

# Emergence of Scaling in Random Networks

Albert-László Barabási and Réka Albert (1999)

February 15, 2023

# Motivation

Better understanding complex (large) networks

- Living beings: proteins, genes, and the chemical interactions between them
- Nervous system: nerve cells connected by axons
- Social sciences: individuals and organizations, and the social relationships between them
- Internet: Webpages and their links to other sites

# Power Law Observed

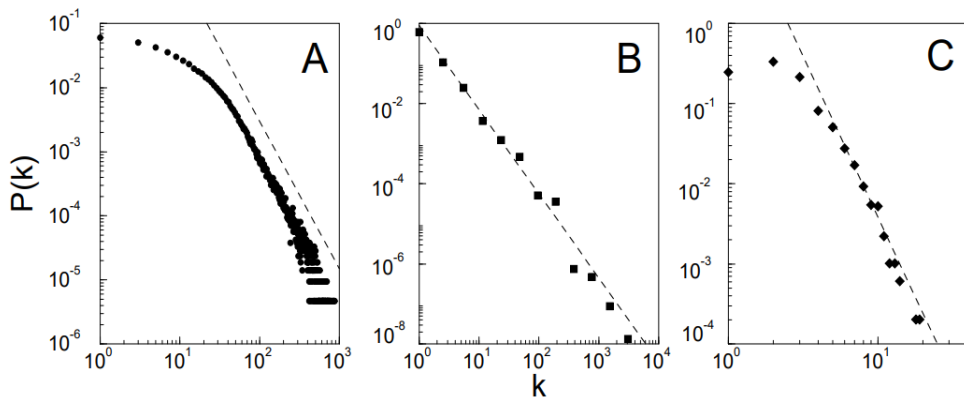
- Power law:  $f(x) = ax^{-\gamma}$
- Probability a vertex is of degree  $P(k) \sim k^{-\gamma}$
- Scale Invariance: Property of a network that roughly follows this probability in the tail

# Topological Data Reviewed

Data Source	N	$\mathbb{E}[k]$	$\hat{\gamma}$
Actor Collaborations	212250	28.78	2.3
Internet Sites	325729	5.46	2.1
Powergrid Configuration	4941	2.67	4

$$P(k) \sim k^{-\gamma}$$

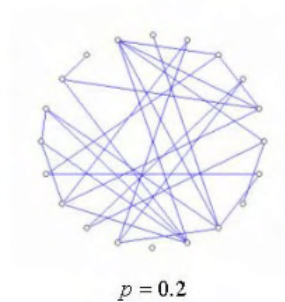
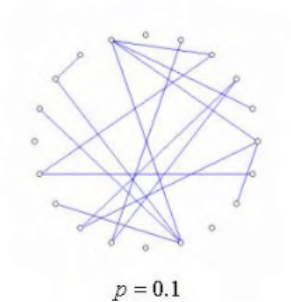
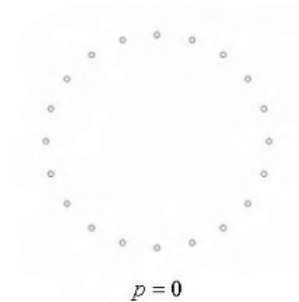
# Topological Data Reviewed



How did existing random graph theory reconcile these empirical findings?

# Erdős-Rényi-Gilbert Model

Every possible edge is considered for connection with probability  $p$ .  
There are  $N$  total vertices.



[https://www.researchgate.net/figure/Erdoes-Renyi-model-of-random-graph-evolution\\_fig10\\_313854183](https://www.researchgate.net/figure/Erdoes-Renyi-model-of-random-graph-evolution_fig10_313854183)

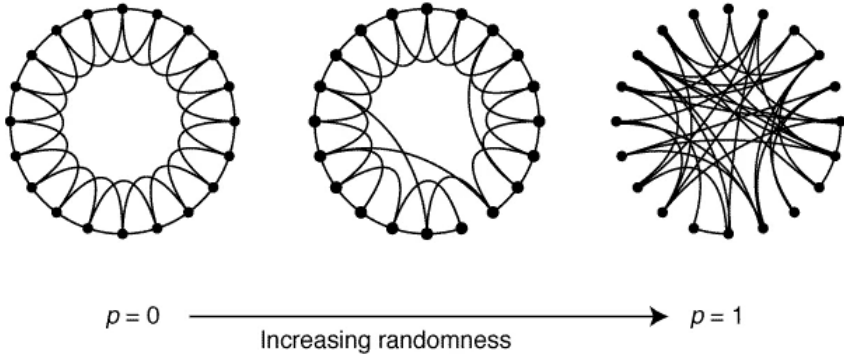
# Small World Model

By Watts and Strogatz (1989)

Algorithm:

- Begin with a lattice where every one of the  $N$  vertex is connected to  $z$  other closest neighboring vertices
- For each original edge, with probability  $p$ , disconnect one end of the edge from the vertex and reconnect to any other vertex the original vertex is not connected to

# Small World Model



<https://www.nature.com/articles/30918>



# Probability of Vertex Degree $k$

- ERG:  $P(k) \sim \text{Poisson}$
- Small World:  $P(k)$  centers around the starting vertex degree  $z$

The power-law tail indicates highly connected vertices have a large chance of occurring, unlike in the existing models of the time.

$$P(k) \sim k^{-\gamma}$$

# New Model: Assumptions

The other models assumed the total number of vertices  $N$  to be fixed, and that edges are randomly connected or reconnected.

Proposed model assumes:

- **Growth:**  $N$  increases over the network's lifetime
- **Preferential Attachment:** new vertices prefer to connect with high-degree vertices

A model built with these assumptions shows the desired power-law decay result.

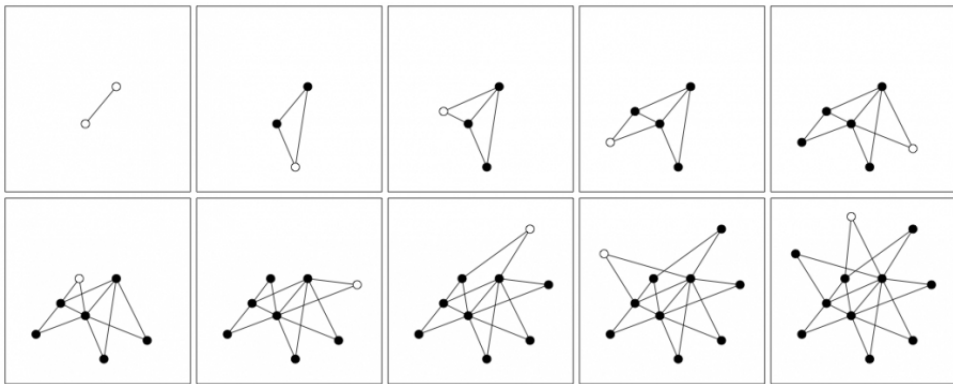
# New Model

- Begin with  $m_o$  vertices (with positive degrees), fix some  $m \leq m_o$
- Every timestep, add a new vertex and connect it to  $m$  existing vertices preferentially
- Probability the new vertex will be connected to vertex  $i = \Pi(k_i)$  where  $k_i$  is the degree of vertex  $i$

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

After  $t$  timesteps, yields a model with  $t + m_o$  vertices and  $tm$  edges.

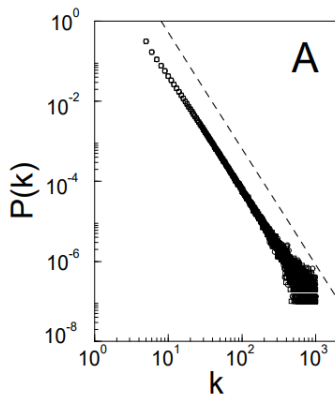
# Visualization, $m_o = m = 2$



<http://networksciencebook.com/chapter/5barabasi-model>

# Model Implications

They found:  $P(k) \sim k^{-\gamma}$      $\gamma_{model} = 2.9 \pm 0.1$



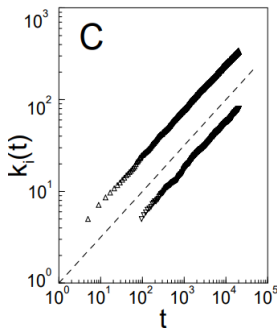
Distribution at  $t = 150,000$  (o) and  $t = 200,000$  (square)

# Model Implications

When either assumption is violated, this result does not occur

- If preferential connectivity is not enforced,  $P(k) \sim \exp(-\beta k)$
- If  $N$  is fixed, eventually all vertices will be directly connected

Also note the degree of a vertex depends on when it was added



# Deriving Gamma

$$\frac{\partial k_i}{\partial t} = m \Pi(k_i) = m \frac{k_i}{\sum_j k_j} = m \frac{k_i}{2mt - m} \approx \frac{k_i}{2t}$$

$$k_i(t) = m(t/t_i)^{0.5}$$

Where  $t_i$  represents the time vertex  $i$  was added to the network

$$\begin{aligned} P(k_i(t) < k) &= P(t_i > m^2 t / k^2) = 1 - P(t_i \leq m^2 t / k^2) \\ &= 1 - P(t_i \leq m^2 t / k^2) = 1 - m^2 t / [k^2(t + m_o)] \end{aligned}$$

Under the assumption that vertices are added at equal time intervals

<https://barabasi.com/f/622.pdf>

# Deriving Gamma

$$\begin{aligned}P(k) &= \partial P(k_i(t) < k) / \partial k \\&= \frac{\partial}{\partial k} (1 - m^2 t / [k^2 (t + m_o)]) \\&= \frac{2m^2 t}{(t + m_o) k^3}\end{aligned}$$

Over long times, they found

$$P(k) = \frac{2m^2}{k^3} \sim k^{-3}$$

$$P(k) \sim k^{-\gamma}$$



# Discussion

- Considered nonlinear preferential attachment  $\Pi(k_i) = \frac{k_i^\alpha}{\sum_j k_j^\alpha}$  but chose  $\Pi(k_i) = \frac{k_i}{\sum_j k_j}$  as simulations showed scaling for only  $\alpha = 1$
- In the empirical networks they looked at,  $\gamma$  ranged from 2.1 to 4
- If  $p$  of the edges are directed  $\gamma(p) = 3 - p$  is reasonable and supported by numerical simulation

# Conclusion

- Growth and preferential attachment are mechanisms common to many complex systems
- Large networks exhibit power-law decay in the probability a vertex has a particular degree (scale-free)
- Networks with very different origins can display similar behavior (self-organization)