

Random Graph models of Social Networks

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Overview

- Networks
- Social Network Metrics:
 - Small-World, Scale-free, Centrality
- Social Network examples:
 - Erdos Number, Kevin Bacon, Facebook
- Erdos-Renyi Random Graph
- Phase Transition in ER random graph
- Configuration model.
- Preferential Attachment model.

Networks

- A network is a set of items (nodes or *vertices*) connected by *edges* or links.
- Types of networks:
 - *Technological networks*: Internet, phone networks, power grid.
 - *Social Networks* : Collaboration network, Facebook, Kevin Bacon Number.
 - *Biological Networks*: Protein Interaction network, Neural Network
- Social Networks
 - Vertices are people, and edges are relations between them.

Random Graph

- Random Graph is the general term to refer to probability distributions over graphs.
- Graph Sequence: A graph sequence is denoted by $(G_n)_{n \geq 1}$, where n denotes the size of the graph G_n , i.e., the number of vertices in G .
- Degree Distribution: $P_k^{(n)}$ denotes the proportion of vertices with degree k in G_n ,

$$P_k^{(n)} = \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{\{d_i^{(n)}=k\}}$$

- Two types of degree distributions:
 - $P(d) = ce^{-\alpha d}$: The distribution falls off as fast as an exponential, for some $\alpha, c > 0$.
 - $P(d) = cd^{-\lambda}$: Power law distribution (Scale-free graph)

Scale-free and Sparse Graph

- Scale-free Graphs:

- We call a graph sequence $(G_n)_{n \geq 1}$ scale free with exponent τ when it is sparse and when

$$\lim_{k \rightarrow \infty} \frac{\log [1 - F(k)]}{\log (1/k)} = \tau - 1, \quad \text{where } F(k) = \sum_{l \leq k} p_l \text{ denotes the cumulative distribution function}$$

corresponding to the probability mass function $(p_k)_{k \geq 0}$.

- Or, $\lim_{k \rightarrow \infty} \frac{\log p_k}{\log (1/k)} = \tau$. i.e the log-log plot is linear.

- Sparse Graph:

- A graph sequence $(G_n)_{n \geq 1}$ is called sparse when $\lim_{n \rightarrow \infty} P_k^{(n)} = p_k$, for some deterministic limiting probability distribution $(p_k)_{k \geq 0}$.

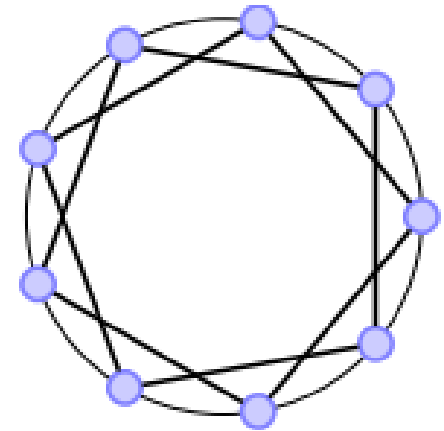
Small-World Graph

- Small-World

- Vertices are separated by relatively short chains of edges.
- A Graph Sequence $(G_n)_{n \geq 1}$ is a small-world graph sequence, when its typical distances satisfy that there exists a constant K such that:

$$\lim_{n \rightarrow \infty} P(H_n \leq k \log n) = 1$$

where H_n is the average path length.



Clustering

- Clustering measures the degree to which neighbours of vertices are also neighbours of one another.
- *Clustering Coefficient*: Clustering coefficient measures the proportion of wedges for which the closing edge is also present.
- $CC(g) = \frac{3 \times \text{Number of Triangles in the graph}}{\text{Number of connected triples of nodes}}$
- Definition: A graph sequence $(G_n)_{n \geq 1}$ is highly clustered when $\lim_{n \rightarrow \infty} CC > 0$

Highly Connected

- Highly Connected:
 - A large part of the vertices is in one large connected component.
 - For a graph $G = ([n], E)$ on n vertices and $v \in [n]$, let $C(v)$ denote the *cluster* or *connected component* of $v \in [n]$,
i.e., $C(v) = \{u \in [n] : \text{dist}_G(u, v) < \infty\}$
 - A graph sequence $(G_n)_{n \geq 1}$ is called highly connected when :
$$\lim_{n \rightarrow \infty} |C_{\max}|/n > 0$$
 - Furthermore, for a highly-connected graph sequence, the *giant component* is unique when
$$\lim_{n \rightarrow \infty} |C_2|/n > 0,$$
 $|C_2|$ being the size of second-largest component.

Centrality

- A measure that captures the importance of a node's position in the network.
 - Closeness Centrality: vertices that are close to many other vertices are deemed to be important.

$$C_i = \frac{n}{\sum_{j \in [n]} \text{dist}_G(i, j)},$$

- Betweenness Centrality: Vertices lying in the shortest paths between any two vertices are deemed important.

$$b_i = \sum_{1 \leq j < k \leq n} n_{jk}^i / n_{jk},$$

n_{jk} : number of shortest paths between vertices j and k .

n_{jk}^i : number of shortest paths between vertices j and k containing i .

Empirical Data

- Empirically, the properties exhibited by real-world social networks are:
 - Small- world networks
 - Scale-free networks
 - Existence of a giant component.

Social Networks: Examples

- Six Degrees of Separation [<http://www.stanleymilgram.com/milgram.php>]
 - Average length between vertices is 6.
 - Established Small-World network.
- Facebook [Ugander et al]
 - 99.91% of the active Facebook users is in the giant component, so that Facebook is indeed very highly connected.
 - The second largest connected component consisting of a meagre 2000 some users. The assortativity coefficient is equal to 0.226
 - This distribution does not resemble a power law (owing to the limit of 5000 friends per person).

Social Networks: Examples

- Kevin Bacon Number [<http://www.cs.virginia.edu/oracle/>]
 - The vertices are movie actors, and two actors share an edge when they have been cast in the same movie.
 - Turn out Kevin Bacon is not the most central vertex in the graph. A more central actor is Sean Connery.
 - A Scale-free distribution, with the power law exponent equal to 2.3.
- Erdos Number [<http://www.ams.org/msnmain/cgd/index.html>]
 - The vertices are mathematicians, and there is an edge between two mathematicians when they have co-authored a paper.
 - One giant component consisting of about 268,000 vertices, so that the graph is highly connected.
 - The average number of collaborators per person is 3.36.

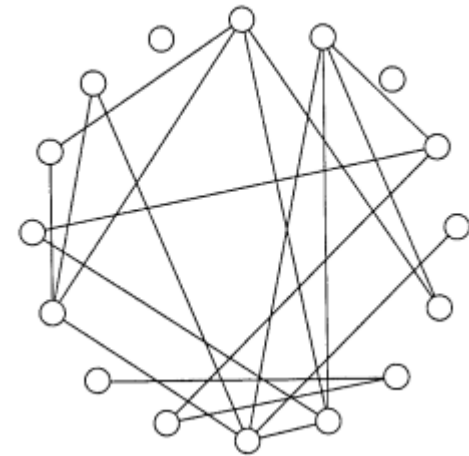
Erdős-Renyi Random Graph Model

- $G(n, p)$ denotes an undirected Erdős-Renyi graph.
- Every edge is formed with probability $p \in (0, 1)$ independently of every other edge.
- Let $I_{ij} \in \{0, 1\}$ be a Bernoulli random variable indicating the presence of edge $\{i, j\}$
- For the Erdos-Renyi model, random variables I_{ij} are independent and

$$I_{ij} = \begin{cases} 1 & \text{with probability } p \\ 0 & \text{with probability } 1 - p \end{cases}$$

- $E[\text{number of edges}] = E[\sum I_{ij}] = \frac{n(n-1)}{2} p$

$N=16, p=1/7$



Erdős-Renyi Random Graph Model

- Let D be a random variable that represents the degree of a node.
- D is a binomial variable with $E[D] = n(n-1)p$
- $P(D = d) = \binom{n-1}{d} p^d (1-p)^{n-1-d}$
- As $n \rightarrow \infty$, D can be approximated with a Poisson random variable with $\lambda = (n - 1)p$.
 - Since this degree distribution falls off faster than an exponential in d , hence it is not a power-law distribution.

Phase Transition

- For a given property A (e.g. connectivity), we define a threshold function $t(n)$ as a function that satisfies:

$$P(\text{property } A) \rightarrow 0 \text{ if } \frac{p(n)}{t(n)} \rightarrow 0, \text{ and}$$

$$P(\text{property } A) \rightarrow 1 \text{ if } \frac{p(n)}{t(n)} \rightarrow \infty$$

- This definition makes sense for “monotone or increasing properties,” i.e., properties such that if a given network satisfies it, any super network (in the sense of set inclusion) satisfies it.
- When such a threshold function exists, we say that a phase transition occurs at that threshold.

Phase Transition Example

- Let property A be = {number of edges > 0}
- We are looking for a threshold $t(n)$ for the emergence of the first edge.
- $E[\text{number of edges}] = \frac{n(n-1)}{2} p(n) \approx \frac{n^2}{2} p(n)$
- Assuming $\frac{p(n)}{n^2} \rightarrow 0$ as $n \rightarrow \infty$. Then, $E[\text{number of edges}] \rightarrow 0$, which implies that $P(\text{number of edges} > 0) \rightarrow 0$.
- Similarly, we next assume that $\frac{p(n)}{n^2} \rightarrow \infty$ as $n \rightarrow \infty$. Then, $E[\text{number of edges}] \rightarrow \infty$.
- Since, the number of edges can be approximated by a Poisson distribution, we have

$$\mathbb{P}(\text{number of edges} = 0) = \left. \frac{e^{-\lambda} \lambda^k}{k!} \right|_{k=0} = e^{-\lambda}$$

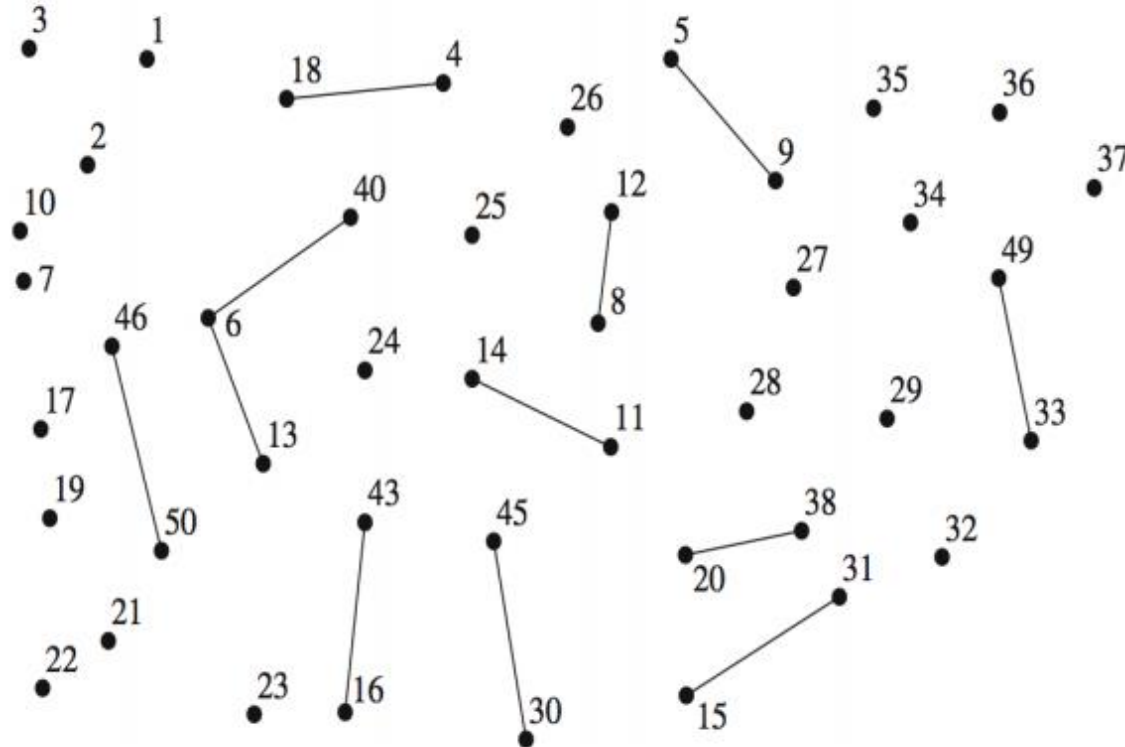
Phase Transition Example

- Since, $\lambda = E[\text{number of edges}] \rightarrow \infty$
- $P(\text{number of edges} = 0) = e^{-\lambda} \rightarrow 0$

Phase Transition

- $t(n) = \frac{1}{n^2}$ is the threshold function for the emergence of the first link.
- $t(n) = \frac{1}{n^2}$ is the threshold function for the emergence of triples in the graph.
- $t(n) = \frac{1}{n^{k-1}}$ is the threshold function to start observing a tree with k nodes.
- $t(n) = \frac{1}{n}$ is the threshold function to start observing a cycle.
- Above the threshold of $1/n$, a giant component emerges, which is the largest component that contains a nontrivial fraction of all nodes, i.e., at least cn for some constant c .
- The giant component grows in size until the threshold of $\log(n)/n$, at which point the network becomes connected.

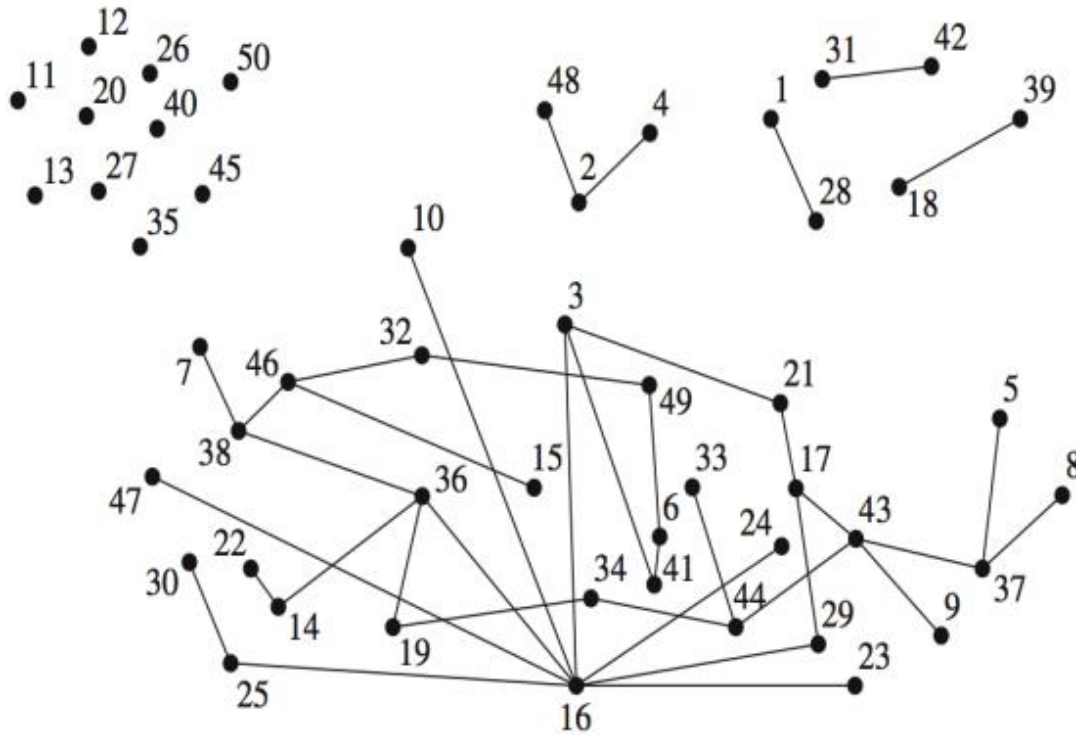
Phase Transition



$N = 50$
 $p = 0.01$

Emergence of a first component with more than two nodes a random network.

Phase Transition

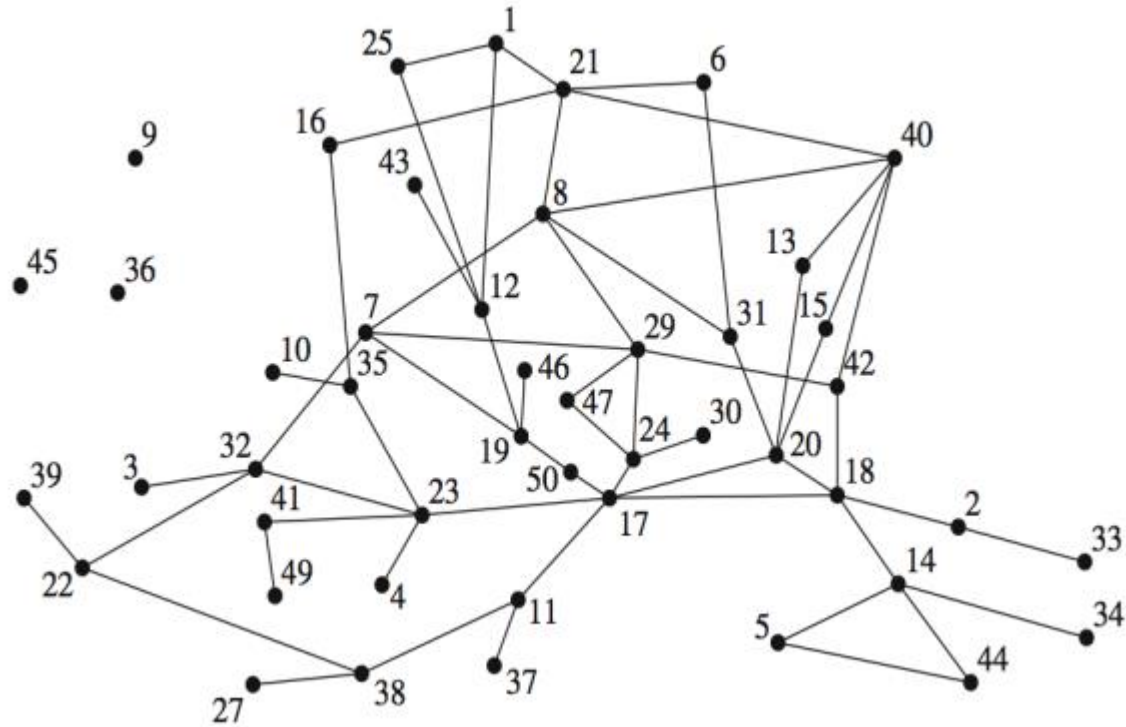


$N = 50$

$p = 0.03$

Emergence of cycles.

Phase Transition

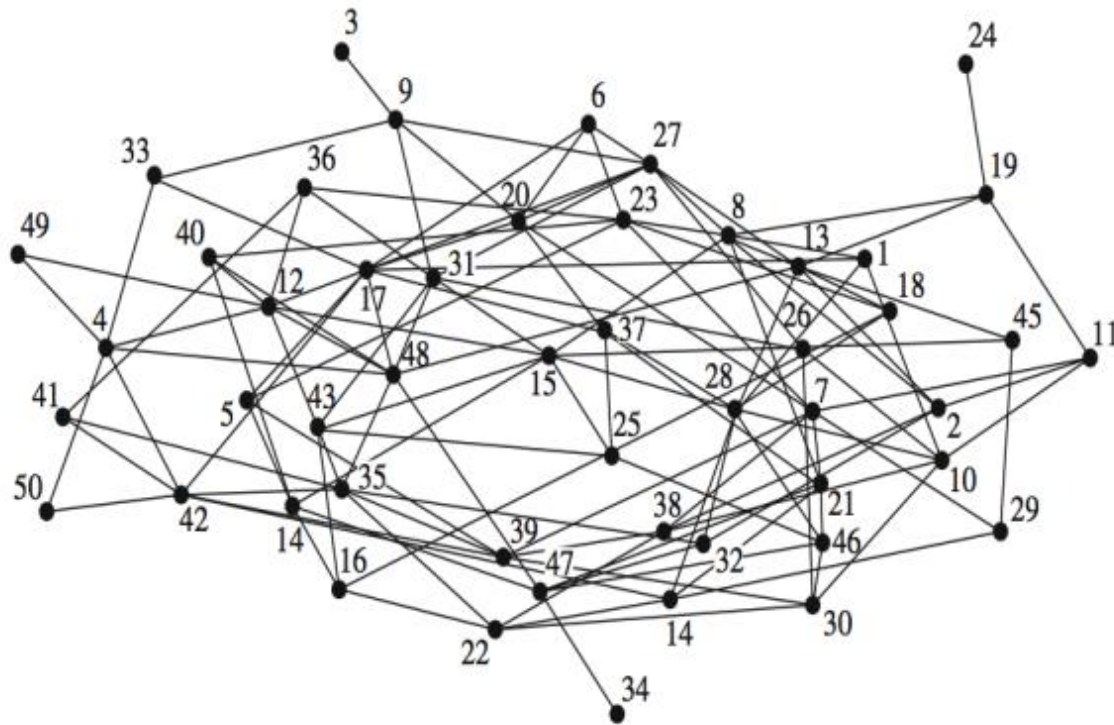


$N = 50$

$p = 0.05$

Emergence of a giant component.

Phase Transition



$N = 50$
 $p = 0.10$

Emergence of connectedness.

Connectivity

- Theorem: (Erdos and Renyi 1961) A threshold function for the connectivity of the Erdos and Renyi model is $t(n) = \frac{\log(n)}{n}$.

- Proof:

We show that when $p(n) = \lambda \frac{\log(n)}{n}$,

If $\lambda < 1$, $P(\text{connectivity}) \rightarrow 0$,

If $\lambda > 1$, $P(\text{connectivity}) \rightarrow 1$

- To prove disconnectedness, it is sufficient to show that the probability that *there exists at least one isolated node* goes to 1.

Connectivity

- Let I_i be a Bernoulli random variable defined as

$$I_i = \begin{cases} 1 & \text{if node } i \text{ is isolated} \\ 0 & \text{otherwise} \end{cases}$$

- The probability that an individual node is isolated as

$$q = P(I_i = 1) = (1 - p)^{n-1} \approx e^{-pn} = e^{-\lambda \log(n)} = n^{-\lambda}$$

(Using $\lim_{n \rightarrow \infty} \left(1 - \frac{a}{n}\right)^n = e^{-a}$ to get the approximation)

- Let $X = \sum_{i=1}^n I_i$ denote the total number of isolated nodes. We have,

$$\mathbb{E}[X] = n \cdot n^{-\lambda}.$$

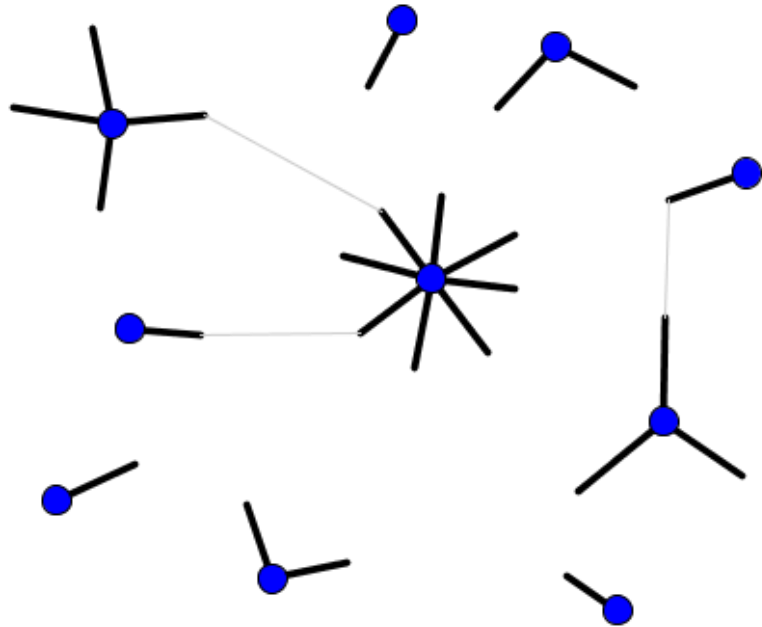
Connectivity

- For $\lambda < 1$, we have $E[X] \rightarrow \infty$. This implies $P(X = 0) \rightarrow 0$.
- It follows that $P(\text{at least one isolated node}) \rightarrow 1$ and therefore, $P(\text{disconnected}) \rightarrow 1$ as $n \rightarrow \infty$.

Configuration Model

- Configuration model is a generalized Erdos-Renyi random graph with a “given degree distribution”(Bender and Canfield, 1978).
- The configuration model is specified in terms of a degree sequence.
- Given (d_1, \dots, d_n) , we construct a sequence where node 1 is listed d_1 times, node 2 is listed d_2 times, and so on: $1, 1, 1, 1, \dots, 1 \mid \{z\} d_1$ entries $2, 2, \dots, 2 \mid \{z\} d_2$ entries $\dots n, n, n \dots, n \mid \{z\}$
- Each node i in the graph can be thought of as “stubs” sticking out of it, which are ends of edges-to-be.
- We randomly pick two elements of the sequence and form a link between the two nodes corresponding to those entries.
- $t(n) = 1/n$ is the threshold for the emergence of the giant component.

Configuration model



Remarks:

- The sum of degrees needs to be even.
- Self-loops are possible.
- More than one edge between two vertices is possible (multigraph).

- Generating Graphs with arbitrary degree distribution.
- Half-edges(stubs) joined

Preferential Attachment

- Erdos-Renyi, Configuration model are all static models, in which edges among “fixed” n nodes are formed via random rules .
- In a preferential attachment model, nodes are born over time, therefore a dynamic model.
- Each node upon birth forms m edges with pre-existing nodes.
- Let $d_i(t)$ be the degree of node i at time t . Initially we have $m+1$ nodes(indexed $0, \dots, m$) all connected to each other
- The probability that an existing node i receives a new link to the newborn node at time t is m times i 's degree relative to the overall degree of all existing nodes at time t , i.e

$$\frac{dd_i(t)}{dt} = m \frac{d_i(t)}{\sum_{j=1}^t d_j(t)}$$

Preferential Attachment

- Since at a time t , there are $2tm$ edges. Therefore, $\sum_{j=1}^t d_j(t) = 2tm$.

$$\frac{dd_i(t)}{dt} = \frac{d_i(t)}{2t}, \text{ with initial condition } d_i(t) = m$$

- The solution to the equation is : $d_i(t) = m\left(\frac{t}{i}\right)^{1/2}$
- Let $i(d)$ be $\frac{i(d)}{t} = \left(\frac{m}{d}\right)^2$, has degree d at time t , or $d_{i(d)}(t) = d$
- Therefore,
- For any d and any time t , let $i(d)$ be a node such that $d_{i(d)}(t) = d$ The resulting cumulative distribution function then is $F_t(d) = 1 - \frac{i(d)}{t}$.
- In this case, $F(d) = 1 - m^2d^{-2}$
- $P(d) = 2m^2d^{-3}$, therefore scale-free(Power-law with exponent -3)