

# Basic Network Properties and the Random Graph Model

CS224W: Social and Information Network Analysis  
Jure Leskovec, Stanford University  
<http://cs224w.stanford.edu>

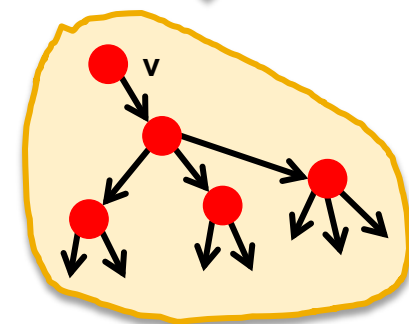


# Announcement: Recitations

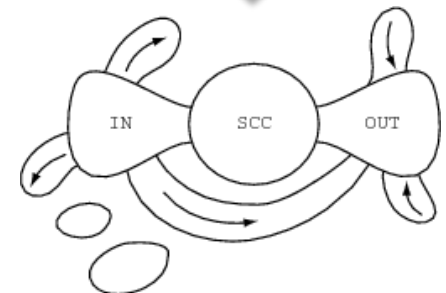
- **Review of basic probability:**
  - Today, Thu 9/29
  - In Gates B01, 4-6pm
- **Review of basic linear algebra:**
  - Tomorrow, Fri 9/30
  - Gates B03, 4-6pm
- **Next week:**
  - Intro to [SNAP](#) (Gates B01, 4-6pm on Thu 10/6)
  - Intro to [NetworkX](#) (Gates B03, 4-6pm on Fri 10/7)

# Structure of Networks

- Recall from the last lecture:
  - 1) We took a real system: **the Web**
  - 2) We represented it as a **directed graph**
  - 3) We used the language of graph theory
    - Strongly Connected Components
  - 4) We designed a **computational experiment**:
    - Find In- and Out-components of a given node  $v$
  - 5) We learned something about the **structure of the Web**
- This class:
  - Define basic terminology and measures that you can compute on networks



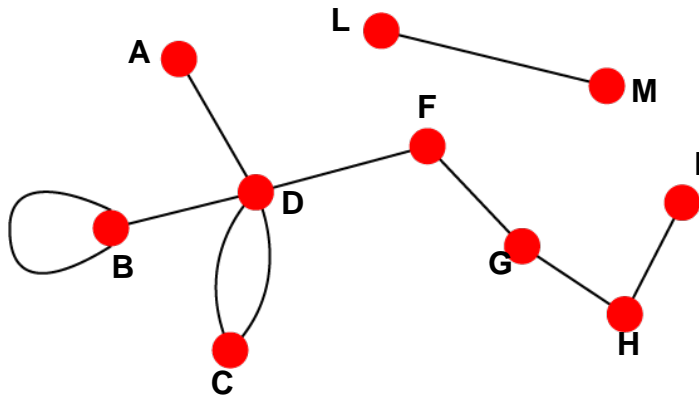
$Out(v)$



# Undirected vs. Directed Networks

## Undirected

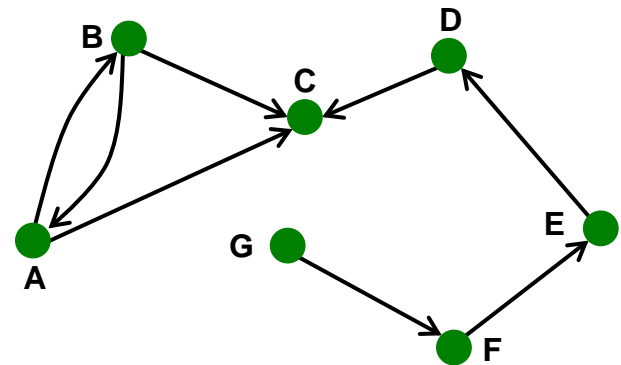
- Links: undirected (symmetrical)



- Undirected links:
  - Collaborations
  - Friendship on Facebook

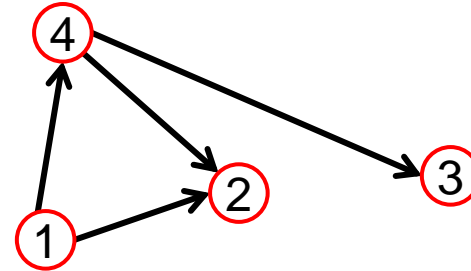
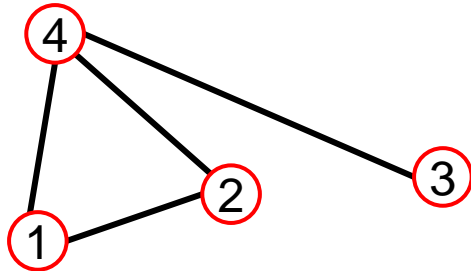
## Directed

- Links: directed (arcs)



- Directed links:
  - Phone calls
  - Following on Twitter

# Adjacency Matrix



$A_{ij}=1$  if there is a link between node  $i$  and  $j$

$A_{ij}=0$  if nodes  $i$  and  $j$  are not connected to each other

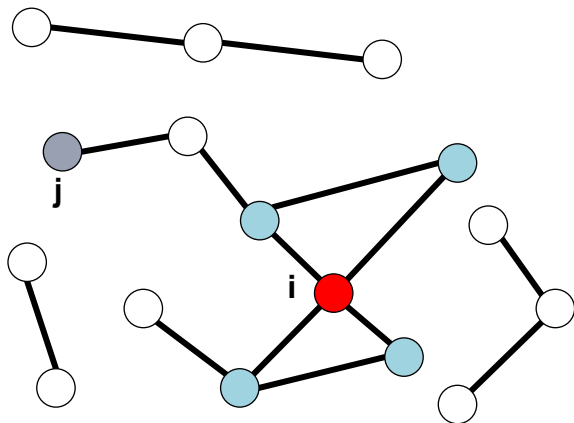
$$A = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}$$

$$A = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$

Note that for a directed graph (right) the matrix is not symmetric.

# Node Degrees

Undirected

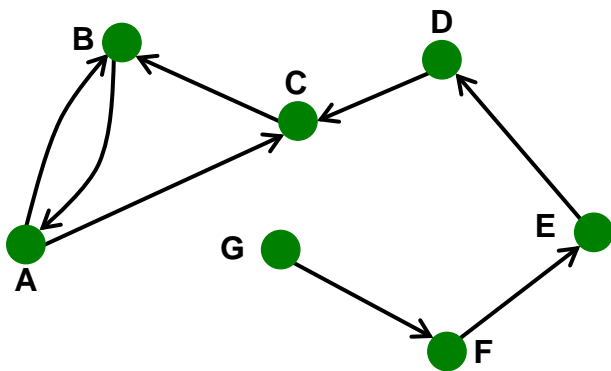


**Node degree:** the number of links connected to the node

$$k_i = 4$$

**Avg. degree:**  $\bar{k} \equiv \frac{1}{N} \sum_{i=1}^N k_i = \frac{2E}{N}$

Directed



**Source:** A node with  $k^{in} = 0$

**Sink:** A node with  $k^{out} = 0$

In directed networks we define an **in-degree** and **out-degree**. The (total) degree of a node is the sum of in- and out-degree.

$$k_C^{in} = 2 \quad k_C^{out} = 1 \quad k_C = 3$$

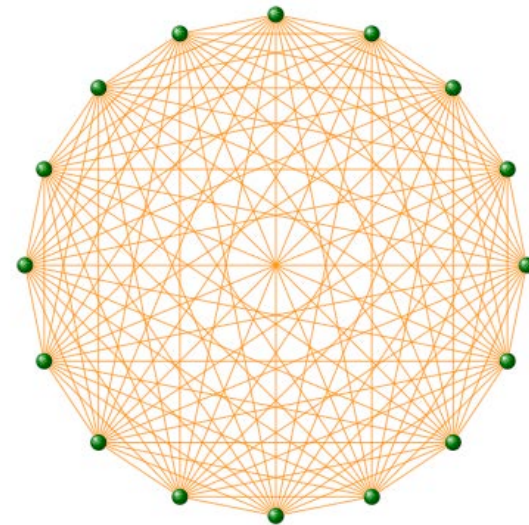
$$\bar{k} = \frac{E}{N}$$

$$\overline{k^{in}} = \overline{k^{out}}$$

# Complete Graph

The maximum number of edges in an undirected graph on  $N$  nodes is

$$E_{\max} = \binom{N}{2} = \frac{N(N-1)}{2}$$



A graph with the number of edges  $E = E_{\max}$  is a **complete graph**, and its average degree is  $N-1$

# Networks are Sparse Graphs

Most real-world networks are **sparse**

$$E \ll E_{\max} \text{ (or } \bar{k} \ll N-1)$$

WWW (Stanford-Berkeley):	$N=319,717$	$\langle k \rangle=9.65$
Social networks (LinkedIn):	$N=6,946,668$	$\langle k \rangle=8.87$
Communication (MSN IM):	$N=242,720,596$	$\langle k \rangle=11.1$
Coauthorships (DBLP):	$N=317,080$	$\langle k \rangle=6.62$
Internet (AS-Skitter):	$N=1,719,037$	$\langle k \rangle=14.91$
Roads (California):	$N=1,957,027$	$\langle k \rangle=2.82$
Protein (S. Cerevisiae):	$N=1,870$	$\langle k \rangle=2.39$

(Source: Leskovec et al., *Internet Mathematics*, 2009)

**Consequence:** Adjacency matrix is filled with zeros!

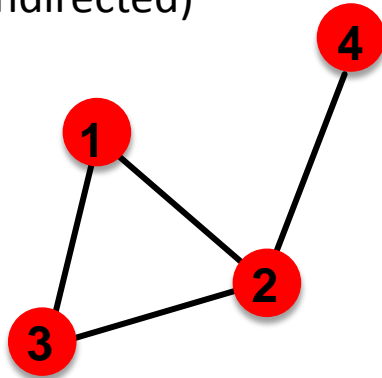
(Density ( $E/N^2$ ): WWW= $1.51 \times 10^{-5}$ , MSN IM =  $2.27 \times 10^{-8}$ )



# More Types of Graphs:

## ■ Unweighted

(undirected)



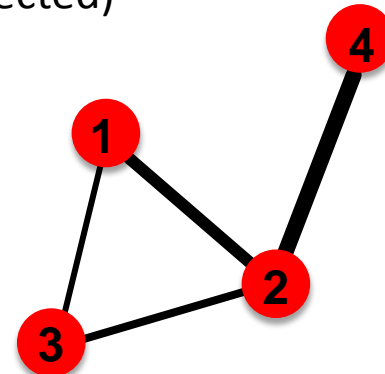
$$A_{ij} = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

$$A_{ii} = 0 \quad A_{ij} = A_{ji}$$
$$E = \frac{1}{2} \sum_{i,j=1}^N A_{ij} \quad \bar{k} = \frac{2E}{N}$$

Friendships, WWW

## ■ Weighted

(undirected)



$$A_{ij} = \begin{pmatrix} 0 & 2 & 0.5 & 0 \\ 2 & 0 & 1 & 4 \\ 0.5 & 1 & 0 & 0 \\ 0 & 4 & 0 & 0 \end{pmatrix}$$

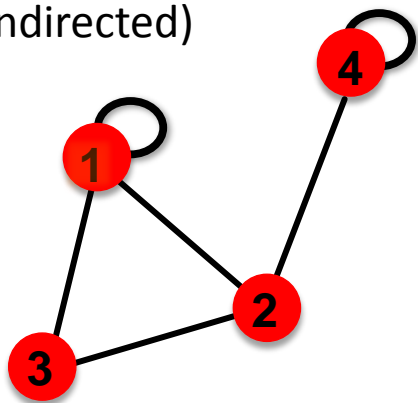
$$A_{ii} = 0 \quad A_{ij} = A_{ji}$$
$$E = \frac{1}{2} \sum_{i,j=1}^N \text{nonzero}(A_{ij}) \quad \bar{k} = \frac{2E}{N}$$

Call graph, Email graph

# More Types of Graphs:

## ■ Self-edges

(undirected)



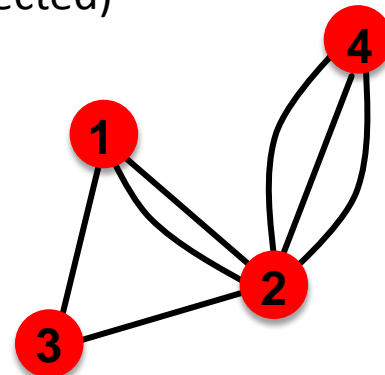
$$A_{ij} = \begin{pmatrix} 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 \end{pmatrix}$$

$$E = \frac{1}{2} \sum_{i,j=1, i \neq j}^N A_{ij} + \sum_{i=1}^N A_{ii} \quad ?$$

WWW, Email

## ■ Multigraph

(undirected)



$$A_{ij} = \begin{pmatrix} 0 & 2 & 1 & 0 \\ 2 & 0 & 1 & 3 \\ 1 & 1 & 0 & 0 \\ 0 & 3 & 0 & 0 \end{pmatrix}$$

$$E = \frac{1}{2} \sum_{i,j=1}^N \text{nonzero}(A_{ij}) \quad \bar{k} = \frac{2E}{N}$$

Social networks, collaboration networks

# Network Representations

WWW >> directed multigraph with self-interactions

Facebook friendships >> undirected, unweighted

Citation networks >> unweighted directed acyclic

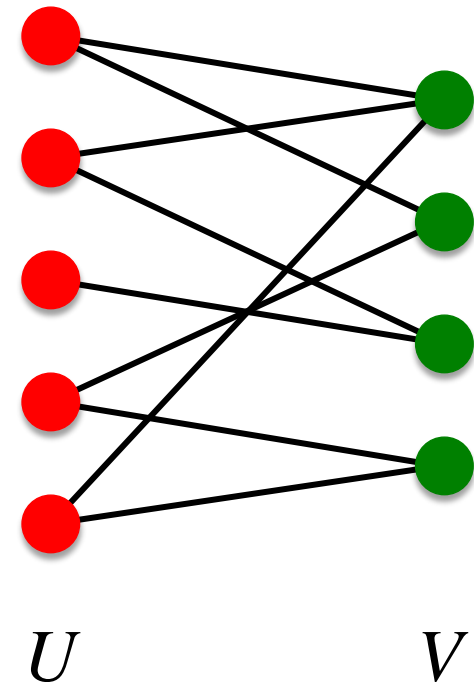
Collaboration networks >> undirected multigraph or weighted

Mobile phone calls >> directed, (weighted?) multigraph

Protein Interactions >> undirected, unweighted with self-interactions

# Bipartite Graph

- **Bipartite graph** is a graph whose nodes can be divided into two disjoint sets  $U$  and  $V$  such that every link connects a node in  $U$  to one in  $V$ ; that is,  $U$  and  $V$  are independent sets.
- **Examples:**
  - Authors-to-papers
  - Movies-to-Actors
  - Users-to-Movies
- **“Folded” networks**
  - Author collaboration networks
  - Actor collaboration networks



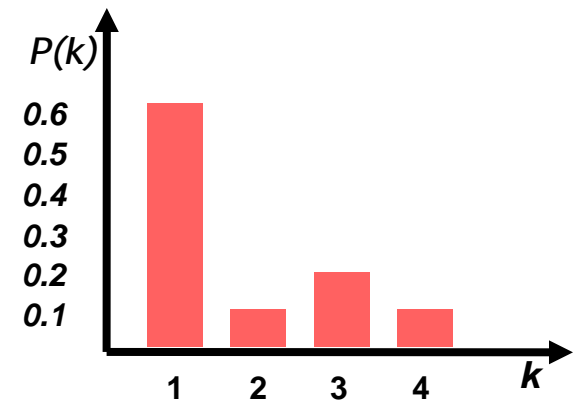
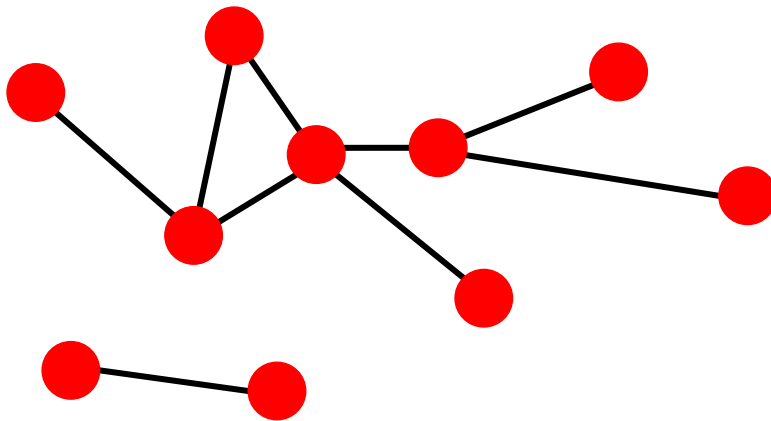
# **Network Properties: How to Characterize a Network?**

# Degree Distribution

- **Degree distribution  $P(k)$ :** Probability that a randomly chosen node has degree  $k$

$N_k = \#$  nodes with degree  $k$

$P(k) = N_k / N \rightarrow$  **plot**

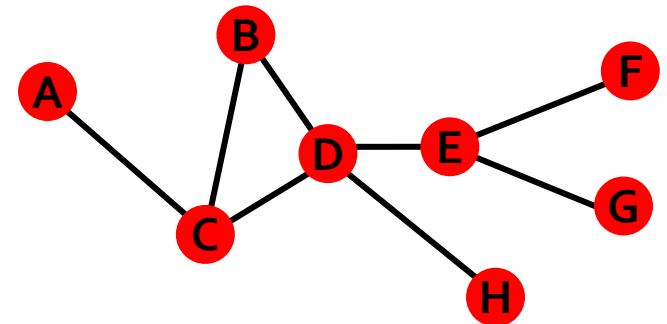


# Paths in a Graph

- A *path* is a sequence of nodes in which each node is adjacent to the next one

$$P_n = \{i_0, i_1, i_2, \dots, i_n\} \quad P_n = \{(i_0, i_1), (i_1, i_2), (i_2, i_3), \dots, (i_{n-1}, i_n)\}$$

- Path can intersect itself and pass through the same edge multiple times
  - E.g.: ACBDCDEG
  - In a directed graph a path can only follow the direction of the “arrow”



# Number of Paths

- **Number of paths between nodes  $u$  and  $v$  :**

- **Length  $h=1$ :** If there is a link between  $u$  and  $v$ ,  
 $A_{uv}=1$  else  $A_{uv}=0$

- **Length  $h=2$ :** If there is a path of length two between  $u$  and  $v$  then  $A_{uk}A_{kv}=1$  else  $A_{uk}A_{kv}=0$

$$H_{uv}^{(2)} = \sum_{k=1}^N A_{uk}A_{kv} = [A^2]_{uv}$$

- **Length  $h$ :** If there is a path of length  $h$  between  $u$  and  $v$  then  $A_{uk} \dots A_{kv}=1$  else  $A_{uk} \dots A_{kv}=0$

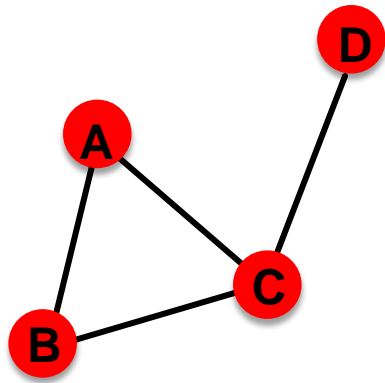
So, the no. of paths of length  $h$  between  $u$  and  $v$  is

$$H_{uv}^{(h)} = [A^h]_{uv}$$

(holds for both directed and undirected graphs)

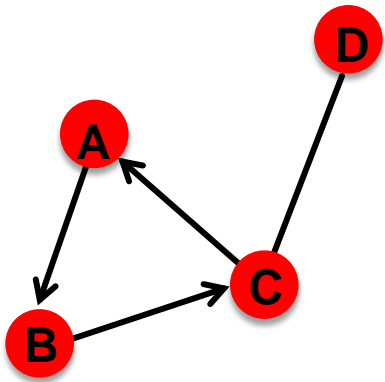


# Distance in a Graph



- **Distance (shortest path, geodesic)** between a pair of nodes is defined as the number of edges along the shortest path connecting the nodes.

- \*If the two nodes are disconnected, the distance is defined as infinite

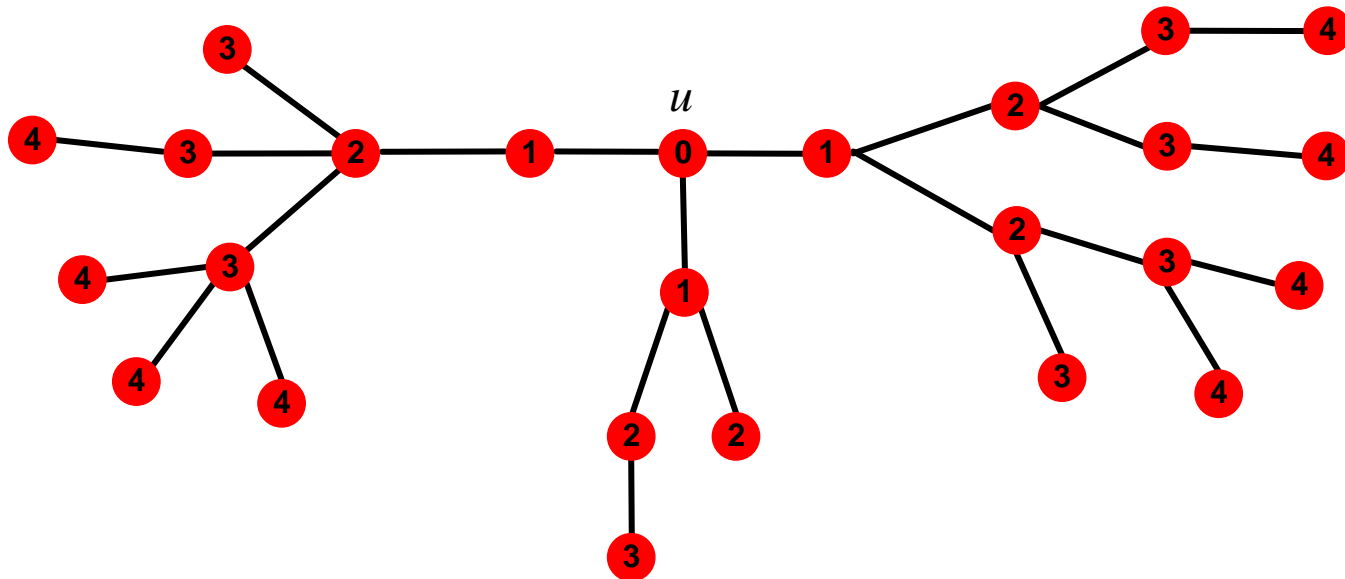


- In **directed graphs** paths need to follow the direction of the arrows.
- Consequence: Distance is not symmetric:  $h(A, C) \neq h(C, A)$

# Finding Shortest Paths

## ■ Breath-First Search:

- Start with node  $u$ , mark it to be at distance  $h_u(u)=0$ , add  $u$  to the queue
- While queue not empty:
  - Take node  $v$  off the queue, put it's unmarked neighbor  $w$  into the queue and mark  $h_u(w)=h_u(v)+1$



# Network Diameter

- **Diameter:** the maximum (shortest path) distance between any pair of nodes in the graph
- **Average path length/distance** for a connected graph (component) or a strongly connected (component of a) directed graph

$$\bar{h} = \frac{1}{2E_{\max}} \sum_{i, j \neq i} h_{ij}$$

where  $h_{ij}$  is the distance from node  $i$  to node  $j$

- Many times we compute the average only over the connected pairs of nodes (*i.e.*, we ignore “infinite” paths)

# Clustering Coefficient

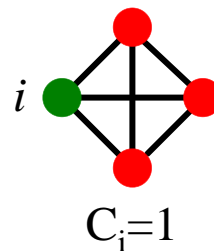
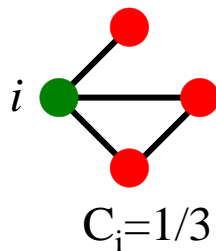
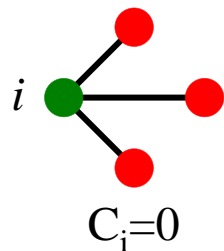
## ■ Clustering coefficient:

- What portion of  $i$ 's neighbors are connected?

- Node  $i$  with degree  $k_i$

- $C_i \in [0, 1]$

- $C_i = \frac{2e_i}{k_i(k_i - 1)}$  where  $e_i$  is the number of edges between the neighbors of node  $i$



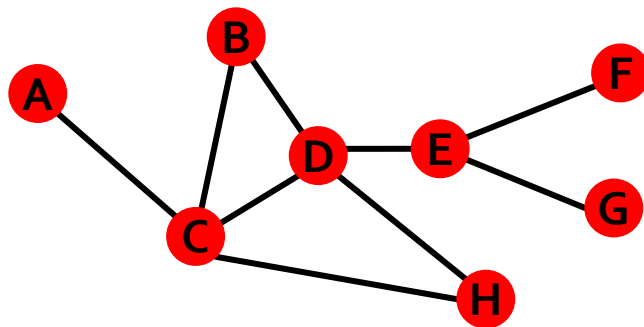
- Average Clustering Coefficient:  $C = \frac{1}{N} \sum_i C_i$

# Clustering Coefficient

## ■ Clustering coefficient:

- What portion of  $i$ 's neighbors are connected?
- Node  $i$  with degree  $k_i$

- $C_i = \frac{2e_i}{k_i(k_i - 1)}$  where  $e_i$  is the number of edges between the neighbors of node  $i$



$$k_B=2, \quad e_B=1, \quad C_B=2/2 = 1$$

$$k_D=4, \quad e_D=2, \quad C_D=4/12 = 1/3$$

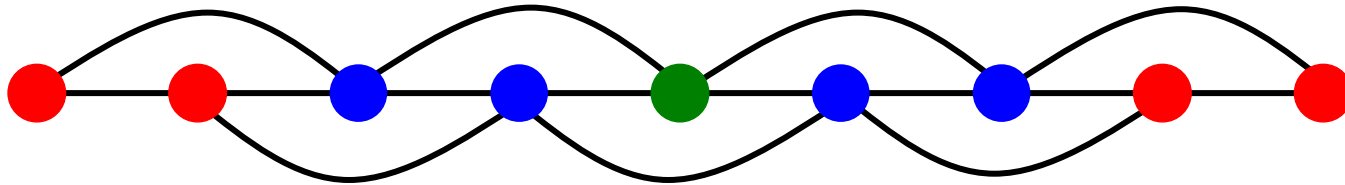
# Key Network Properties

**Degree distribution:**  $P(k)$

**Path length:**  $h$

**Clustering coefficient:**  $C$

# Regular Lattice: 1D



- $P(k) = \delta(k-4)$        $k=4$  for each node
- $C = 1/2$  for each node if  $N > 6$
- Path length:

$$h_{\max} \approx \frac{N}{2}$$

Alternative calculation:

$$\sum_{h=1}^{h_{\max}} 4 \approx N \Rightarrow h_{\max} \approx \frac{N}{4}$$

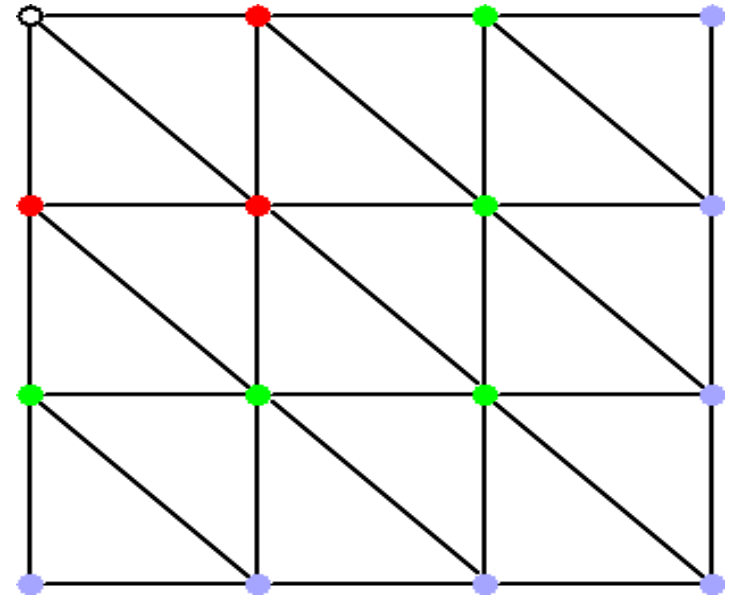
- The average path-length is  $\bar{h} \approx N$
- Constant degree, constant clustering coefficient.

# Regular Lattice: 2D

- $P(k) = \delta(k-6)$ 
  - $k=6$  for each inside node
- $C = 6/15$  for inside nodes
- Path length:

$$\sum_{h=1}^{h_{\max}} 6h \approx N \Rightarrow h_{\max} \propto \sqrt{N}$$

- In general, for lattices:
  - average path-length is  $\bar{h} \approx N^{1/D}$
  - Constant degree, constant clustering coefficient

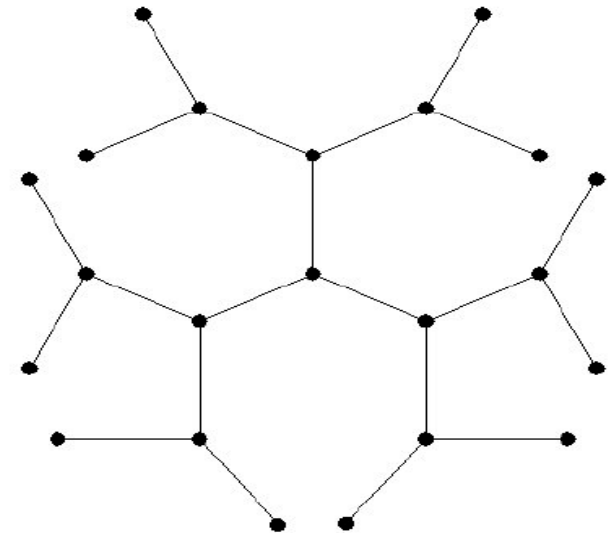




# 3-way Cayley Tree

- Degree:  $\bar{k} = 2$ 
  - $k=3$  for non-leaves
  - $k=1$  for leaves
- $C = 0$
- Path length:

$$3 \sum_{h=1}^{h_{\max}} 2^{h-1} \approx N \Rightarrow h_{\max} \propto \log_{\bar{k}} N = \frac{\log N}{\log \bar{k}}$$



$$\int_1^{h_{\max}} 2^{h-1} dx = \frac{2^h}{h} \Big|_1^{h_{\max}} = \frac{2^{h_{\max}}}{h_{\max}} - 2 \approx 2^{h_{\max}}$$
$$2^{h_{\max}} = N \Rightarrow h_{\max} = \log_2 N$$

- Distances vary logarithmically with  $N$ .  
Constant degree, no clustering.

# Erdős-Renyi Random Graph Model

# Simplest model of graphs?

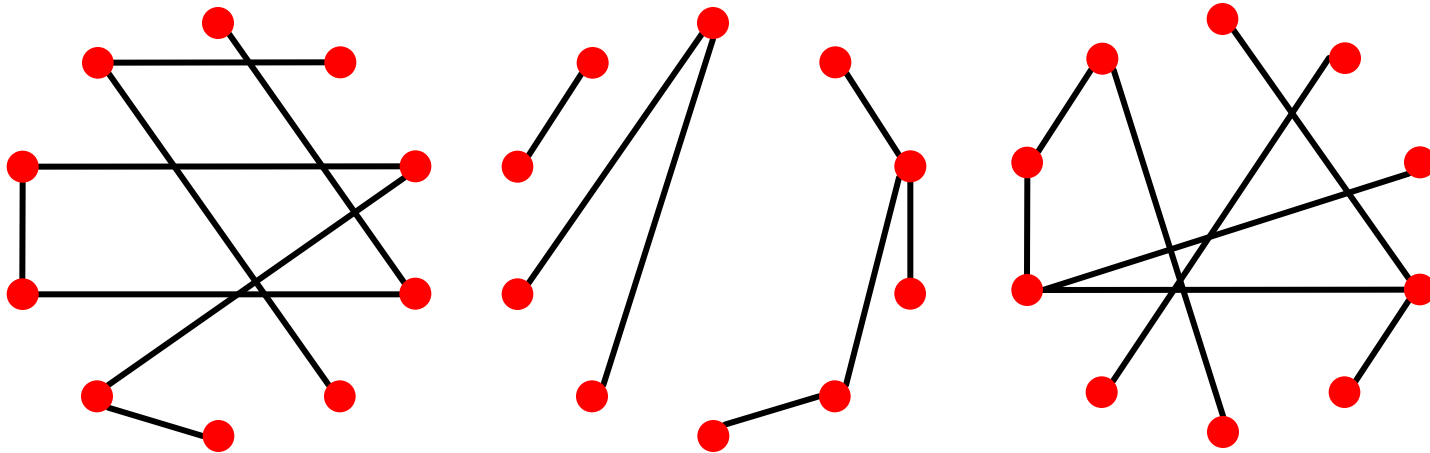
- **Erdős-Renyi Random Graph** [Erdős-Renyi, '60]
- Two variants:
  - $G_{n,p}$ : undirected graph on  $n$  nodes and each edge  $(u,v)$  appears i.i.d. with probability  $p$
  - $G_{n,m}$ : undirected graph with  $n$  nodes, and  $m$  uniformly at random picked edges

What kinds of networks does such model produce?

# Random Graph Model

- $n$  and  $p$  do not uniquely define the graph
- We can have many different realizations.

How many?



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

The probability of  $G_{np}$  to form a *particular* graph  $G(N, E)$  is

$$P(G(N, E)) = p^E (1 - p)^{\frac{N(N-1)}{2} - E}$$

That is, each concrete graph  $\mathbf{G}(\mathbf{N}, \mathbf{E})$  appears with probability  $\mathbf{P}(\mathbf{G}(\mathbf{N}, \mathbf{E}))$ .

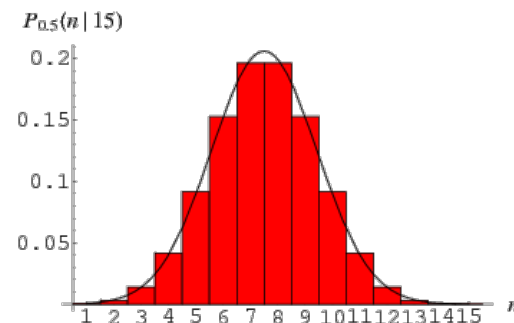
# Random Graph Model: Edges

- How many 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

**Binomial distribution >>>**



# Node Degrees in a Random Graph

- What is expected degree of a node?
- Let  $X_v$  be a random var. measuring the degree of the node  $v$ :  $E[X_v] = \sum_{j=0}^{n-1} j P(X_v = j)$

- Linearity of expectation:

- For any random variables  $Y_1, Y_2, \dots, Y_k$
- If  $Y = Y_1 + Y_2 + \dots + Y_k$ , then  $E[Y] = \sum_i E[Y_i]$

- Easier way:

- Decompose  $X_v$  in  $X_v = X_{v1} + X_{v2} + \dots + X_{vn-1}$ 
  - where  $X_{vu}$  is a  $\{0, 1\}$ -random variable which tells if edge  $(v, u)$  exists or not

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

**How to think about this?**

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

# Degree Distribution

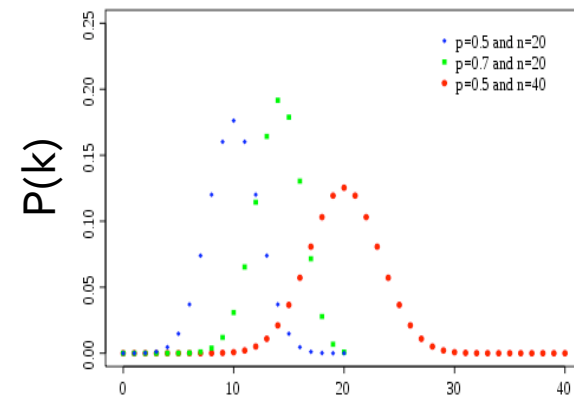
- Degree distribution of  $G_{np}$  is Binomial.
- Let  $P(k)$  denote a fraction of nodes with degree  $k$ :

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

Select  $k$  nodes  
from  $n-1$

Probability of  
having  $k$  edges

Probability of  
missing  $n-1-k$   
edges



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

$$\sigma_k^2 = p(1-p)(n-1)$$

$$\frac{\sigma_k}{\bar{k}} = \left[ \frac{1-p}{p} \frac{1}{(n-1)} \right]^{1/2} \approx \frac{1}{(n-1)^{1/2}}$$

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 $G_{np}$

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

Since edges in  $G_{np}$  appear i.i.d with probability  $p$

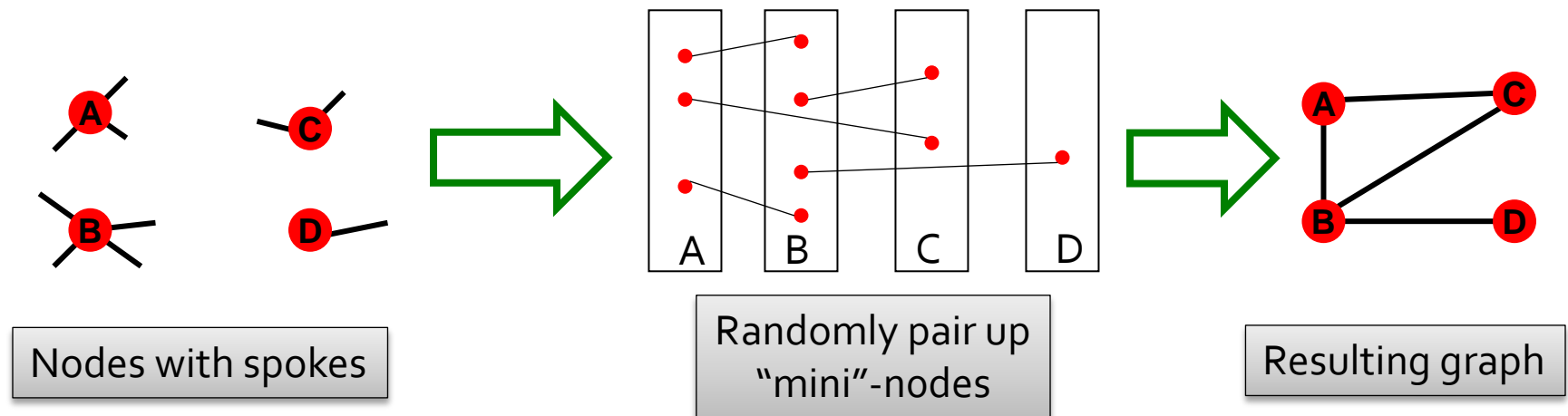
$$e_i \cong p \frac{k_i(k_i - 1)}{2} \quad \Rightarrow \quad C \cong p = \frac{\bar{k}}{N}$$

Clustering coefficient of a random graph is small.  
For a fixed degree  $C$  decreases with the graph size  $N$ .



# Side-note: Configuration Model

## ■ Configuration model:



- Assume a degree sequence  $k_1, k_2, \dots, k_N$
- Useful for as a “null” model of networks
  - We can compare the real network  $G$  and a “random” graph  $G'$  which has the same degree sequence as  $G$