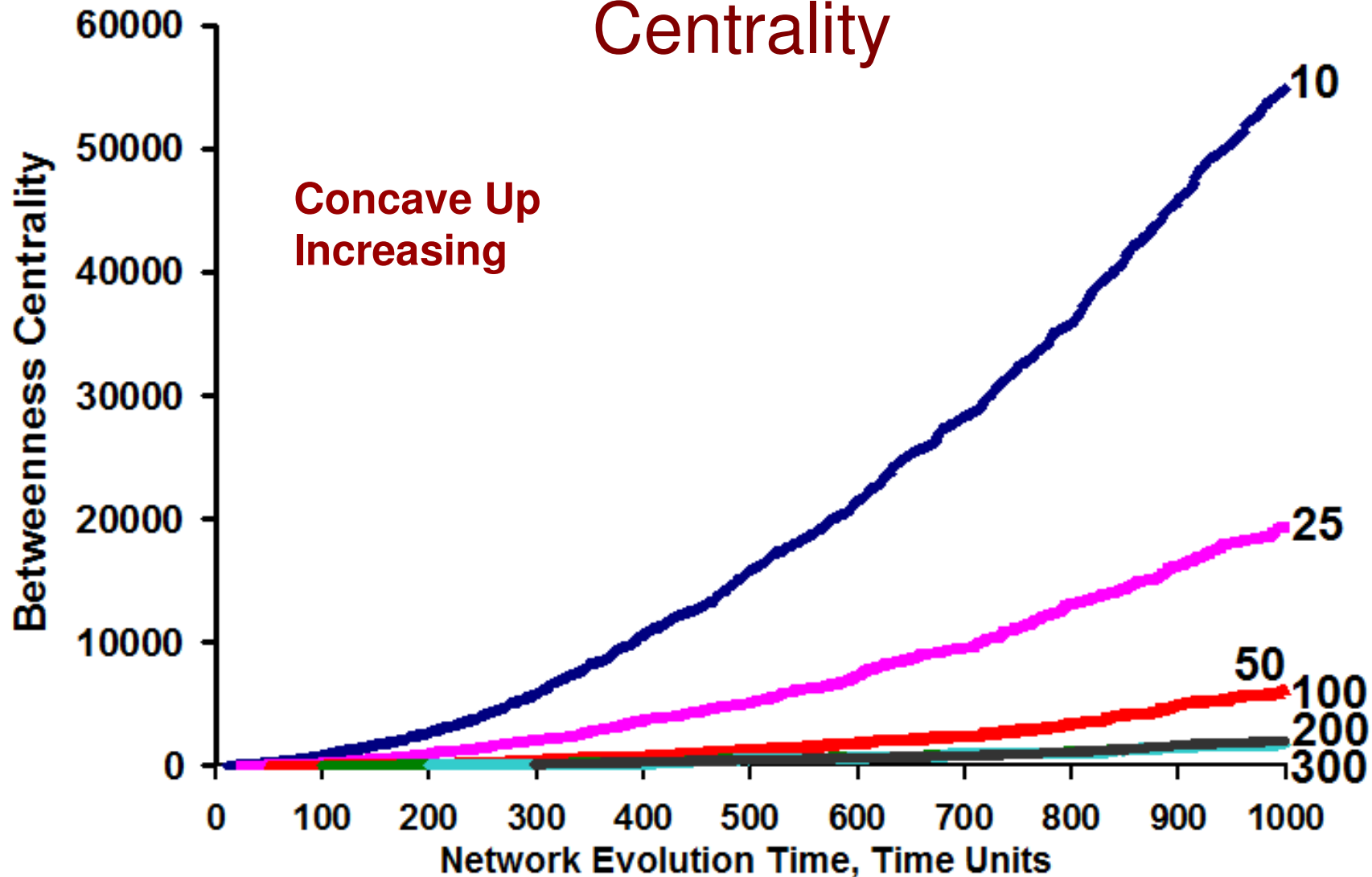


Concave Up (the rate of increase or decrease increases with time)



Concave Down (the rate of increase or decrease decreases with time)

Time-Dependent Variation of Betweenness Centrality



N. Meghanathan, "Time-Dependent Variation of the Centrality Measures of the Nodes during the Evolution of a Scale-Free Network," *Journal of Networks*, vol. 10, no. 7, pp. 431-442, July 2015.
<http://ojs.academypublisher.com/index.php/jnw/article/view/jnw1007431442/10670>

Bianconi-Barabasi (BB) Model

Motivation

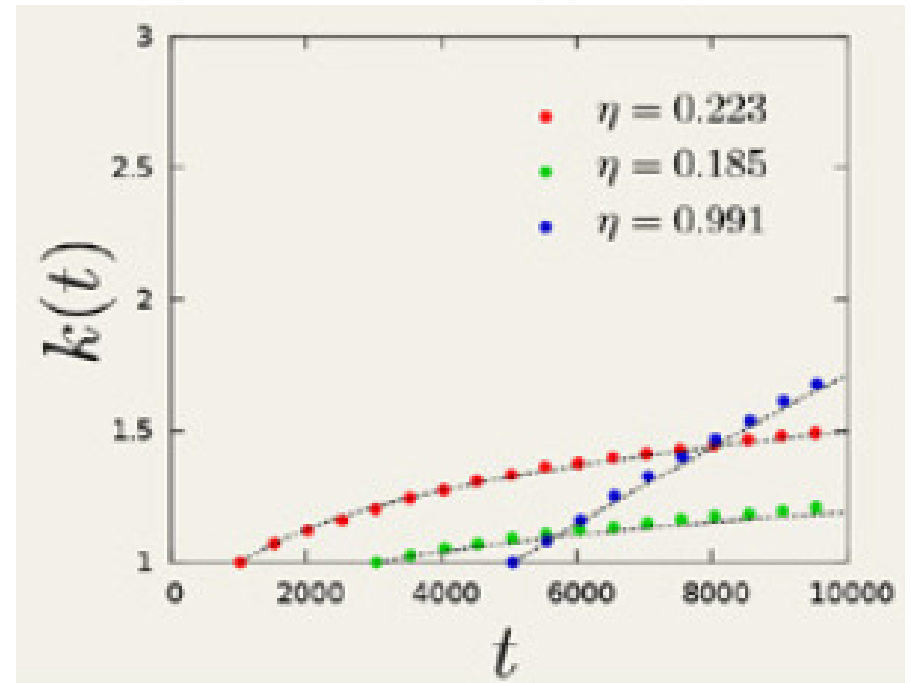
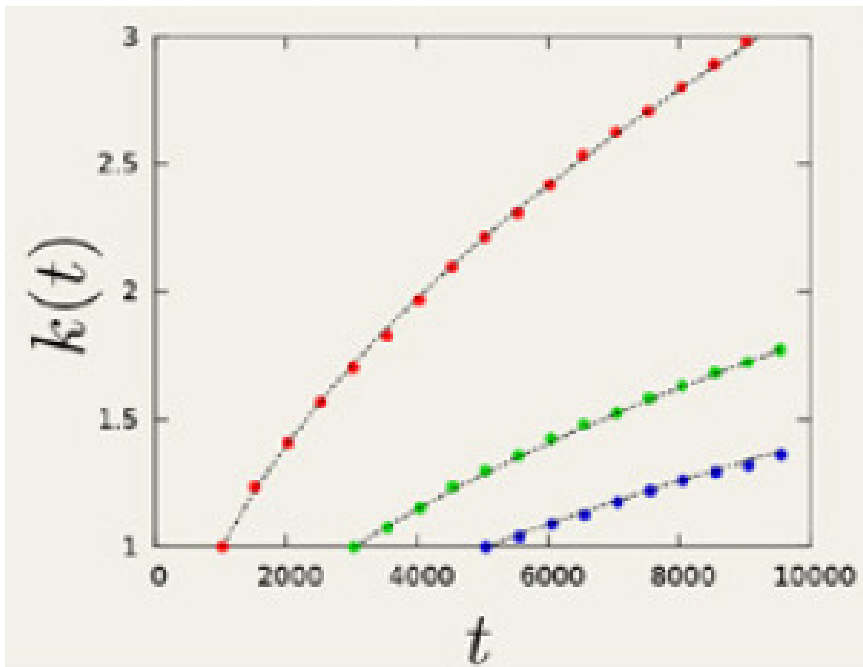
- The Barabasi-Albert model leads to a scenario where the late nodes can never turn into the largest hubs.
- In reality, a node's growth does not depend on the node's age only.
 - Instead web pages, companies or actors have intrinsic qualities that influence the rate at which they acquire links.
 - Some show up late and nevertheless grab most links within a short timeframe.
 - Example: Though, Facebook came later than Google, Facebook is the most linked node in the Internet.
- The goal of this model is to understand how the differences in the node's ability to acquire links, and other processes not captured by the Barabasi-Albert model, like node and link deletion or aging, affect the network topology.

Bianconi-Barabasi (BB) Model

- Fitness – the intrinsic property of a node that propels more nodes towards it.
- The Barabasi-Albert model assumed that a node's growth rate is determined solely by its degree.
- The BB model incorporates the role of fitness and assumes that preferential attachment is driven by the product of a node's fitness, η , and its degree k .
- Growth: In each timestep, a new node j with m links and fitness η_j is added to the system, where η_j is a random number chosen from a distribution $\rho(\eta)$ [for example: uniform distribution].
 - Once assigned, a node's fitness does not change.
- Preferential Attachment: The probability that a link of a new node connects to a pre-existing node i is proportional to the product of node i 's degree k_i and its fitness η_i .

$$\Pi_i = \frac{\eta_i k_i}{\sum_j \eta_j k_j}$$

BA Model vs. BB Model



BB Model

$$\frac{\partial k_i}{\partial t} = m \frac{\eta_i k_i}{\sum_k \eta_j k_j}$$

$$k_{\eta_i}(t, t_i) = m \left(\frac{t}{t_i} \right)^{\beta(\eta_i)}$$

where $\beta(\eta_i)$ is a fitness-dependent dynamic exponent of node i .

A node with a higher fitness will increase its degree faster.

Example-1: BA & BB Model

- Consider the following degree distribution of the nodes and their fitness.
- Determine the probability with which each node is likely to get the first link with a newly joining node under the BA and BB models.
- Let a new node join the network with 2 links under the BA and BB models. Determine which nodes are likely to get connected to the new node.

ID	Degree	Fitness	BA Model (First Link)	
ID	Degree		Probability of a node getting the first link	Cumulative Probability
1	1	5	0.05	0.05
2	4	4	0.20	0.25
3	5	7	0.25	0.50
4	3	10	0.15	0.65
5	3	8	0.15	0.80
6	2	9	0.10	0.90
7	2	6	0.10	1.00
Sum	20			

$$\Pi(k_i) = \frac{k_i}{\sum_j k_j}$$

Generate a random number
I got 0.2429 using the
Random number generator
Program I gave you.

**Node 2 gets selected for
the first link**

Example-1: BA & BB Model

ID	Degree	Fitness
1	1	5
2	4	4
3	5	7
4	3	10
5	3	8
6	2	9
7	2	6

Probability of a node getting the second link
↓
Cumulative Probability

ID	Degree	Probability	Cumulative Probability
1	1	0.06	0.06
3	5	0.31	0.38
4	3	0.19	0.56
5	3	0.19	0.75
6	2	0.13	0.88
7	2	0.13	1.00
Sum	16		

**BA Model
(Second Link)**

Generate a random number
I got 0.0022 using the
Random number generator
Program

**Node 1 gets selected for
the second link**

The newly joining node gets connected to nodes 2 and 1 (first and second link respectively)

Example-1: BA & BB Model

BB Model (First Link)

ID	Degree	Fitness
1	1	5
2	4	4
3	5	7
4	3	10
5	3	8
6	2	9
7	2	6

ID	Degree	Fitness	Degree [*]	Fitness	Probability of a node getting the second link	Cumulative Probability
1	1	5	5	0.04	0.04	
2	4	4	16	0.11	0.15	
3	5	7	35	0.25	0.40	
4	3	10	30	0.21	0.61	
5	3	8	24	0.17	0.79	
6	2	9	18	0.13	0.91	
7	2	6	12	0.09	1.00	
Sum			140			

Generate a random number
I got 0.2584 using the
Random number generator
Program I gave you.

Node 3 gets selected for
the first link

Example-1: BA & BB Model

BB Model (Second Link)

ID	Degree	Fitness
1	1	5
2	4	4
3	5	7
4	3	10
5	3	8
6	2	9
7	2	6

ID	Degree	Fitness	Degree*	Fitness	Probability of a node getting the second link	Cumulative Probability
1	1	5	5	0.05	0.05	
2	4	4	16	0.15	0.20	
4	3	10	30	0.29	0.49	
5	3	8	24	0.23	0.71	
6	2	9	18	0.17	0.89	
7	2	6	12	0.11	1.00	
		Sum	105			

The newly joining node gets connected to nodes 3 and 4 (first and second link respectively)

Generate a random number
I got 0.4885 using the
Random number generator
Program I gave you.

Node 4 gets selected for
the second link

Example-2: BA Model

- At some time unit t , if the degree of a node that joined the network at time 10 units is 50, compute the degree of the node that joined the network at time 100 units.
- Solution:
- $K_{10}(t) = m(t/10)^{1/2} = 50$
→ $m \cdot t^{1/2} = 50 \cdot 10^{1/2} = 158.11$
- $K_{100}(t) = m(t/100)^{1/2} = mt^{1/2} / 100^{1/2}$
 $= 158.11/10 = 15.81$

Example-3: BA Model

- Consider a scale-free network that has evolved according to the BA model. Let there be two nodes P and Q such that the rate at which node P acquires new links is twice the rate at which node Q acquires new links. If node P joined the network at time 100 units, find the time at which node Q joined the network.

- Solution:

$$\frac{dk_i(t)}{dt} = \frac{m}{2} \frac{1}{\sqrt{t_i t}}$$

$$\boxed{\frac{dK_i(t)}{dt}}_P = 2 * \boxed{\frac{dK_i(t)}{dt}}_Q$$

$$\frac{1}{\sqrt{100}} = 2 * \frac{1}{\sqrt{t_Q}}$$

$$\frac{m}{2} \frac{1}{\sqrt{t_P t}} = 2 * \frac{m}{2} \frac{1}{\sqrt{t_Q t}}$$

$$\sqrt{t_Q} = 2 * \sqrt{100}$$

$$t_Q = 4 * 100 = 400$$

Time at which node Q joined the network is 400 units.

Example-4: BB Model

- Consider the BB model for scale-free networks .
- Let the parameter $\beta(\eta_i)$ for any node i be equal to the fitness of node i , η_i . Consider two nodes A and B such that the fitness of node B is twice the fitness of node A.
- Node A joins the network at time 10 units and node B joins the network at time 100 units.
- If the degree of the nodes increase for every time unit (when a new node joins), **what is the *minimum* value of the time unit starting from which the degree of node B would always be greater than the degree of node A?**

$$k_{\eta_i}(t, t_i) = m \left(\frac{t}{t_i} \right)^{\beta(\eta_i)}$$

$$m (t/100)^{\eta_B} > m (t/10)^{\eta_A}$$

$$t^{\eta_B} / 100^{\eta_B} > t^{\eta_A} / 10^{\eta_A}$$

$$t^{\eta_B} / t^{\eta_A} > 100^{\eta_B} / 10^{\eta_A}$$

$$K_A(t, 10) = m (t/10)^{\eta_A}$$

$$K_B(t, 100) = m (t/100)^{\eta_B}$$

$$\text{Given that: } \eta_B = 2 * \eta_A$$

We want to find the minimum value of

time instant t for which $K_B(t, 100) > K_A(t, 10)$

$$t^{2\eta_A} / t^{\eta_A} > 100^{2\eta_A} / 10^{\eta_A} = 10^{4\eta_A} / 10^{\eta_A}$$

$$t^{\eta_A} > 10^{3\eta_A}$$

Hence, $t > 10^3 \rightarrow t > 1000$ time units

Example-5: BB Model

- Consider the BB model for scale-free networks .
- Let the degree of a node A be 50 at time 100 units. If the fitness of node A is 2, compute the degree of node A at time 400 units.

$$k_{\eta_i}(t, t_i) = m \left(\frac{t}{t_i} \right)^{\beta(\eta_i)}$$

$$KA(100, t_A) = 50 = m (100 / t_A)^2$$

$$KA(400, t_A) = ?$$

$$KA(400, t_A) = m (400 / t_A)^2$$

From $KA(100, t_A) = 50$

We get,

$$\frac{m}{t_A^2} = \frac{50}{100^2}$$

$$KA(400, t_A) = \frac{m}{t_A^2} * 400^2$$

$$KA(400, t_A) = \frac{50}{100^2} * 400^2$$

$$KA(400, t_A) = 50 * 16 = 800$$

Example-6: BA Model

- At time 500 units, the following is the degree distribution of the nodes that joined at the time units indicated below. Determine the number of links added per node introduction (m) and the network's dynamical exponent (β). Estimate the degree of a node that joined the network at time 40 units.

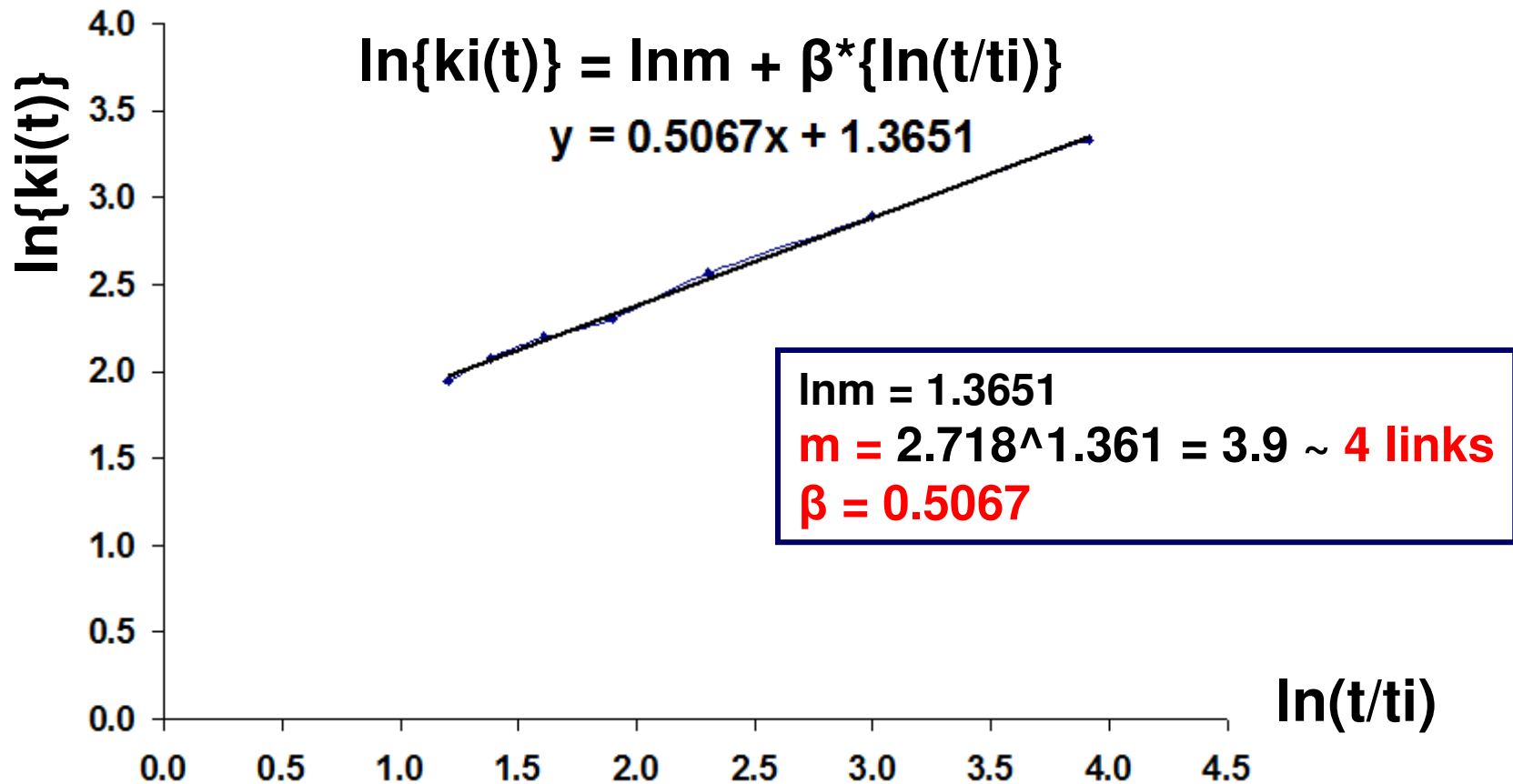
Node joining Time, t_i	Degree at Time $t = 500$	$\ln(t/t_i)$ $\ln(500/t_i)$	$\ln\{k_i(t)\}$
10	28	3.912	3.332
25	18	2.996	2.890
50	13	2.302	2.565
75	10	1.897	2.302
100	9	1.609	2.197
125	8	1.386	2.079
150	7	1.204	1.946

$$k_i(t) = m \left(\frac{t}{t_i} \right)^\beta$$

$$\ln\{k_i(t)\} = \ln m + \beta \cdot \{\ln(t/t_i)\}$$

$$Y = Q + (\text{slope}) \cdot X$$

Example-6 (1): BA Model



$$k_i(t) = m \left(\frac{t}{t_i} \right)^\beta$$

At time $t = 500$ units,
 Degree of the node that joined the network at $t_i = 40$ units
 $= 4 * (500/40)^{0.5067} = 14.38 \sim 14.$

Example-7: BB Model

- A node joined the network at time 10 units. Given below is the degree of the node at various time units. Determine the number of links added per node introduction and the fitness of the node. Under the BB model of evolution, assume the dynamical exponent value for a node is equal to the fitness of the node itself. Estimate the degree of the node at time 250 units.

Time Unit t	Degree at Time t	ln(t/t _i) ln(t/10)	ln{ki(t)}
50	52	1.609	3.951
75	93	2.015	4.533
100	142	2.302	4.956
125	196	2.526	5.278
150	256	2.708	5.545
175	320	2.862	5.768
200	388	2.996	5.961

Given t_i = 10

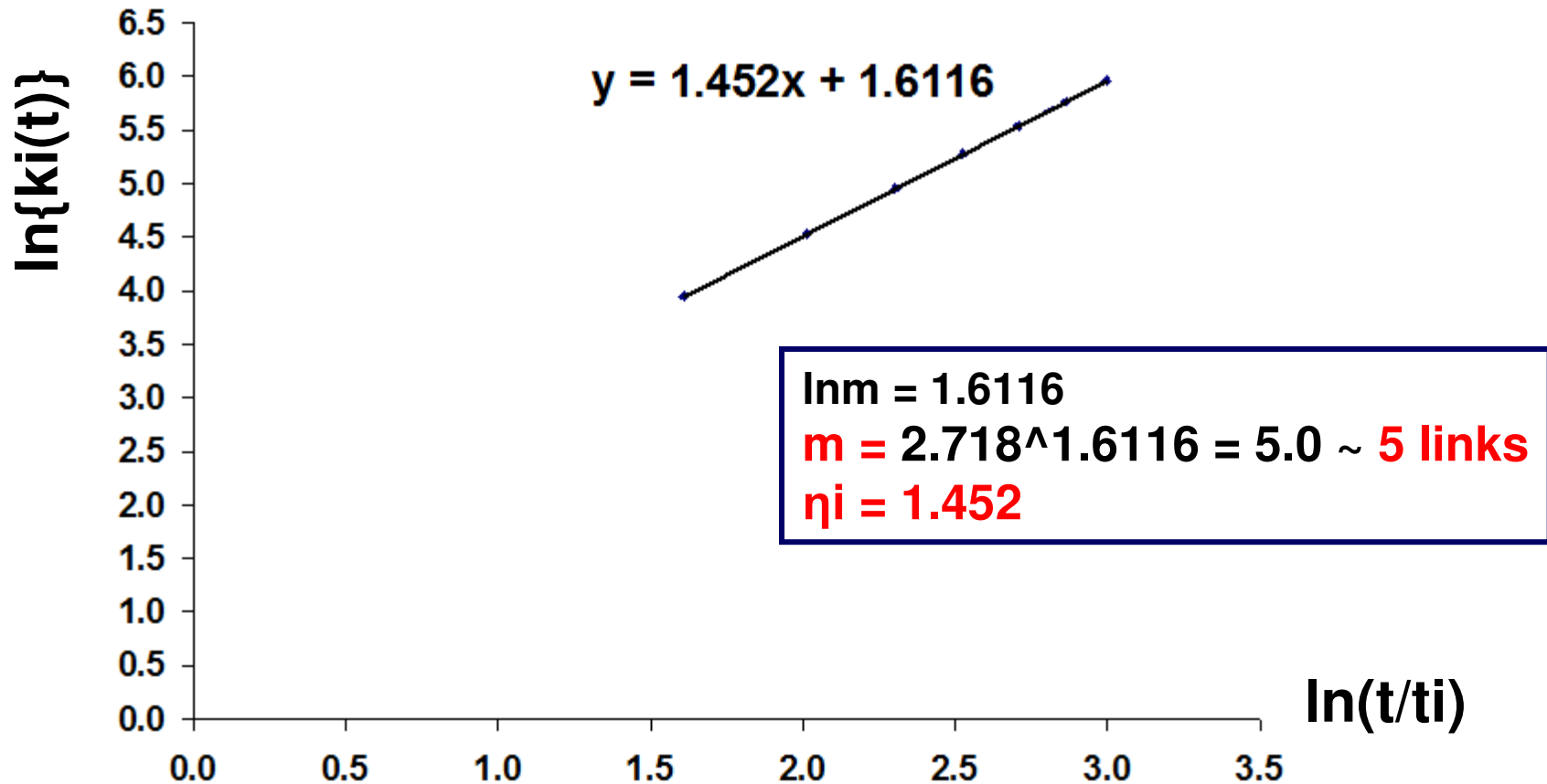
$\beta(\eta_i) = \eta_i$

$$k_{\eta_i}(t, t_i) = m \left(\frac{t}{t_i} \right)^{\beta(\eta_i)}$$

$$\ln\{k_i(t)\} = \ln m + \eta_i \cdot \{\ln(t/t_i)\}$$

$$Y = Q + (\text{slope}) \cdot X$$

Example-7 (1): BB Model



$$k_{\eta_i}(t, t_i) = m \left(\frac{t}{t_i} \right)^{\beta(\eta_i)}$$

At time $t = 250$ units,
 Degree of the node that joined the network at $t_i = 10$ units
 $= 5 * (250/10)^{1.452} = 535.5 \sim 536.$

Example-8: BB Model

- Consider a node i that joined the network (with 4 new links) at time t_i according to the BB model. Its degree at future time instants 100 and 200 are 45 and 125 respectively. The dynamical exponent value of a node is given by: $\beta(\eta_i) = \eta_i^2 + \eta_i$, where η_i is the fitness of node i . Determine the joining time (t_i) and fitness η_i of node i .

$$k_{\eta_i}(t, t_i) = m \left(\frac{t}{t_i} \right)^{\beta(\eta_i)}$$

$$\beta(\eta_i) = \ln(2.78) / \ln(2) = 1.475$$

$$\beta(\eta_i) = \eta_i^2 + \eta_i = 1.475$$

$$\boxed{\eta_i^2 + \eta_i - 1.475 = 0}$$

$$K(t = 100) = 45 = 4 \cdot (100/t_i)^{\beta(\eta_i)} \quad \dots (1)$$

$$K(t = 200) = 125 = 4 \cdot (200/t_i)^{\beta(\eta_i)} \quad \dots (2)$$

Dividing (2) by (1), we get

$$\frac{125}{45} = \frac{200^{\beta(\eta_i)}}{100^{\beta(\eta_i)}} \quad \text{i.e., } 2.78 = 2^{\beta(\eta_i)}$$

$$\eta_i = \frac{(-1) + \sqrt{1^2 - 4 \cdot 1 \cdot (-1.475)}}{2(1)}$$

$$\boxed{\eta_i = 0.813}$$

Example-8: BB Model

- Consider a node i that joined the network (with 4 new links) at time t_i according to the BB model. Its degree at future time instants 100 and 200 are 45 and 125 respectively. The dynamical exponent value of a node is given by: $\beta(\eta_i) = \eta_i^2 + \eta_i$, where η_i is the fitness of node i . Determine the joining time (t_i) and fitness η_i of node i .

$$k_{\eta_i}(t, t_i) = m \left(\frac{t}{t_i} \right)^{\beta(\eta_i)}$$

$$t_i^{1.475} = \frac{4 * (100^{1.475})}{45} = 79.22$$

$$K(t = 100) = 45 = 4 * (100/t_i)^{\beta(\eta_i)} \dots (1)$$

$$K(t = 200) = 125 = 4 * (200/t_i)^{\beta(\eta_i)} \dots (2)$$

$$\beta(\eta_i) = \ln(2.78) / \ln(2) = 1.475$$

Substituting $\beta(\eta_i) = 1.475$ in (1), we get

$$45/4 = (100/t_i)^{1.475}$$

$$t_i \sim 19.38 \sim 20 \text{ time units.}$$

Small World Networks

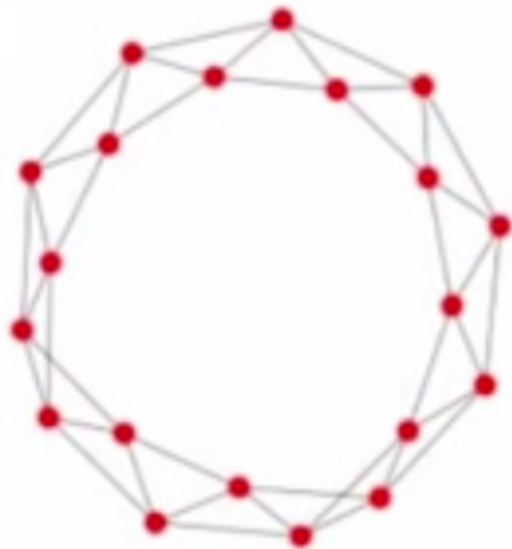
Dr. Natarajan Meghanathan
Professor of Computer Science
Jackson State University, Jackson, MS
E-mail: natarajan.meghanathan@jsums.edu

Small-World Networks

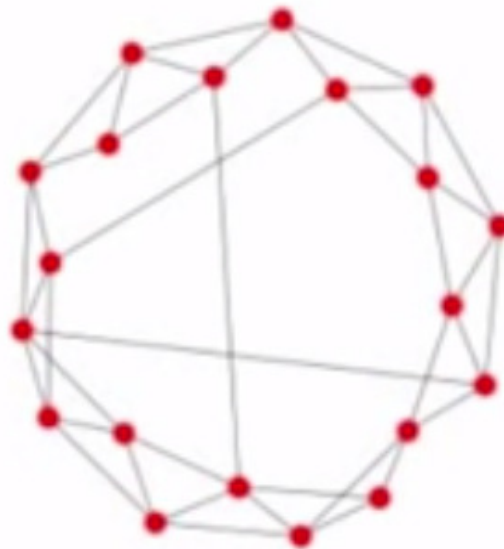
- A small-world network is a type of graph in which most nodes are not neighbors of one another, but most nodes can be reached from every other by a small number of hops.
- Specifically, a small-world network is defined to be a network where the typical distance L (the number of hops) between two randomly chosen nodes grows proportionally to the logarithm of the number of nodes in the network.
- Examples of Small-World Networks:
 - Road maps, food chains, electric power grids, metabolite processing networks, networks of brain neurons, voter networks, telephone call graphs, gene regulatory networks.

Small Worlds

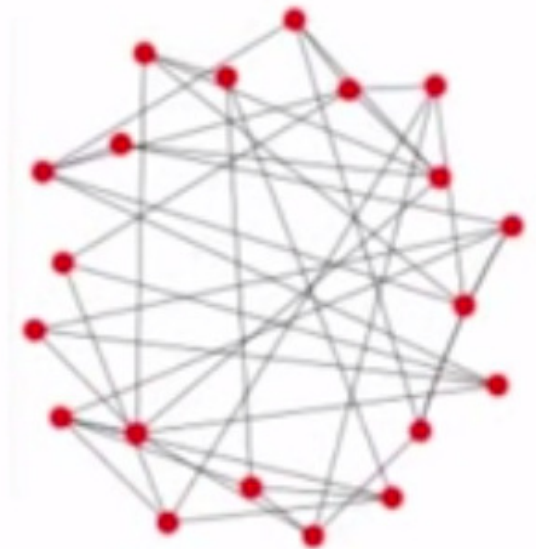
- Two major properties of small world networks
 - High average clustering coefficient
 - The neighbors of a node are connected to each other
 - Nodes' contacts in a social network tend to know each other.
 - Short average shortest path length
 - Shorter paths between any two nodes in the network



(Regular graph)



(Small-world network)



(Random graph)

0

Randomness

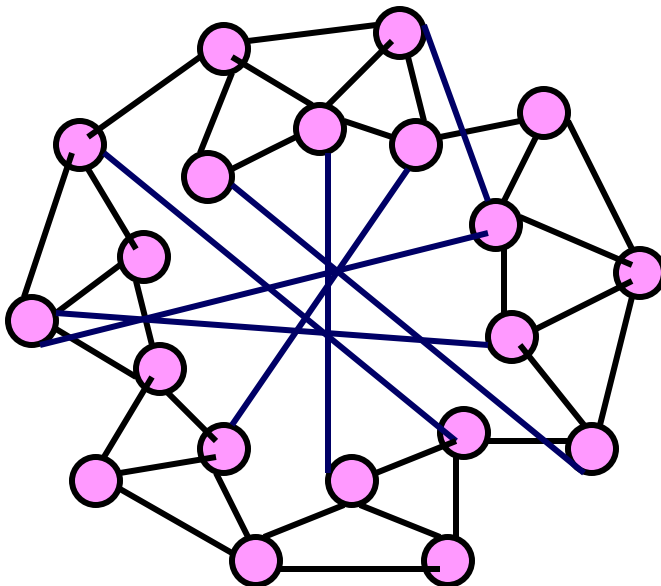
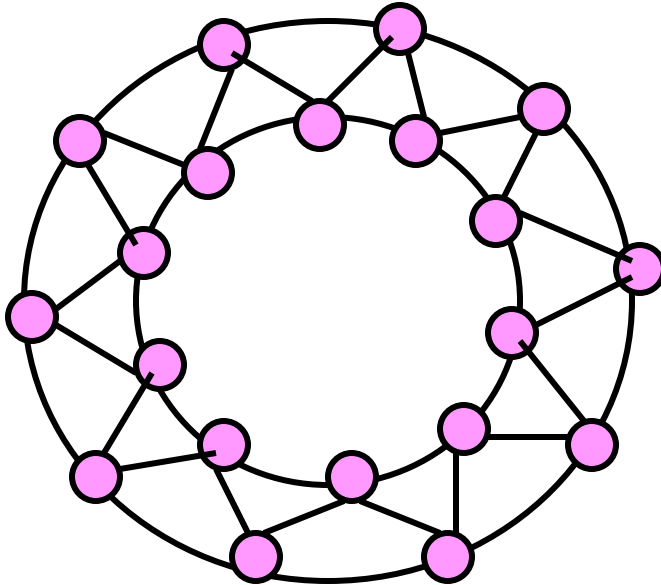
69

1

Small Worlds

- Note that for the same number of nodes and edges, we could create:
 - Random graphs (with edges arbitrarily inserted between any two nodes) and
 - Regular graphs (with some specific pattern of how edges are inserted between nodes)
- Regular graphs tend to have relatively high average clustering coefficient
- Random graphs tend to have relatively low average shortest path length
- We could bring the best of the two graphs by generating a small world network as follows:
 - Remove a small fraction of the edges in a regular graph and re-insert them between any two randomly chosen nodes. This will not appreciably affect the average clustering coefficient of the nodes; but would significantly lower the average lengths of the shortest paths.

WS Model



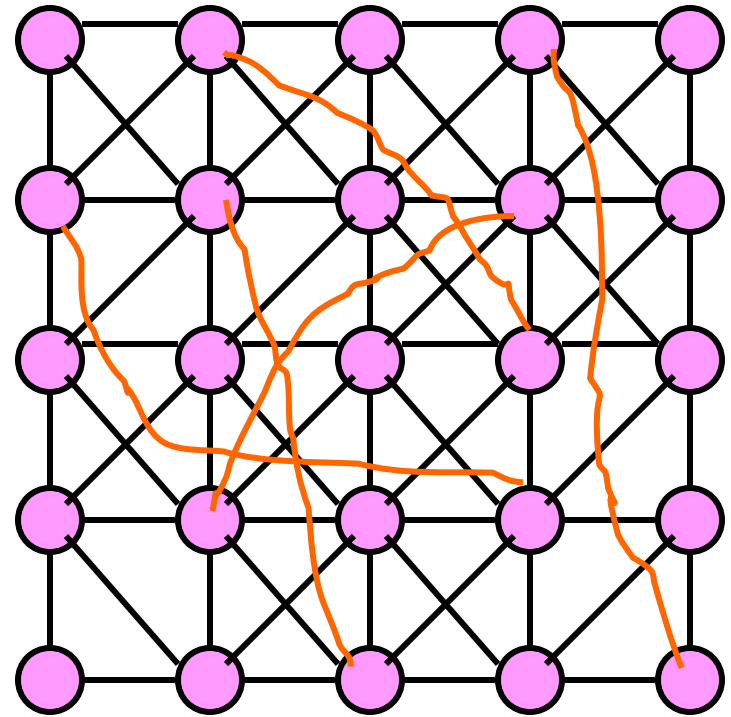
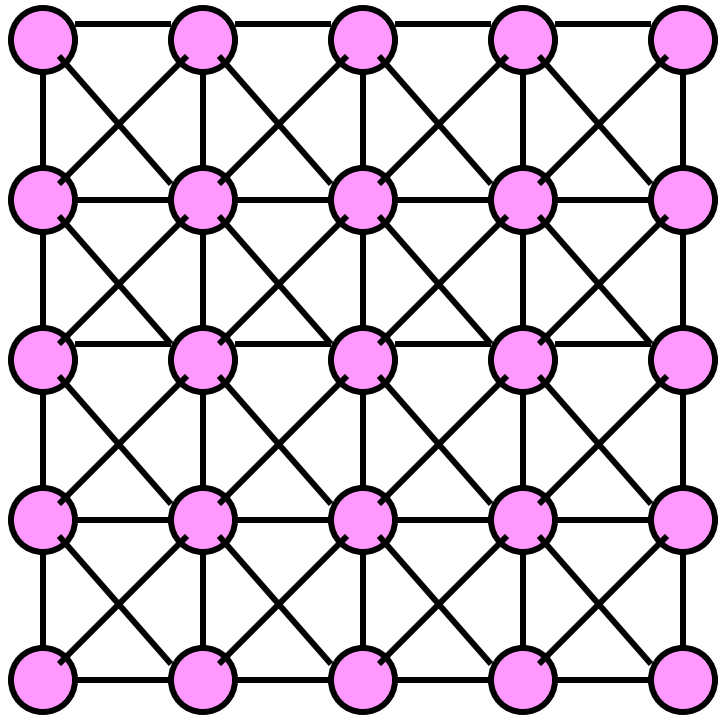
- Watts and Strogatz (WS) Model:
The WS model interpolates between an ER graph and a regular ring lattice.

- Let N be the number of nodes and K (assumed to be even) be the mean degree.
- Assume $N \gg K \gg \ln(N) \gg 1$.
- There is a rewiring parameter β ($0 \leq \beta \leq 1$).
- Initially, let there be a regular ring lattice of N nodes, with K neighbors ($K/2$ neighbors on each side).
- For every node $n_i = n_0, n_1, \dots, n_{N-1}$, rewire the edge (n_i, n_j) , where $i < j$, with probability β . Rewiring is done by replacing (n_i, n_j) with (n_i, n_k) where n_k is chosen uniformly-randomly among all possible nodes that avoid self-looping and link duplication.

$\beta = 0 \rightarrow$ Regular ring lattice

$\beta = 1 \rightarrow$ Random network

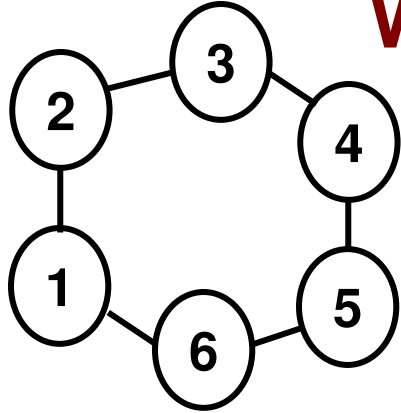
WS Model for Grid Lattice (2-dim)



We have a $n \times n$ two-dimensional grid.
The nodes are identified with lattice points
i.e., a node v is identified with the
lattice point (i, j) with $i, j = \{1, 2, \dots, n\}$

For every node u , we remove one of
its associated edges to the neighbor
nodes with a probability β and connect
the node to a randomly chosen node
 v , as long as there is no self-loops
and link duplication.

WS Model Illustration



Given Network

Links (u, v): $u < v$

1 – 2

1 – 6

2 – 3

3 – 4

4 – 5

5 – 6

Let the rewiring

Probability (β) be 0.7

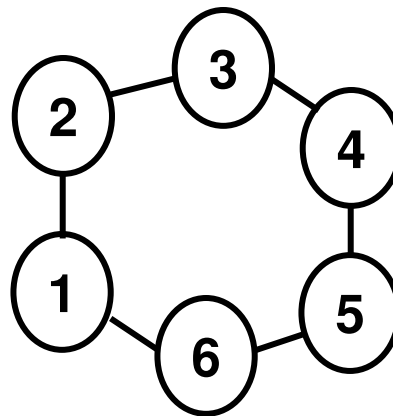
Link	Random #	Selected	
1 – 2	0.933	NO	We select a link for rewiring if the random number generated for the link is less than or equal to the rewiring probability
1 – 6	0.907	NO	
2 – 3	0.541	YES	
3 – 4	0.346	YES	
4 – 5	0.835	NO	
5 – 6	0.361	YES	

Rewiring (#1): Link 2 – 3

We cannot pick vertices 3 and 1 as they are connected to vertex 2 in the original graph.

The candidates are: 4, 5, 6

There is a 1/3 probability for each of them to be considered.



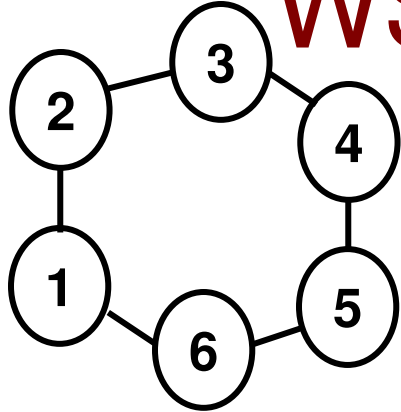
Cand.	Prob.	Cum Prob.
4	1/3	1/3 = 0.33
5	1/3	2/3 = 0.67
6	1/3	3/3 = 1.00

Vertex 2 is rewired to Vertex 5.

Generate a random Number = 0.422

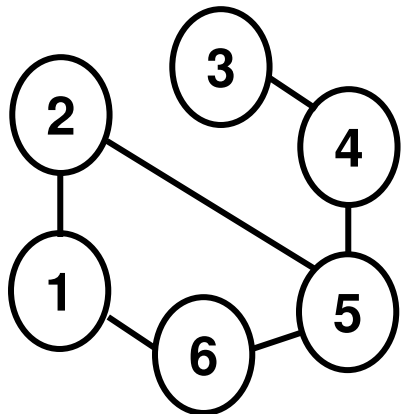


WS Model Illustration (1)

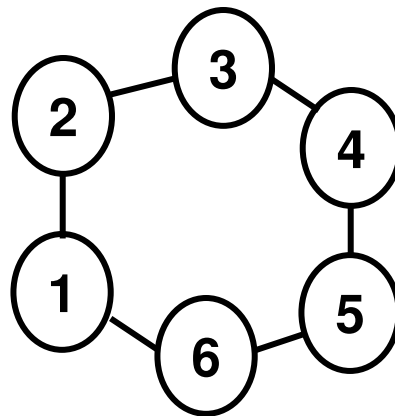


Given Network

Link	Random #	Selected	
1 – 2	0.933	NO	We select a link for rewiring if the random number generated for the link is less than or equal to the rewiring probability
1 – 6	0.907	NO	
2 – 3	0.541	YES	
3 – 4	0.346	YES	
4 – 5	0.835	NO	
5 – 6	0.361	YES	



After Rewiring # 1



Rewiring (#2): Link 3 – 4

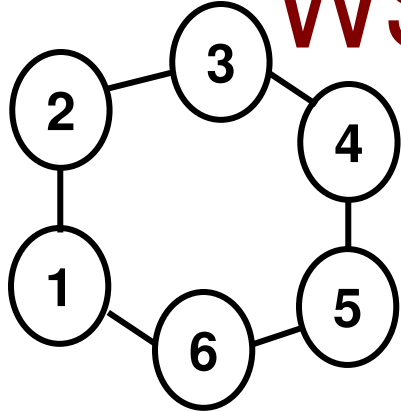
We cannot pick vertices 4 and 2 as they are connected to vertex 3 in the original graph. The candidates are: 1, 5, 6. There is a 1/3 probability for each of them to be considered.

Cand.	Prob.	Cum Prob.
1	1/3	1/3 = 0.33
5	1/3	2/3 = 0.67
6	1/3	3/3 = 1.00

Vertex 3 is rewired to Vertex 5.

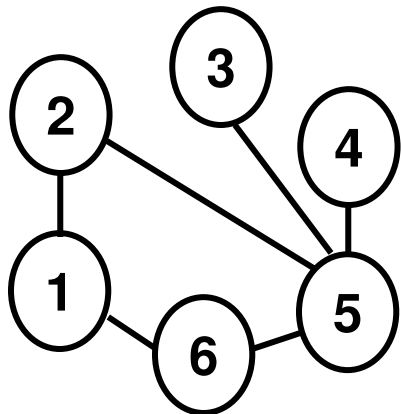
Generate a random Number = 0.665 →

WS Model Illustration (2)

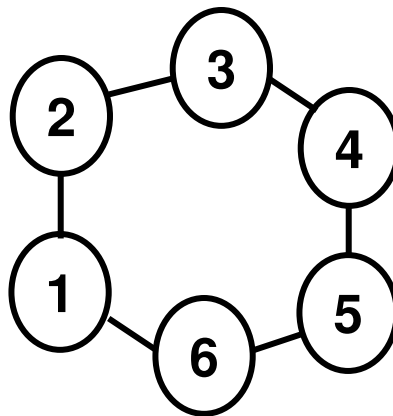


Given Network

Link	Random #	Selected	
1 – 2	0.933	NO	We select a link for rewiring if the random number generated for the link is less than or equal to the rewiring probability
1 – 6	0.907	NO	
2 – 3	0.541	YES	
3 – 4	0.346	YES	
4 – 5	0.835	NO	
5 – 6	0.361	YES	



After Rewiring # 2



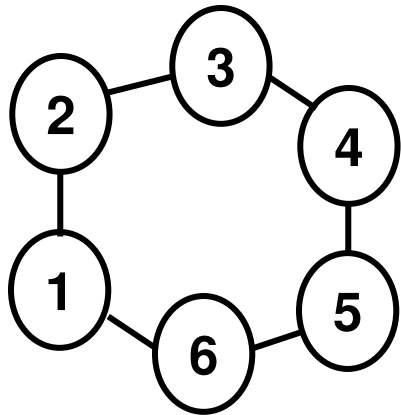
Rewiring (#3): Link 5 – 6

We cannot pick vertices 6 and 4 as they are connected to vertex 5 in the original graph as well cannot pick vertices 2 and 3 as they are connected to vertex 5 in the rewired graph. Hence, the only candidate vertex available is vertex 1.

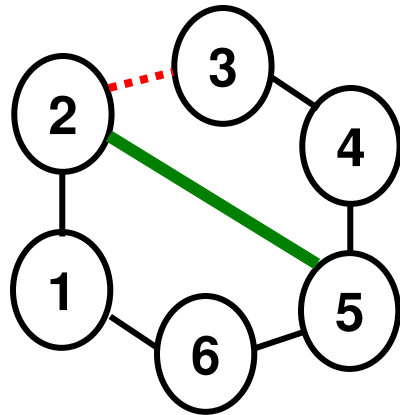
Cand.	Prob.	Cum Prob.
1	1/1	1/1 = 1.0

Vertex 5 is rewired to Vertex 1.

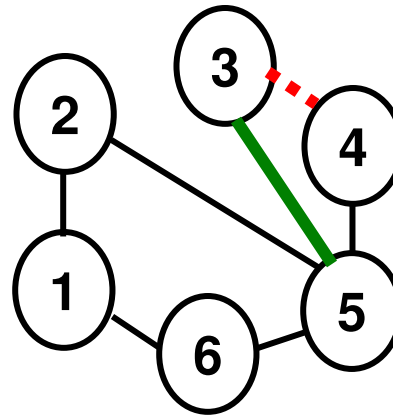
Generate a random Number = 0.763



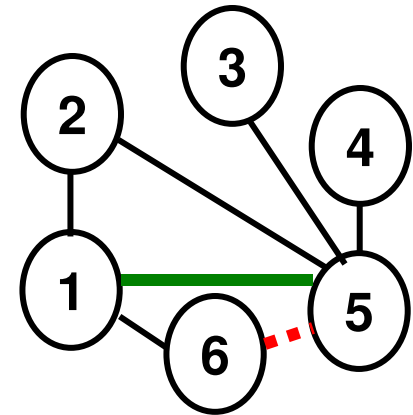
Given Network



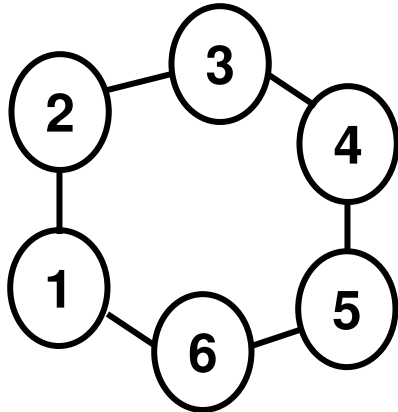
Rewiring # 1



Rewiring # 2

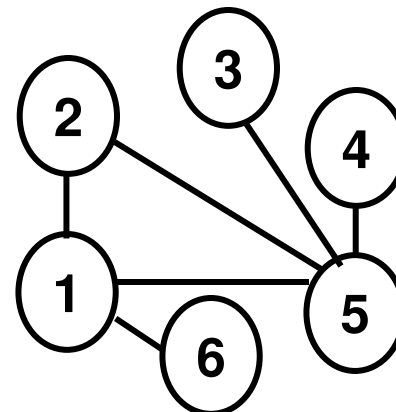


Rewiring # 3



Avg. Path Length
 $= 54 / (6 \cdot 5)$
 $= 1.8$

	1	2	3	4	5	6	Sum
1	0	1	2	3	2	1	9
2	1	0	1	2	3	2	9
3	2	1	0	1	2	3	9
4	3	2	1	0	1	2	9
5	2	3	2	1	0	1	9
6	1	2	3	2	1	0	9



Avg. Path Length
 $= 52 / (6 \cdot 5)$
 $= 1.73$

	1	2	3	4	5	6	Sum
1	0	1	2	2	1	1	7
2	1	0	2	2	1	2	8
3	2	2	0	2	1	3	10
4	2	2	2	0	1	3	10
5	1	1	1	1	0	2	6
6	1	2	3	3	2	0	11

Small-World Network: WS Model

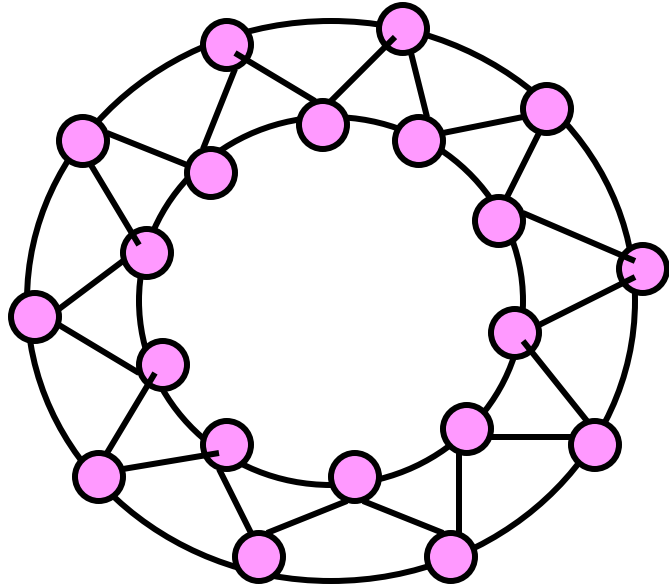
- The underlying lattice structure of the model produces a locally clustered network, and the random links dramatically reduce the average path lengths
- The algorithm introduces about $(\beta NK/2)$ non-lattice edges.
- Average Path Length (β):
 - Ring lattice $L(0) = (N/2K) \gg 1$
 - Random graph $L(1) = (\ln N / \ln K)$
 - For $0 < \beta < 1$, the average path length reduces significantly even for smaller values of β .
- Clustering Coefficient (β):

$$C(0) = \frac{3(K - 2)}{4(K - 1)}$$

$$C'(\beta) = C(0) * (1 - \beta)^3$$

- For $0 < \beta < 1$, the clustering coefficient remains close to that of the regular lattice for low and moderate values of β and falls only at relatively high β .
- For low-moderate values of β , we thus capture the small-world phenomenon where the average path length falls rapidly, while the clustering coefficient remains fairly high.

Avg. Path Length and Clus. Coeff.



N = 20 nodes; K = 4

Avg. Path Length

Ring Lattice (Regular Net)

$$= N / 2K = 20 / (2 \cdot 4) = 2.5$$

Random Network

$$= \ln N / \ln K = \ln(20) / \ln(4) = 2.16$$

$$C(0) = \frac{3(K-2)}{4(K-1)}$$

$$C(0) = \frac{3(4-2)}{4(4-1)}$$

$$C(0) = \frac{3 \cdot 2}{4 \cdot 3} = 0.5$$

$$C'(\beta) = C(0) * (1 - \beta)^3$$

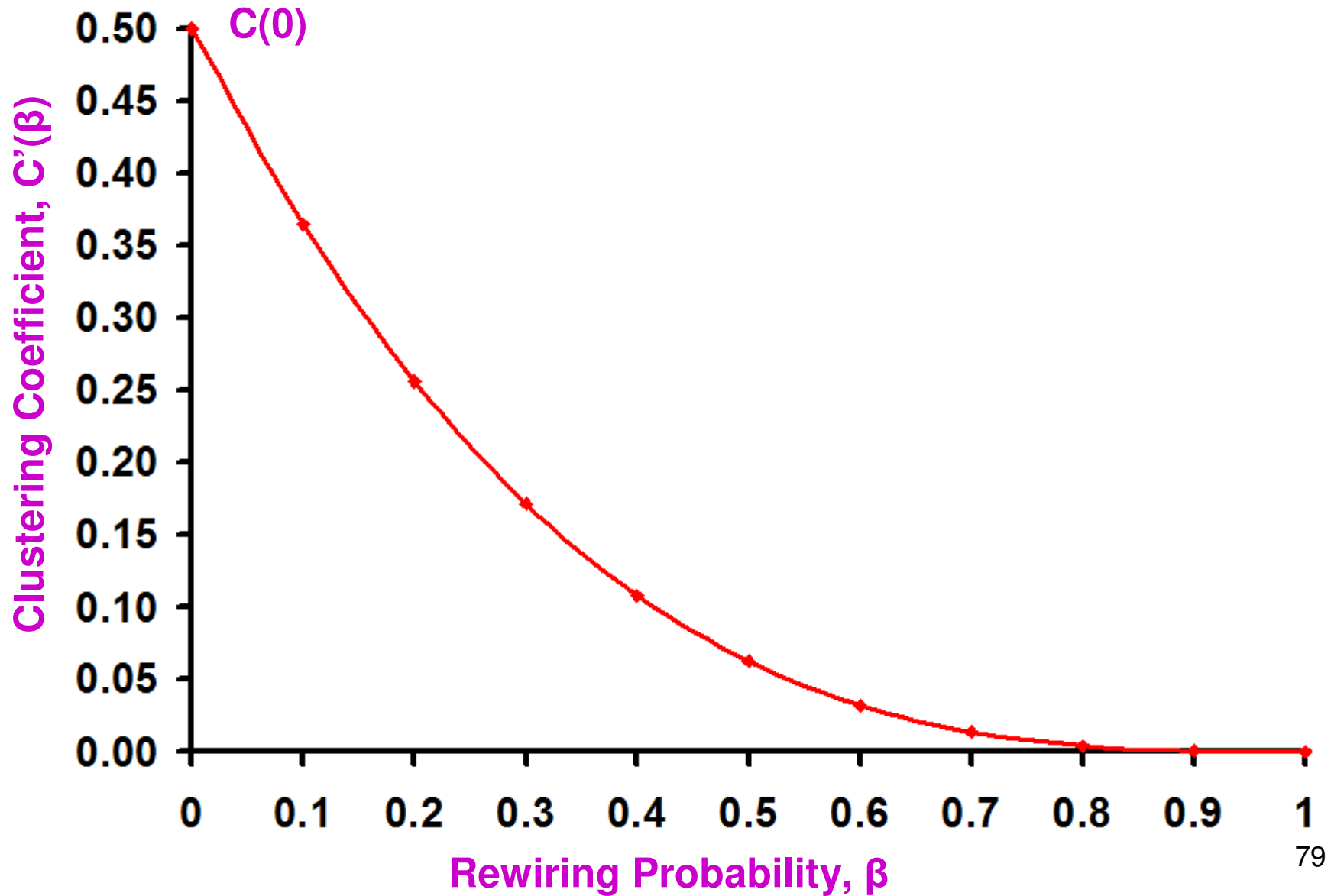
$$C'(0.1) = 0.5 * (1 - 0.1)^3 = 0.3645$$

$$C'(0.2) = 0.5 * (1 - 0.2)^3 = 0.256$$

$$C'(0.5) = 0.5 * (1 - 0.5)^3 = 0.0625$$

$$C'(0.9) = 0.5 * (1 - 0.9)^3 = 0.0005$$

Rewiring Prob. Vs. Clus. Coeff.



Example 1: Small-World Model

- Consider a regular ring lattice of degree 8 for every node. This regular graph is transformed to a small-world network by arbitrarily re-wiring the edges with probability β . Let the clustering coefficient of the small-world network generated out of this re-wiring be 0.4. **Determine the re-wiring probability β .**

$$C(0) = \frac{3(K-2)}{4(K-1)}$$

$$C(0) = \frac{3(8-2)}{4(8-1)} = \frac{3 \cdot 6}{4 \cdot 7} = 0.643$$

$$C'(\beta) = C(0) * (1 - \beta)^3$$

$$C'(\beta) = 0.4 = 0.643 * (1 - \beta)^3$$

$$(1 - \beta)^3 = 0.4/0.643 = 0.622$$

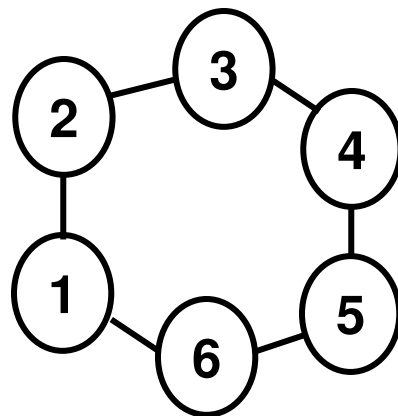
$$1 - \beta = (0.622)^{1/3}$$

$$1 - \beta = 0.854$$

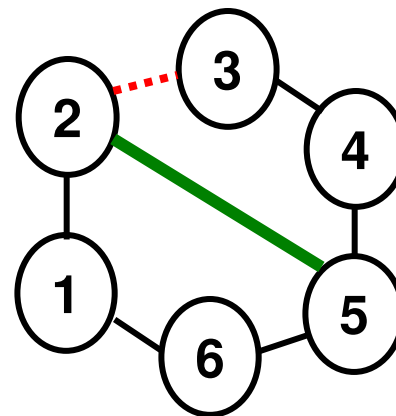
$$\beta = 0.146$$

Limitations of the WS Model

- The WS model introduced the notion of random edges to infuse shorter path lengths amidst larger clustering coefficient.
- However, the long-range edges span between any two nodes in the network and do not mimic the edges of different lengths seen in real-world networks (like in the US road map or airline map).
 - Path lengths could not be as small as they are in real networks.
 - Need some edges to nodes that are few hops away, rather than edges to some arbitrarily chosen nodes.



Given Network



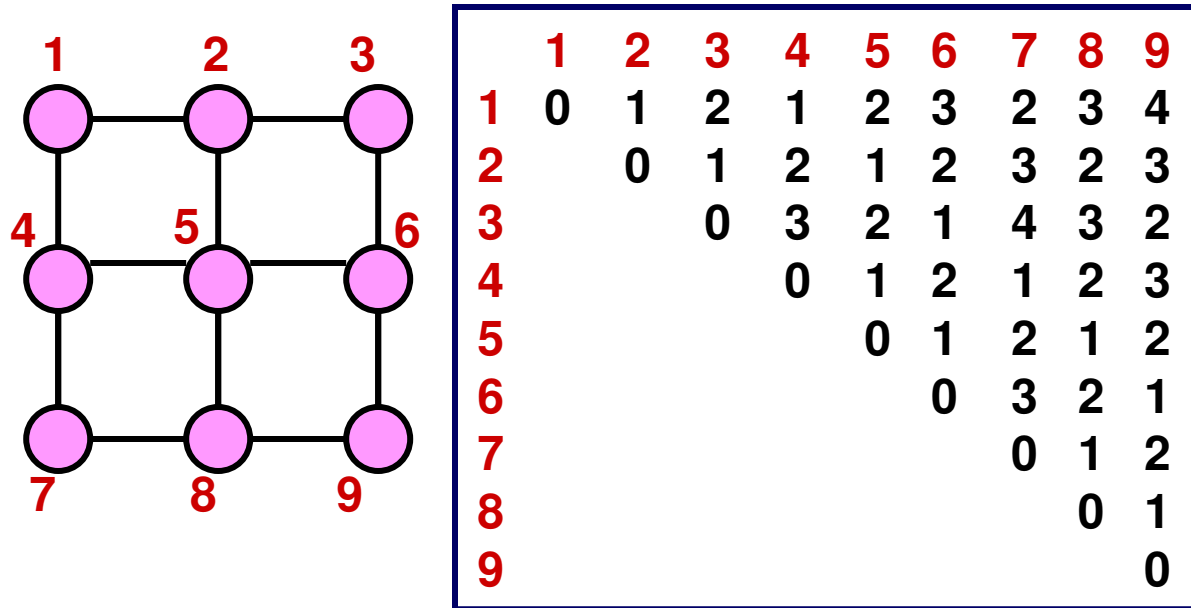
After Rewiring # 1

Vertex 5 is chosen for rewiring to Vertex 2 even though the two vertices are three hops away. There were two Candidate Vertices (4 and 6) two hops away.

Enhancement to the WS Model

- In addition to the re-wiring parameter β , another parameter called the clustering exponent (q) is introduced.
- An (u, v) edge is selected for re-wiring with a probability β . After being selected, we do not randomly re-wire u with a node w . Instead, we pick a pair (u, w) for re-wiring with a probability (weight) of $[d(u, w)^{-q}] / 2 \log n$, where
 - For optimal results, q must be the dimensionality of the network modeled. **For a ring lattice, $q = 1$.**
 - n is the number of nodes in the network.
 - $d(u, w)$ is the minimum number of hops between u and w in the original network layout (before enhancement)
 - The ring lattice is a single-dimension network
 - A grid is a two-dimensional network.

Ex -2: Enhanced Small-World Model

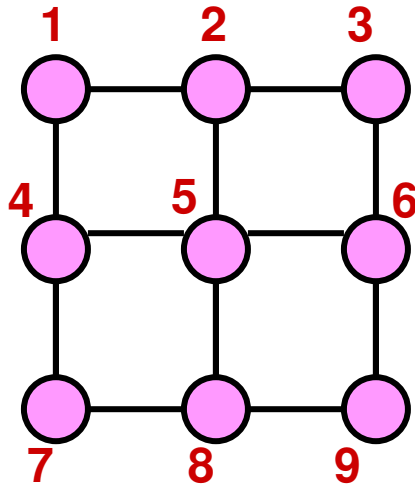


Weight for a pair (u, w) at a distance $d(u, w)$ is $[d(u, w)^{-q}] / 2\log n$

We have $q = 2$
and $n = 9$

$d(u, w)$	$[d(u, w)^{-q}] / 2\log n$
1	$(1^{-2}) / (2 * \log 9) = 0.524$
2	$(2^{-2}) / (2 * \log 9) = 0.131$
3	$(3^{-2}) / (2 * \log 9) = 0.058$
4	$(4^{-2}) / (2 * \log 9) = 0.033$

Dist.	Orig. Weight	Pairs
1	0.524	(1, 2); (1, 4); (2, 3); (2, 5); (3, 6); (4, 5); (4, 7); (5, 6); (5, 8); (6, 9); (7, 8); (8, 9)
2	0.131	(1, 3); (1, 5); (1, 7); (2, 4); (2, 6); (2, 8); (3, 5); (3, 9); (4, 6); (4, 8); (5, 7); (5, 9); (6, 8); (7, 9)
3	0.058	(1, 6); (1, 8); (2, 7); (2, 9); (3, 4); (3, 8); (4, 9); (6, 7)
4	0.033	(1, 9); (3, 7)



Dist.	Orig. Weight	Pairs
1	0.524	(1, 2); (1, 4); (2, 3); (2, 5); (3, 6); (4, 5); (4, 7); (5, 6); (5, 8); (6, 9); (7, 8); (8, 9)
2	0.131	(1, 3); (1, 5); (1, 7); (2, 4); (2, 6); (2, 8); (3, 5); (3, 9); (4, 6); (4, 8); (5, 7); (5, 9); (6, 8); (7, 9)
3	0.058	(1, 6); (1, 8); (2, 7); (2, 9); (3, 4); (3, 8); (4, 9); (6, 7)
4	0.033	(1, 9); (3, 7)

Assume we want to rewire the edge 1 – 2

Scaled Prob. = Orig. Weight / 0.542

The pairs that could be considered are

(everything except (1, 2) and (1, 4)):

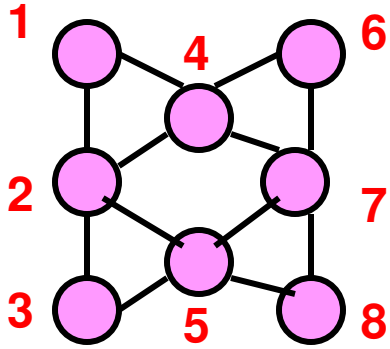
(1, 3); (1, 5); (1, 6); (1, 7); (1, 8); (1, 9)

Pair	Orig. Weight	Scaled Prob.	Cum. Scaled Prob.
1 – 3	0.131	0.242	0.242
1 – 5	0.131	0.242	0.484
1 – 6	0.058	0.107	0.591
1 – 7	0.131	0.242	0.833
1 – 8	0.058	0.107	0.940
1 – 9	0.033	0.060	1.000
Sum	0.542		

Generate a random number: 0.2525

We will rewire node 1 to node 5.

Ex -3: Enhanced Small-World Model



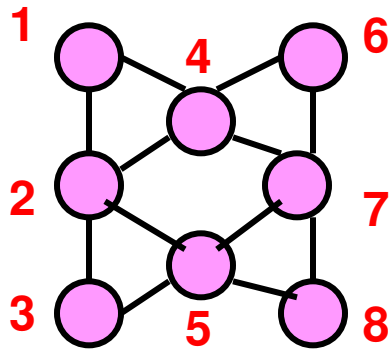
	1	2	3	4	5	6	7	8
1	0	1	2	1	2	2	2	3
2		0	1	1	1	2	2	2
3			0	2	1	3	2	2
4				0	2	1	1	2
5					0	2	1	1
6						0	1	2
7							0	1
8								0

Weight for a pair (u, w) at a distance $d(u, w)$ is $[d(u, w)^{-q}] / 2 \log n$

We have $q = 1$
and $n = 8$

$d(u, w)$	$[d(u, w)^{-q}] / 2 \log n$
1	$(1^{-1}) / (2 * \log 8) = 0.554$
2	$(2^{-1}) / (2 * \log 8) = 0.277$
3	$(3^{-1}) / (2 * \log 8) = 0.185$

Dist.	Orig. Weight	Pairs
1	0.554	(1, 2); (1, 4); (2, 3); (2, 4); (2, 5); (3, 5); (4, 6); (4, 7); (5, 7); (5, 8); (6, 7); (7, 8)
2	0.277	(1, 3); (1, 5); (1, 6); (1, 7); (2, 6); (2, 7); (2, 8); (3, 4); (3, 7); (3, 8); (4, 5); (4, 8); (5, 6); (6, 8)
3	0.185	(1, 8); (3, 6)



Dist.	Orig. Weight	Pairs
1	0.554	(1, 2); (1, 4); (2, 3); (2, 4); (2, 5); (3, 5); (4, 6); (4, 7); (5, 7); (5, 8); (6, 7); (7, 8)
2	0.277	(1, 3); (1, 5); (1, 6); (1, 7); (2, 6); (2, 7); (2, 8); (3, 4); (3, 7); (3, 8); (4, 5); (4, 8); (5, 6); (6, 8)
3	0.185	(1, 8); (3, 6)

Assume we want to rewire the edge 3 – 5

The pairs that could be considered are

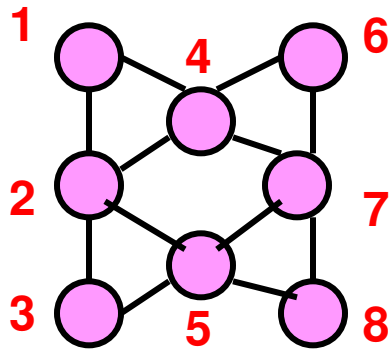
(1, 3); (3, 4); (3, 6); (3, 7); (3, 8)

Scaled Prob. = Orig. Weight / 1.293

Pair	Orig. Weight	Scaled Prob.	Cum. Scaled Prob.
1 – 3	0.277	0.214	0.214
3 – 4	0.277	0.214	0.428
3 – 6	0.185	0.143	0.571
3 – 7	0.277	0.214	0.785
3 – 8	0.277	0.214	0.999
Sum	1.293		

Generate a random number: 0.9338

We will rewire node 3 to node 8.



Dist.	Orig. Prob.	Pairs
1	0.554	(1, 2); (1, 4); (2, 3); (2, 4); (2, 5); (3, 5); (4, 6); (4, 7); (5, 7); (5, 8); (6, 7); (7, 8)
2	0.277	(1, 3); (1, 5); (1, 6); (1, 7); (2, 6); (2, 7); (2, 8); (3, 4); (3, 7); (3, 8); (4, 5); (4, 8); (5, 6); (6, 8)
3	0.185	(1, 8); (3, 6)

Assume we want to rewire the edge 5 – 7

The pairs that could be considered are

(1, 5); (4, 5); (5, 6)

Scaled Prob. = Orig. Weight / 0.831

Pair	Orig. Weight	Scaled Prob.	Cum. Scaled Prob.
1 – 5	0.277	0.333	0.333
4 – 5	0.277	0.333	0.667
5 – 6	0.277	0.333	1.000
Sum	0.831		

← Generate a random number: 0.9113

We will rewire node 5 to node 6.

Ex-4: Enhanced WS Model

- Consider the enhanced WS model for small-world networks. Let there be a regular graph that is transformed to a small-world network. For every edge (u, v) selected for re-wiring, the probability that a node w of distance 2 hops to u is picked for re-wiring is 0.2 and the probability that a node w' of distance 4 hops to u is picked for re-wiring is 0.08. Find the value for the **parameter q** in the enhanced WS model.

Prob. for a pair (u, w)
at a distance $d(u, w)$ is
 $[d(u, w)^{-q}] / 2\log n$

$$\frac{(2^2)^q}{2^q} = \frac{2^{2q}}{2^q} = 2^q = 2.5$$

Given: $P(u, w) = 0.2 = 2^{-q} / 2\log n \dots\dots (1)$
 $P(u, w') = 0.08 = 4^{-q} / 2\log n \dots\dots (2)$

$q = \ln(2.5) / \ln(2) = 1.322$

$$\begin{array}{l} (1) \quad 0.2 \quad 2^{-q} \quad 4^q \\ \hline \rightarrow \quad \hline = \quad \hline \rightarrow \quad \hline = 2.5 \\ (2) \quad 0.08 \quad 4^{-q} \quad 2^q \end{array}$$