



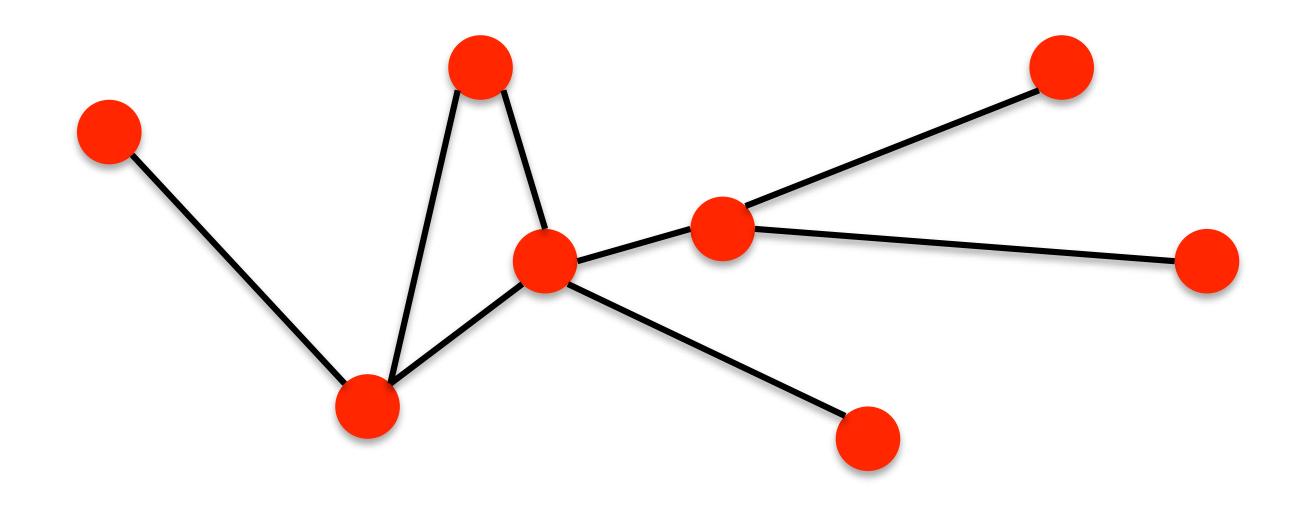
Network theory Part I

Complexity in Social Systems AA 2023/2024 **Maxime Lucas** Lorenzo Dall'Amico





components



- components: nodes, vertices
- interactions: links, edges
- system:

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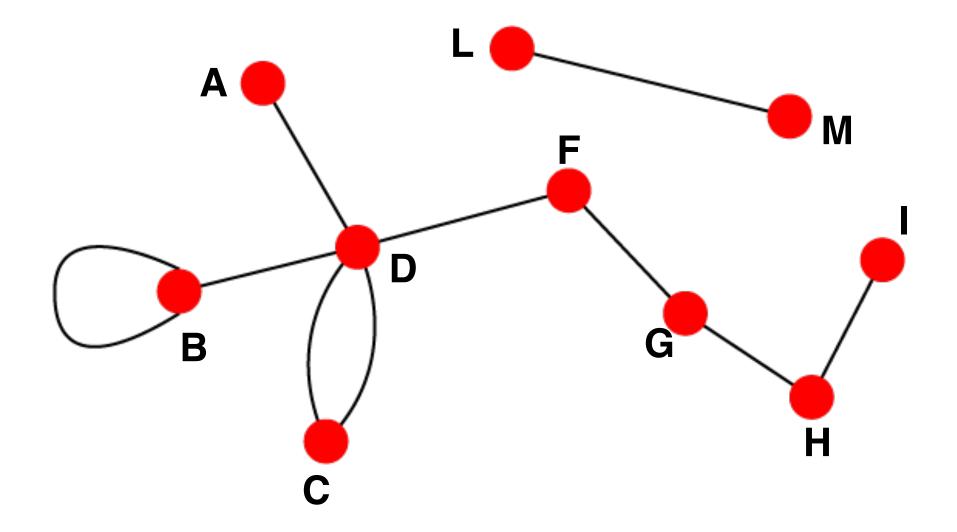
network, graph

(N,L)

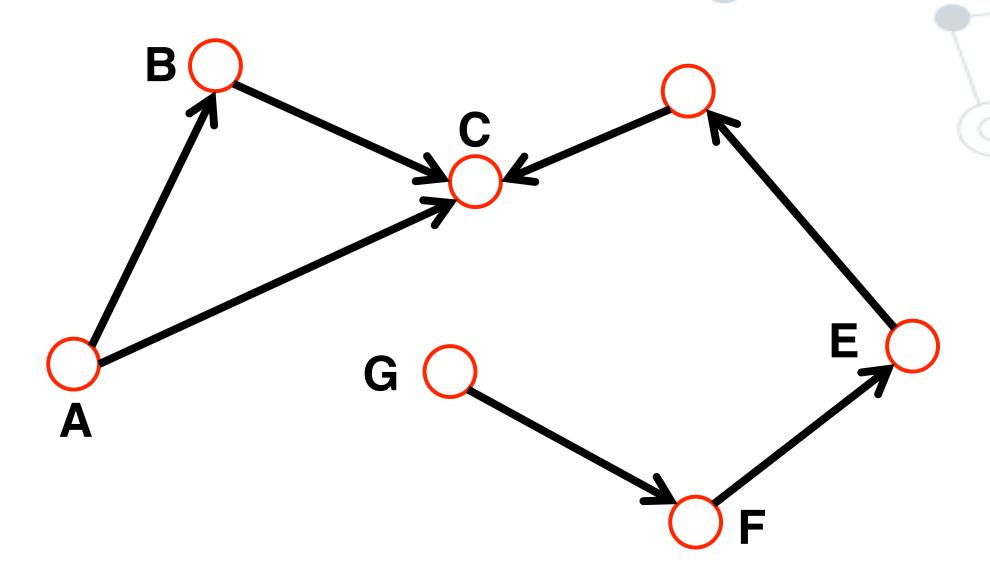
Ν



undirected vs directed



co-authorship actor networks co-occurrence



phone calls hyperlinks scientific citations



reference networks

Network	Nodes	Links	Directed / Undirected	Ν	L	< K >
Internet	Routers	Internet connections	Undirected	192,244	609,066	6.34
WWW	Webpages	Links	Directed	325,729	1,497,134	4.60
Power Grid	Power plants, transformers	Cables	Undirected	4,941	6,594	2.67
Mobile-Phone Calls	Subscribers	Calls	Directed	36,595	91,826	2.51
Email	Email addresses	Emails	Directed	57,194	103,731	1.81
Science Collaboration	Scientists	Co-authorships	Undirected	23,133	93,437	8.08
Actor Network	Actors	Co-acting	Undirected	702,388	29,397,908	83.71
Citation Network	Papers	Citations	Directed	449,673	4,689,479	10.43
E. Coli Metabolism	Metabolites	Chemical reactions	Directed	1,039	5,802	5.58
Protein Interactions	Proteins	Binding interactions	Undirected	2,018	2,930	2.90

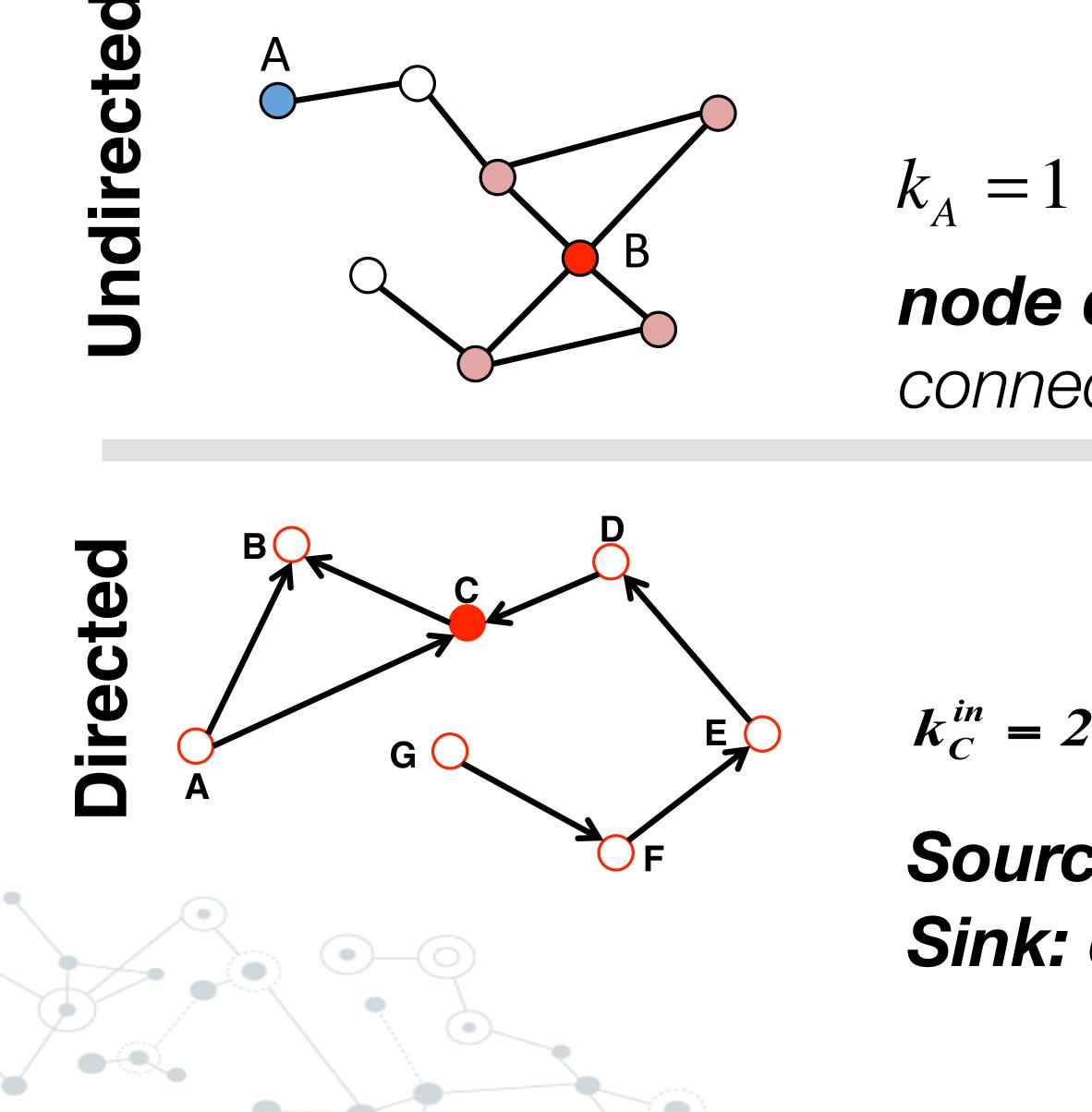


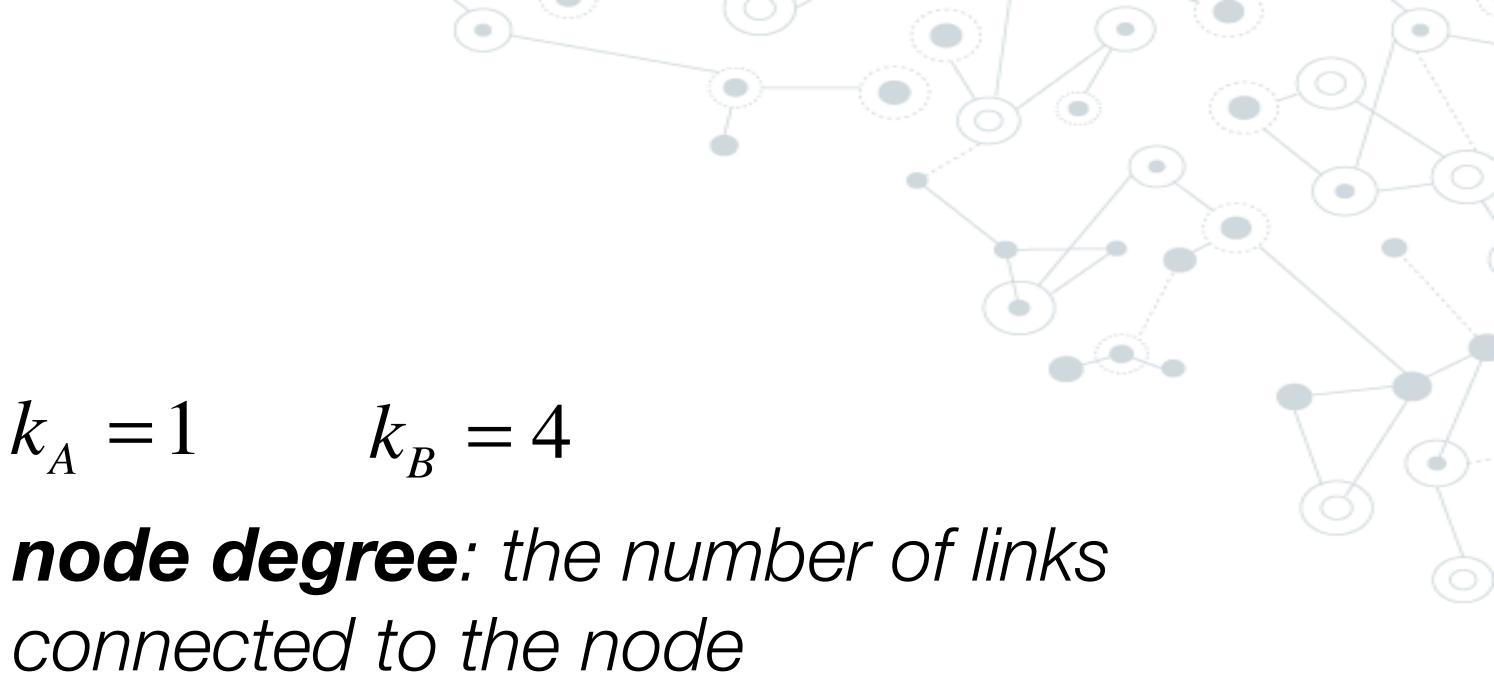


degree and degree distribution









$k_{C}^{in} = 2$ $k_{C}^{out} = 1$ $k_{C} = 3$

Source: degree in = 0 **Sink:** degree out = 0 **BRIEF STATISTICS REVIEW**

Four key quantities characterize a sample of *N* values $x_1, ..., x_N$:

$$\equiv \frac{1}{N} \sum_{i=1}^{N} \frac{2L}{\sum_{i=1}^{N} \frac{2L}{N}}$$

$$\langle x \rangle = \frac{x_1 + x_2 + \dots + x_N}{N} = \frac{1}{N} \sum_{i=1}^N x_i$$

*The n*th *moment*:

$$k_{i} = k_{i}^{in} + \langle k_{i}^{n} \rangle^{ut} = \frac{x_{1}^{n} + x_{2}^{n} + \dots + x_{N}^{n}}{N} = \frac{1}{N} \sum_{i=1}^{N} x_{i}^{n}$$



N

 \mathcal{A}

$$\sigma_x = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \langle x \rangle)^2}$$

Distribution of x:

$$p_x = \frac{1}{N} \sum_i \delta_{x,x}$$

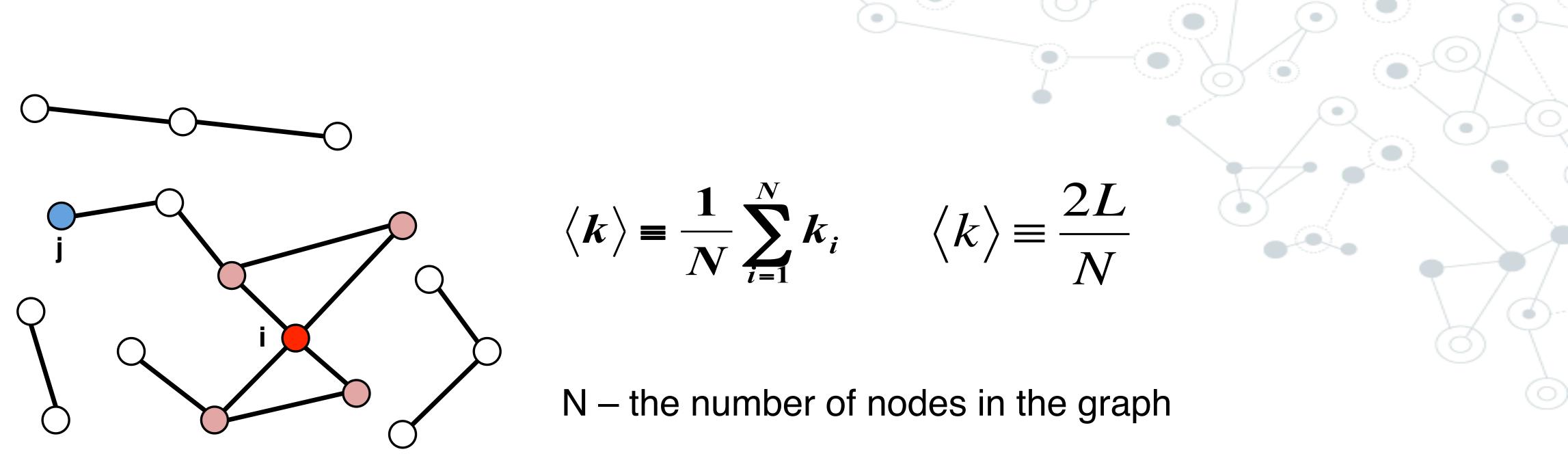
where p_x follows

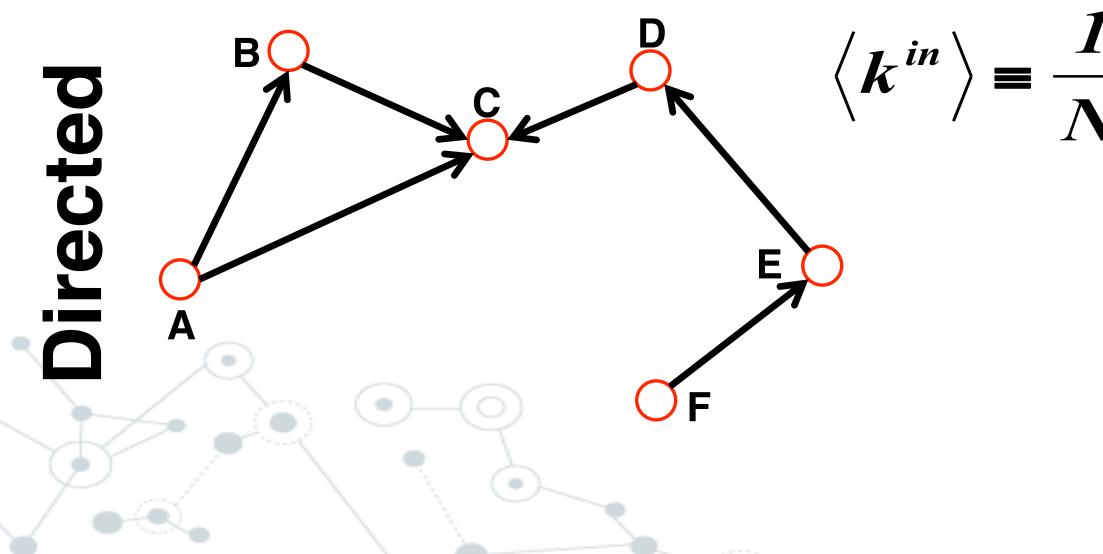
$$\sum_{i} p_x = 1 \left(\int p_x \, dx = 1 \right)$$



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 $\left\langle k^{in} \right\rangle = \frac{1}{N} \sum_{i=1}^{N} k_i^{in}, \quad \left\langle k^{out} \right\rangle = \frac{1}{N} \sum_{i=1}^{N} k_i^{out}, \quad \left\langle k^{in} \right\rangle = \left\langle k^{out} \right\rangle$

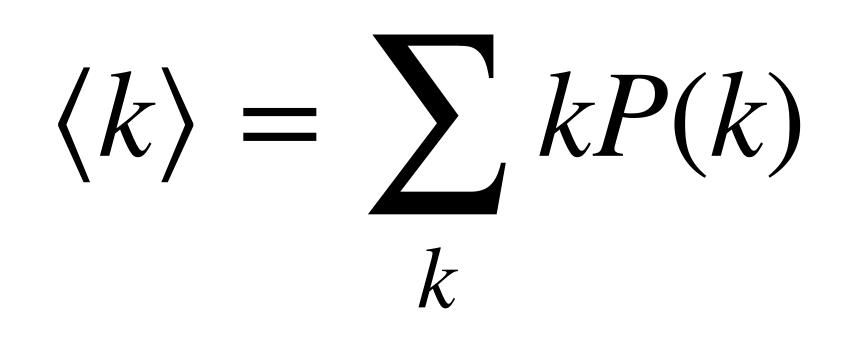
 $\left\langle k \right\rangle \equiv rac{L}{N}$





 $\frac{IN_k}{NI}$ *P*(*k*) =

probability that a random chosen node has degree k



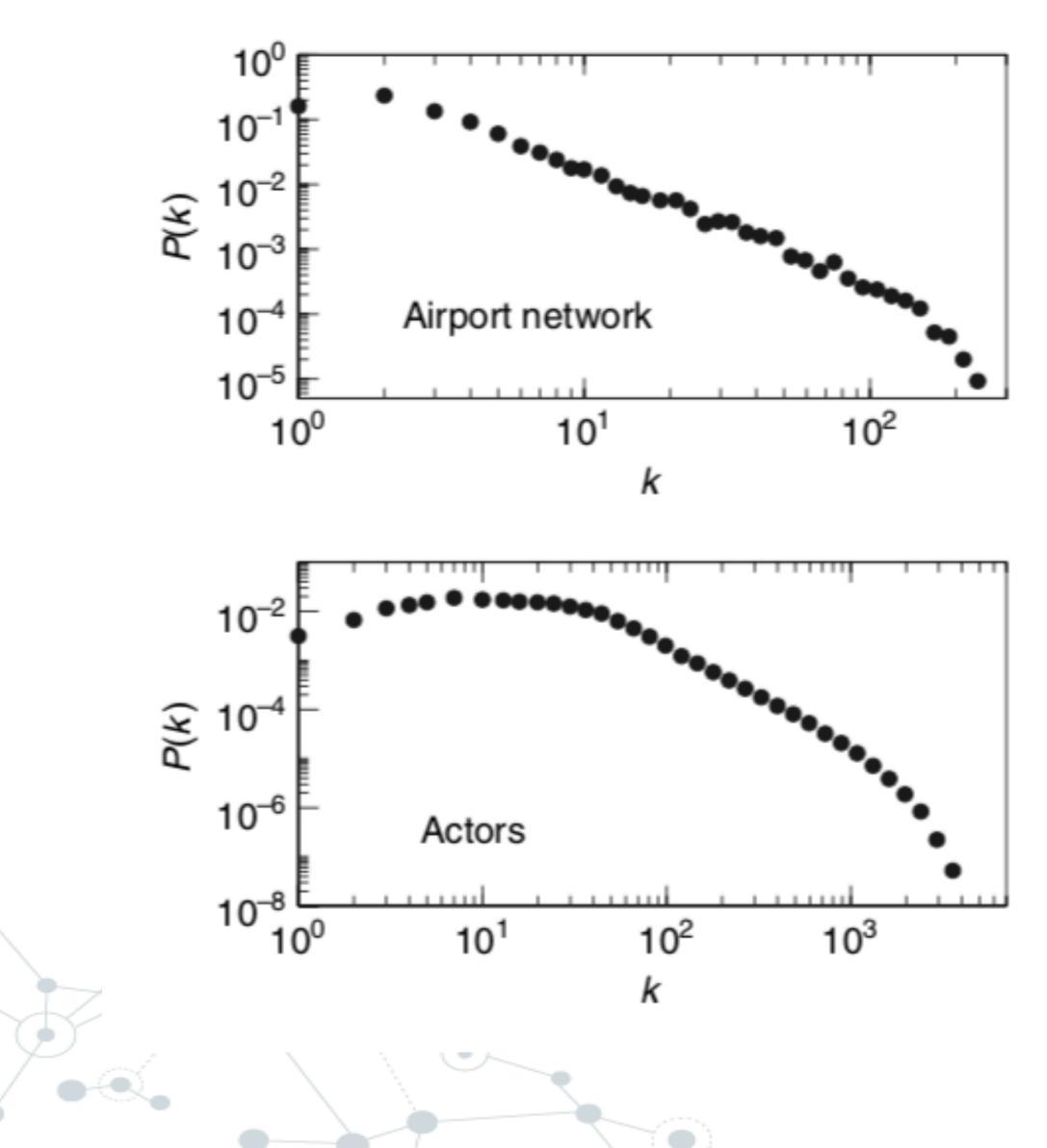


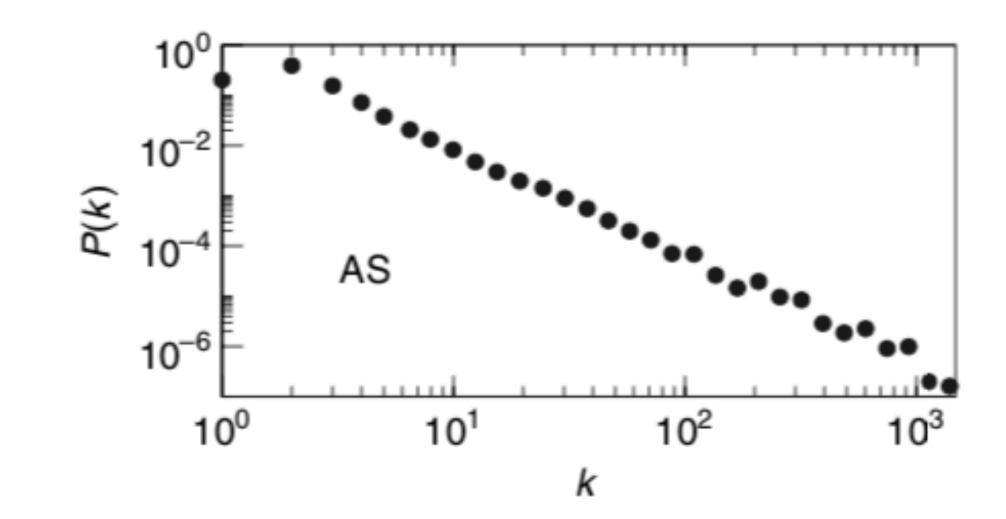
degree distribution

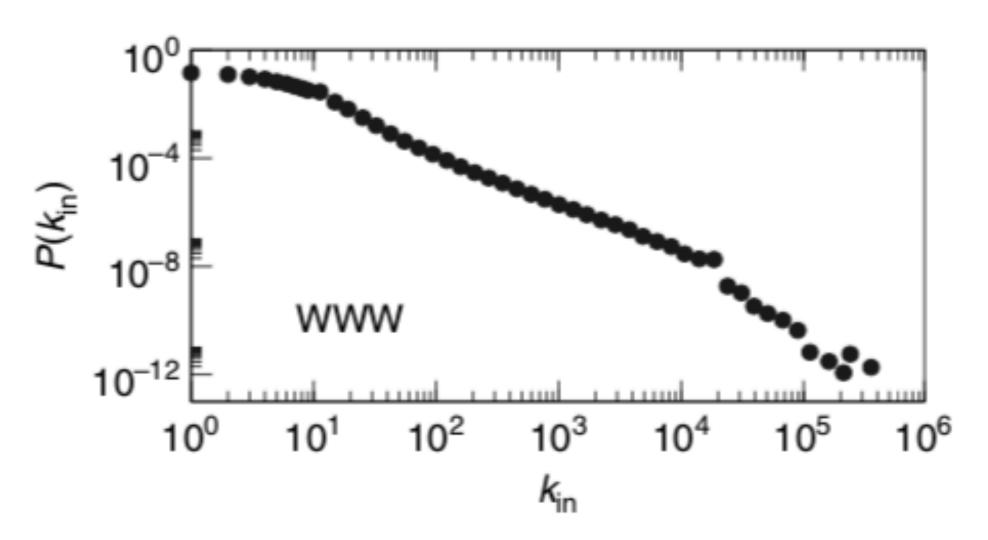
 $\sigma^2 = \langle k^2 \rangle - \langle k \rangle^2$ $\langle k^2 \rangle = \sum k^2 P(k)$



real world networks

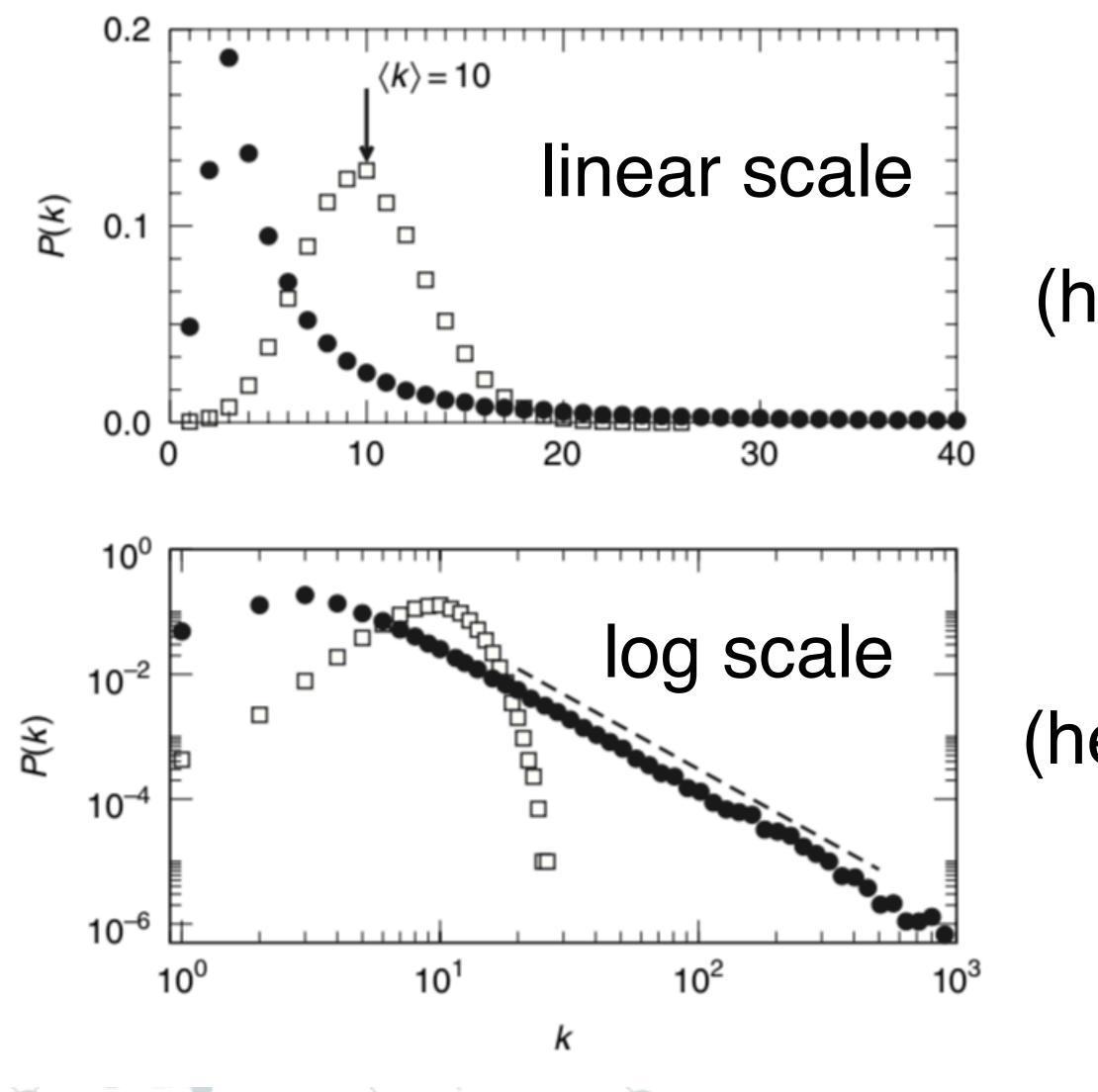








real world networks



Poisson (homogeneous)

Broad degree distributions

VS

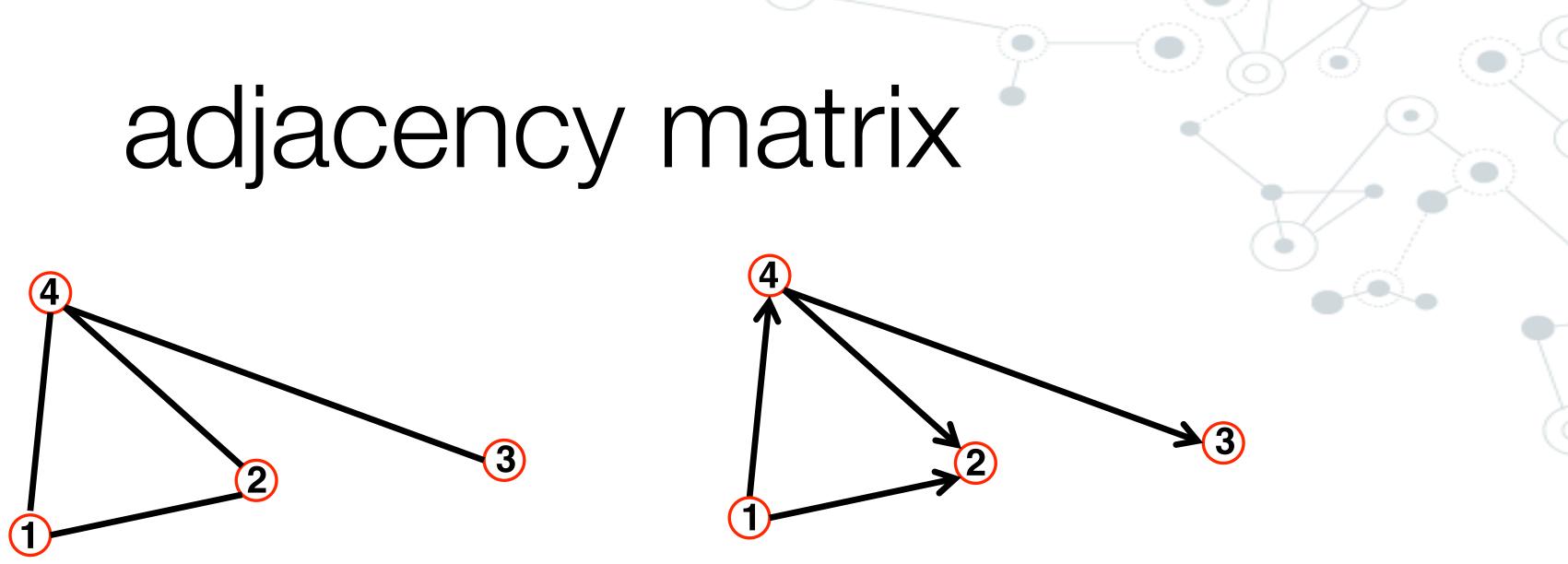
Power-law tails

 $P(k) \sim k^{-\gamma}, 2 < \gamma < 3$

power-law (heterogeneous) No characteristic scale







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

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

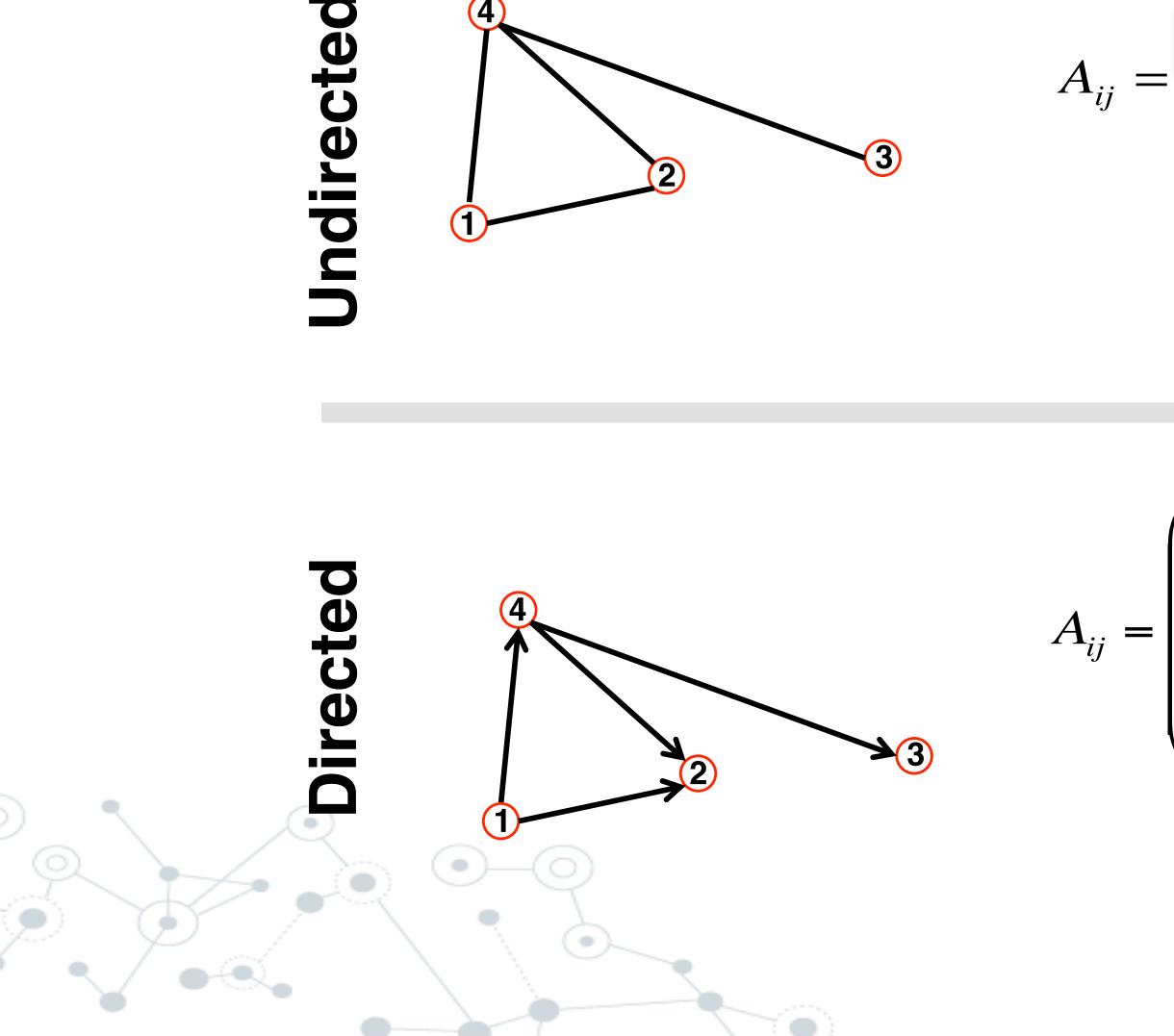
- $A_{ii}=0$ if nodes *i* and *j* are not connected to each other.

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

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



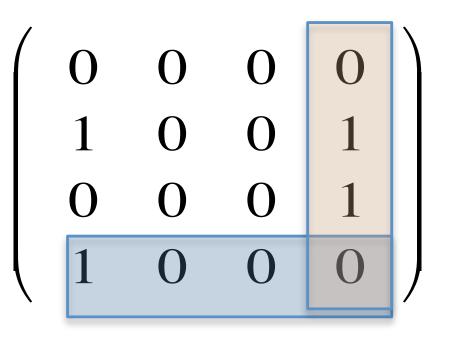




adjacency matrix 1 0 $\mathbf{0}$ 1 1 0 0 1 $A_{ij} =$ 0 0 0 1 1 0 1 $A_{ij} = A_{ji}$ $A_{ii} = 0$

 $k_j = \sum_{i=1}^{N} A_{ij}$

$$L = \frac{1}{2} \sum_{i=1}^{N} k_i = \frac{1}{2} \sum_{ij}^{N} A_{ij}$$



 $A_{ij} \neq A_{ji}$ $A_{ii} = 0$

$$k_i^{in} = \sum_{j=1}^{N} A_{ij}$$
$$k_j^{out} = \sum_{i=1}^{N} A_{ij}$$

$$L = \sum_{i=1}^{N} k_i^{in} = \sum_{j=1}^{N} k_j^{out} = \sum_{i,j}^{N} A_{ij}$$



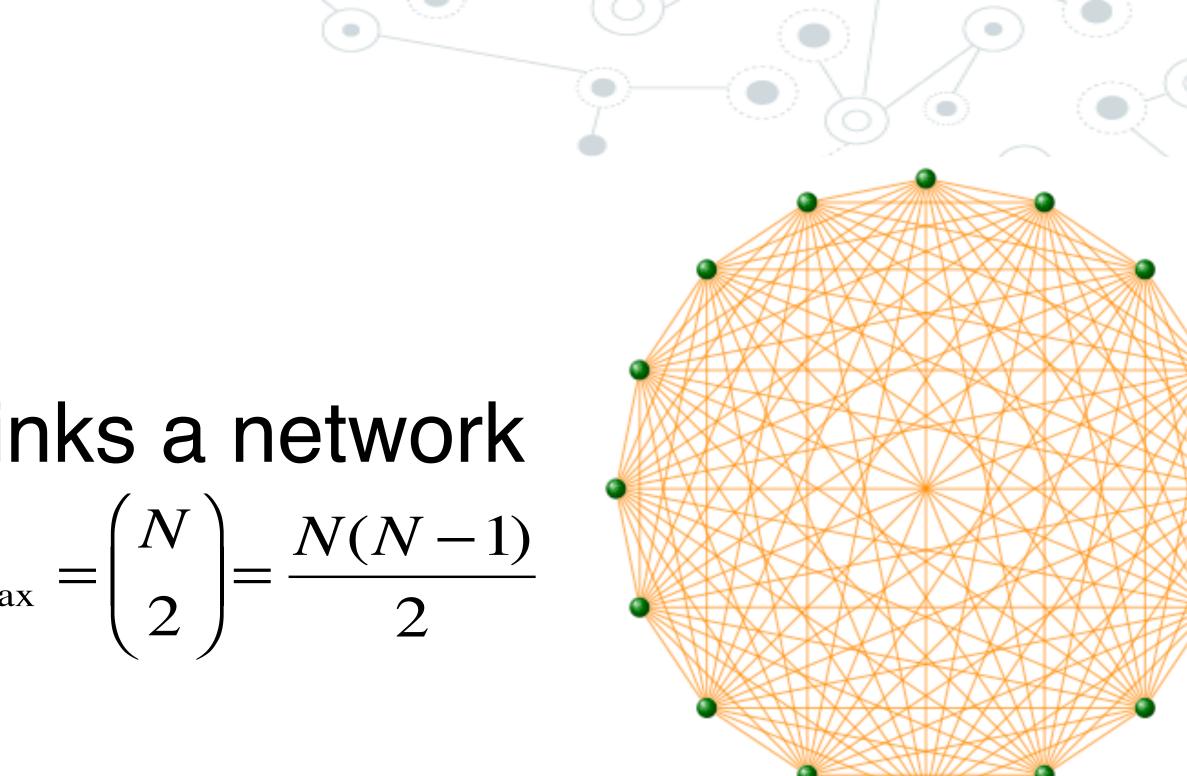
Real networks are sparse!





The maximum number of links a network of N nodes can have is: $L_{\text{max}} = {N \choose 2} = \frac{N(N-1)}{2}$

A graph with degree $L=L_{max}$ is called a complete graph, and its average degree is <k>=N-1





Most networks observed in real systems are sparse

WWW (ND Sample): Protein (*S. Cerevisiae*): Coauthorship (Math): Movie Actors:

N=325,729; N= 1,870; N= 70,975; N=212,250;

 $L \ll L_{max} \langle k \rangle \ll N - 1$

L=1.4 10⁶ L=4,470 L=2 10⁵ L=6 10⁶

$$\begin{array}{ll} L_{max} = 10^{12} & = 4.51 \\ L_{max} = 10^7 & = 2.39 \\ L_{max} = 3 \ 10^{10} & = 3.9 \\ L_{max} = 1.8 \ 10^{13} & = 28.78 \end{array}$$

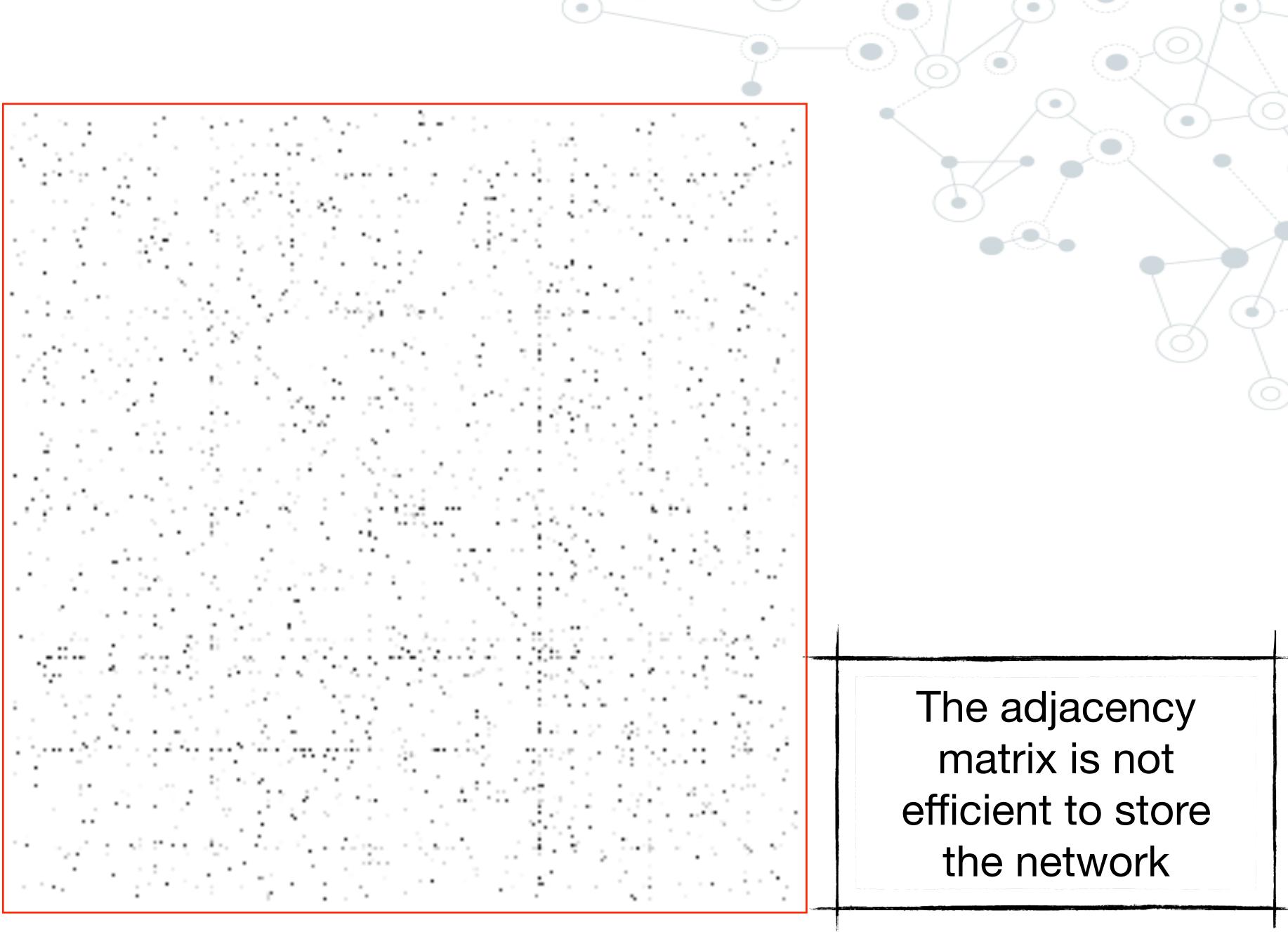
(Source: Albert, Barabasi, RMP2002)





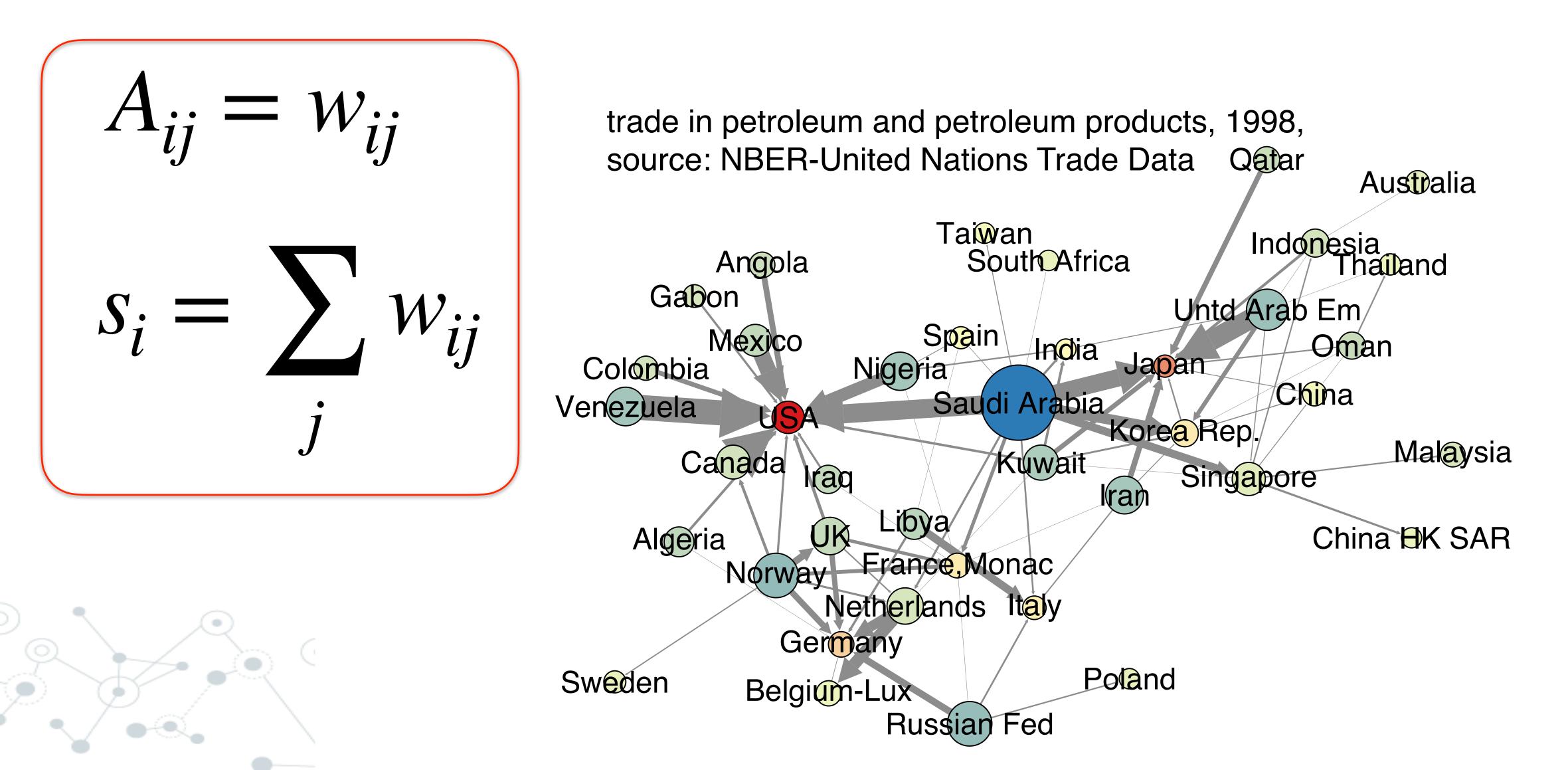
The adjacency matrix of the yeast protein-protein interaction network, consisting of 2,018 nodes, each representing a yeast protein.

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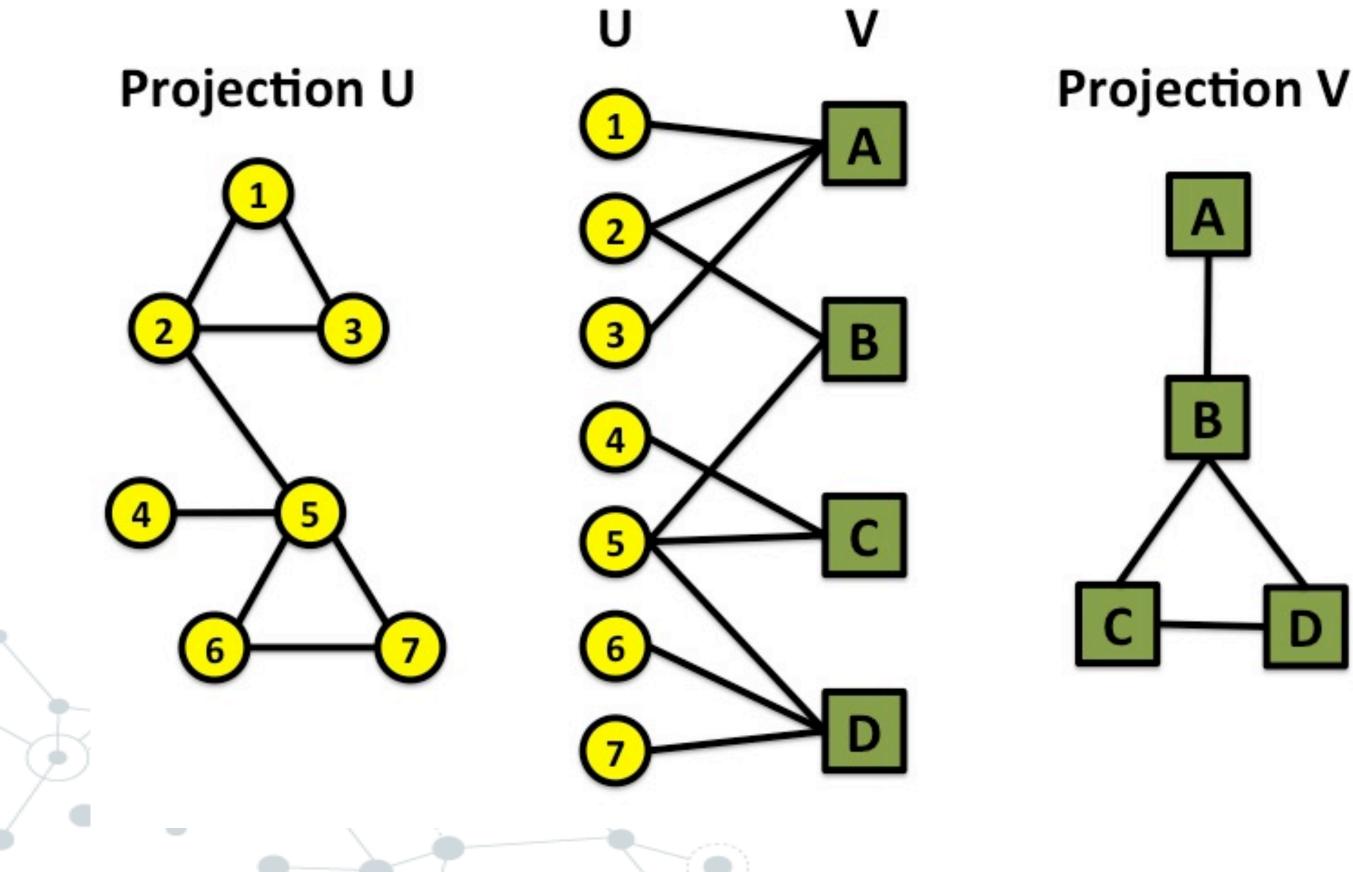
weighted networks





bipartite networks

bipartite graph (or **bigraph**) is a <u>graph</u> 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 <u>independent sets</u>.



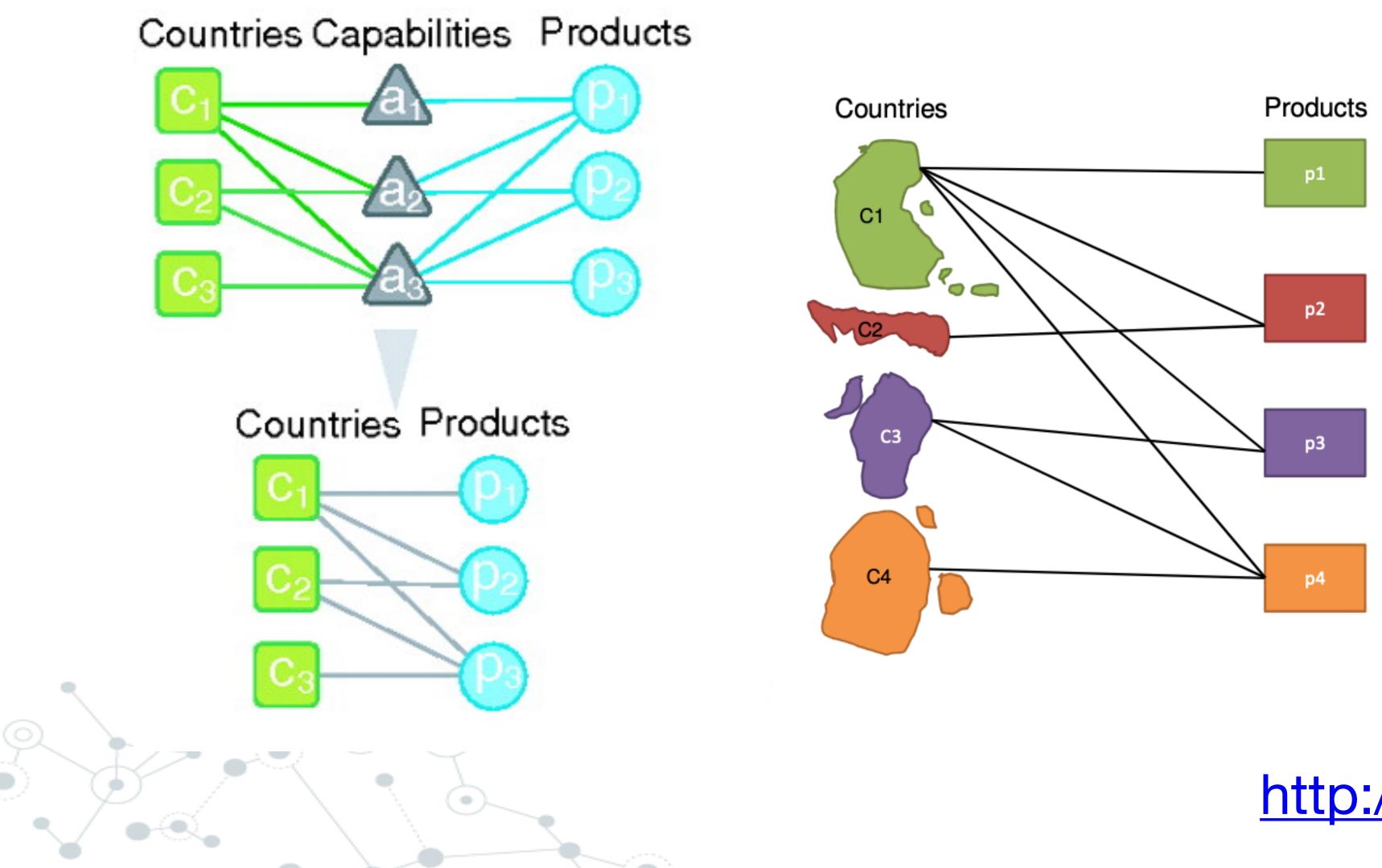
Examples

- actor network
- collaboration network
- host-pathogen networks





bipartite networks



The Atlas of **Economic Complexity**

C. Hidalgo

http://atlas.cid.harvard.edu/

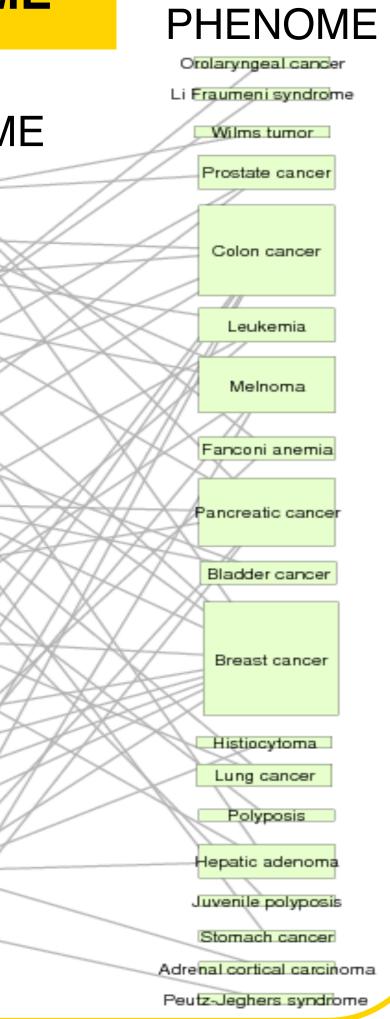


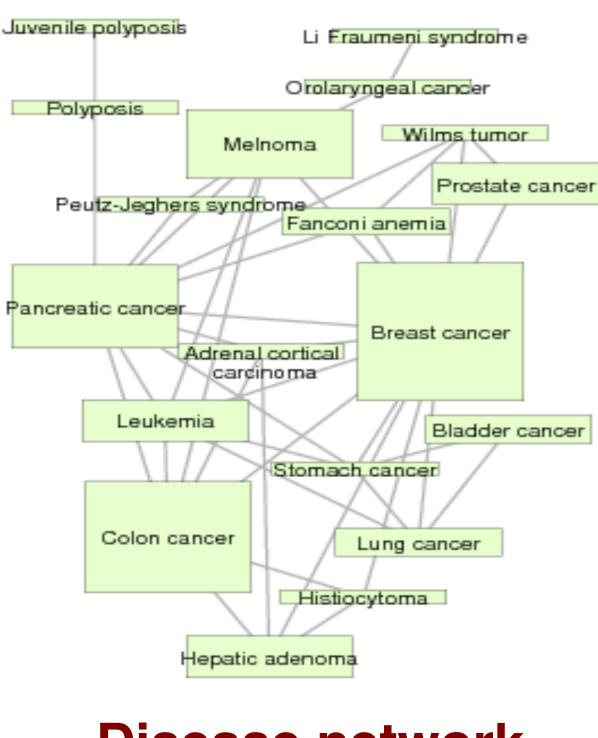




bipartite networks DISEASOME PHENOME Orolaryngeal cancer Li Fraumeni syndrome GENOME Wilms tumor FGFR3 NF1 Prostate cancer BRCA2 TP53 BRCA2 BRIP1 BRAF Colon cancer CCND1 PDGFRD PIK3CA (CDKN2A Leukemia BRAF AB CTNNB1 CTNNB1 Melnoma SMAD4 CHEK2 SLC22A18 (FGFR3) Fanconi anemia CHEK2 KRAS BRAF XRCC3 Pancreatic cance CCND1 SMAD4 Bladder cancer STK11 NF1 CDKN2A) SLC22A18 KRAS Breast cancer PDGFRL AR PIK3CA Histiocytoma BRIP1 Lung cancer XRCC3 Gene network BRAF Polyposis Hepatic adenoma TP53 Juvenile polyposis STK11 Stomach cancer Adrenal cortical carcinoma Peutz-Jeghers syndrome







Disease network

Goh, Cusick, Valle, Childs, Vidal & Barabási, PNAS (2007)





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

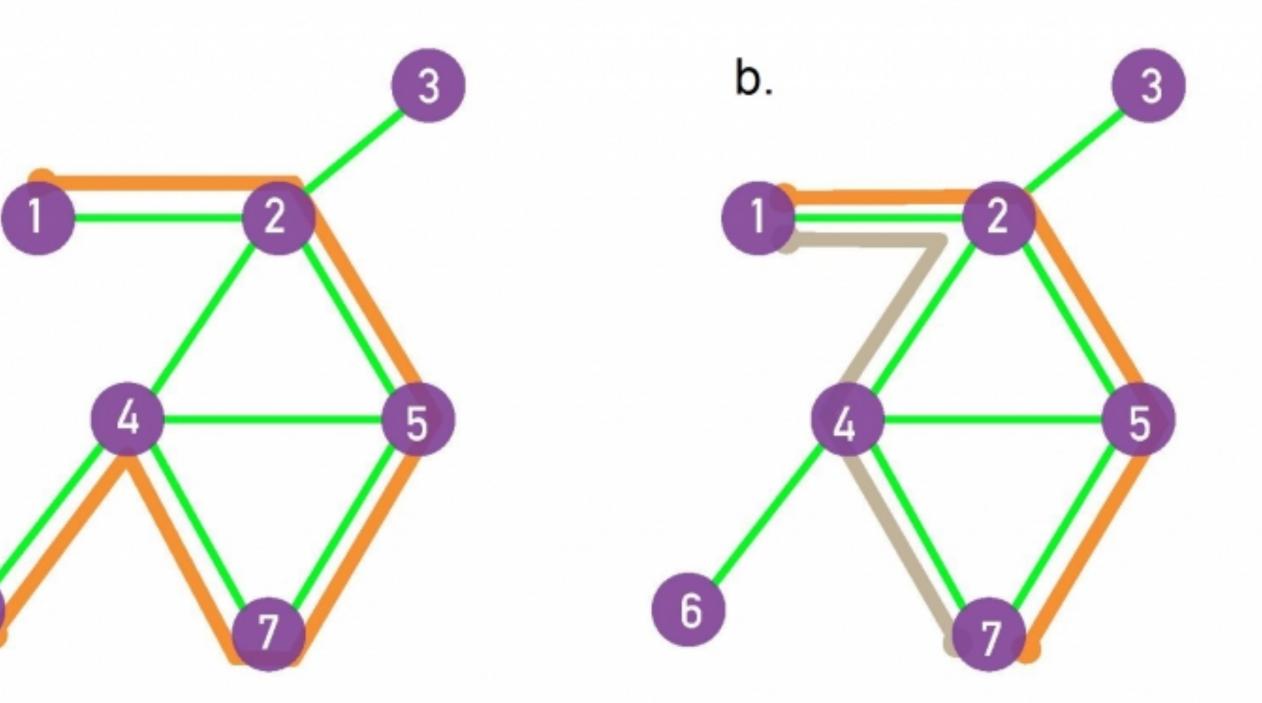
 $P_{i0,in}$ of length *n* between nodes i_0 and i_n is an ordered collection of *n+1* nodes and *n* links

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

а.

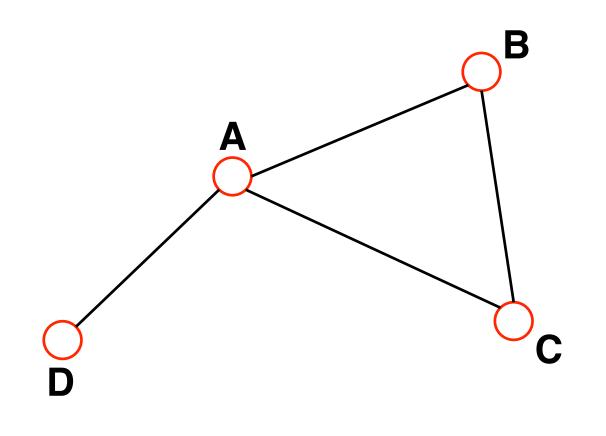
(a) path of length 5 (b) two paths of equal length

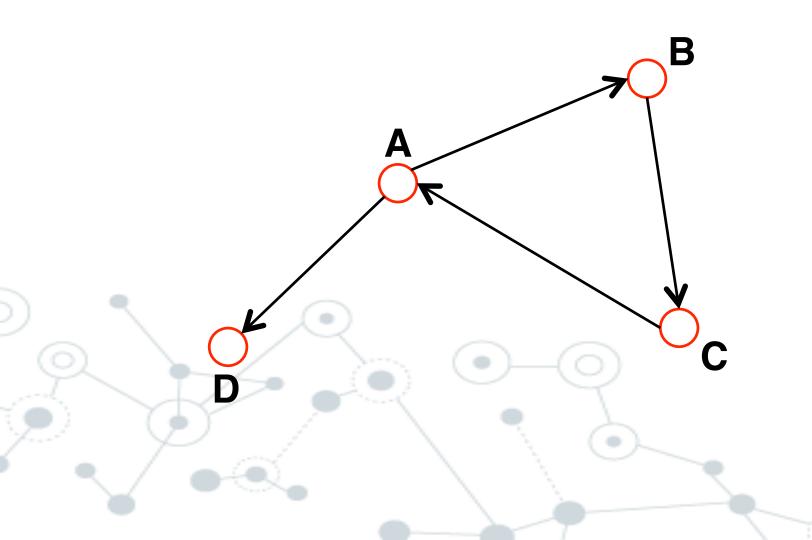
paths





distance





the arrows. (on a BCA path).

- The *distance (shortest path, geodesic path)* between two nodes is defined as the number of edges along the shortest path connecting them. The *diameter of a graph* is the length of the longest geodesic path between any pair of vertices in the network for which a path actually exists.
- *If the two nodes are disconnected, the distance is infinity.
- In directed graphs each path needs to follow the direction of
- Thus in a digraph the distance from node A to B (on an AB) path) is generally different from the distance from node B to A



N_{ii}, number of paths between any two nodes *i* and *j*:

Length n=1: If there is a link between *i* and *j*, then $A_{ii}=1$ and $A_{ii}=0$ otherwise.

<u>Length n=2</u>: If there is a path of length two between *i* and *j*, then $A_{ik}A_{ki}=1$, and $A_{ik}A_{ki}=0$ otherwise. The number of paths of length 2:

$$N_{ij}^{(2)} = \sum_{k=1}^{N} A_{ik} A_{kj} = [A^2]_{ij}$$

<u>Length n</u>: In general, if there is a path of length n between i and j, then $A_{ik} \dots A_{li} = 1$ and $A_{ik}...A_{li}=0$ otherwise.

The number of paths of length *n* between *i* and *j* is^{*}

$$N_{ij}^{(n)} = \left[A^n\right]_{ij}$$

paths

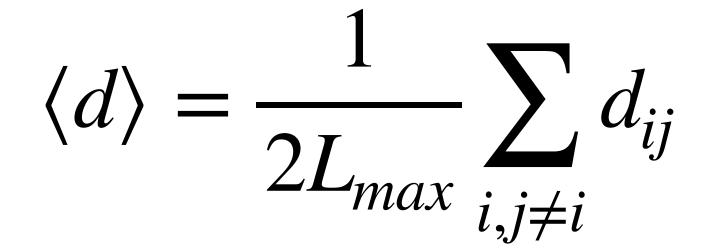


Diameter: **d**_{max} the maximum distance between any pair of nodes in the graph.

Average path length/distance, <d>, for a connected graph: average distance between all pairs of nodes in the network, where d_{ii} is the distance from node i to node j

In an *undirected graph* $d_{ij} = d_{ji}$, so we only need to count them once: $\langle d \rangle = \frac{1}{r} \sum_{i=1}^{r} \sum_{j \in I} \frac{1}{r}$

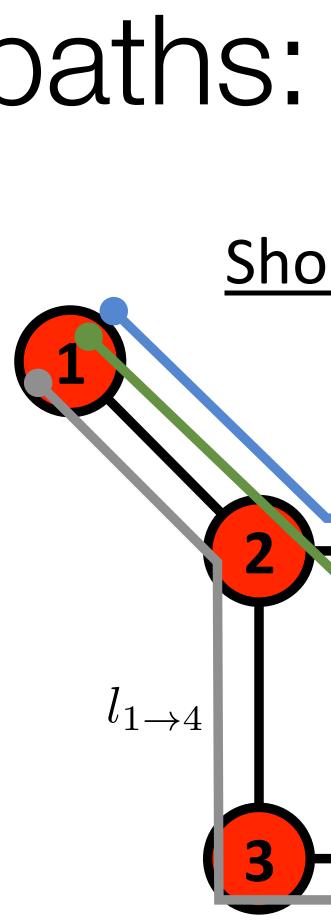
paths







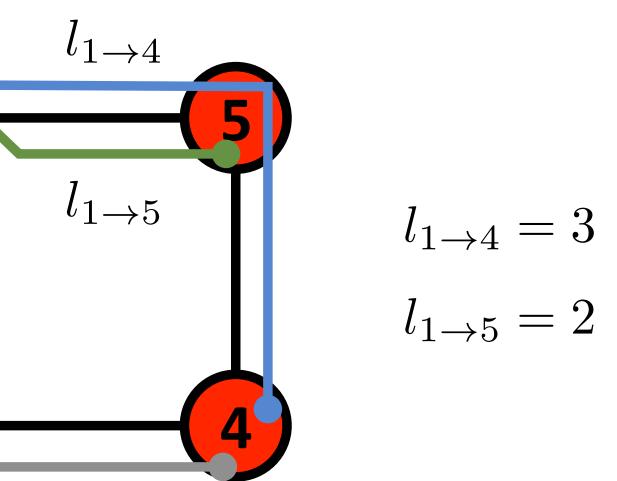
L_{max} i,j>i



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paths: summary

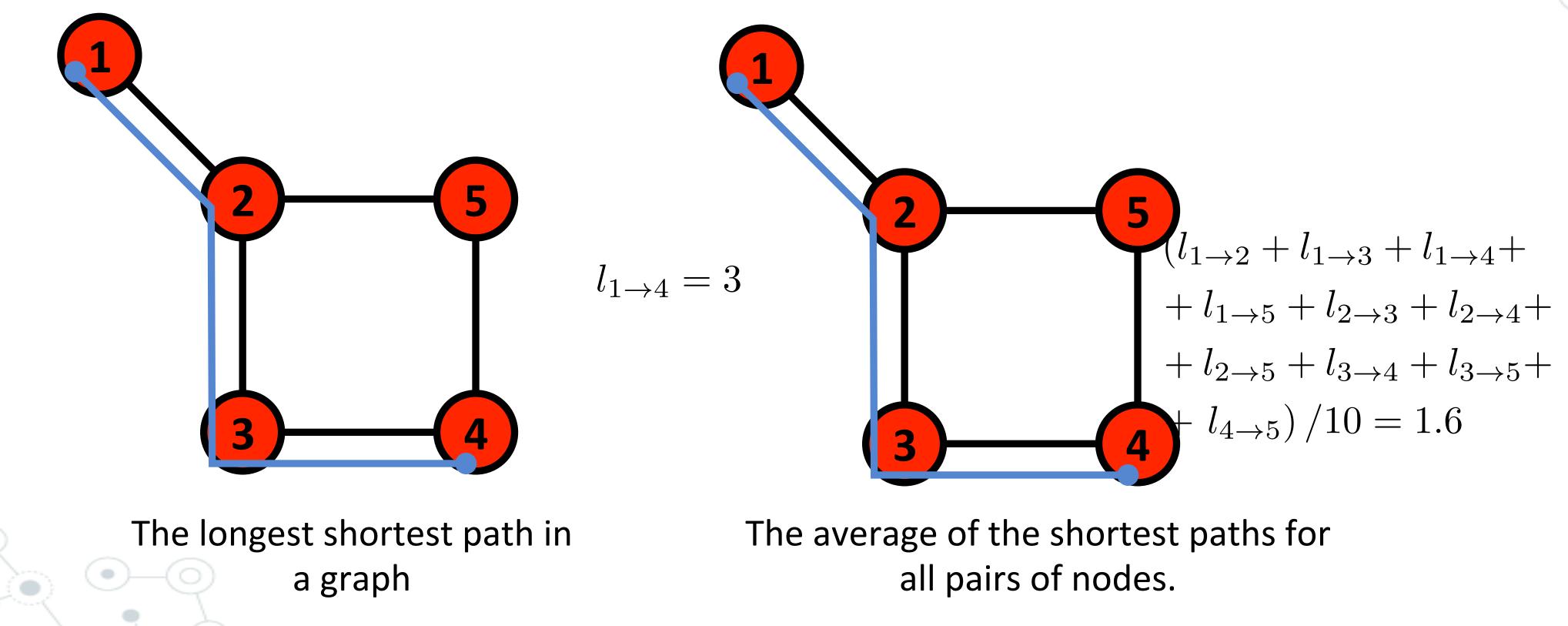
Shortest Path



The path with the shortest length between two nodes (distance).



<u>Diameter</u>



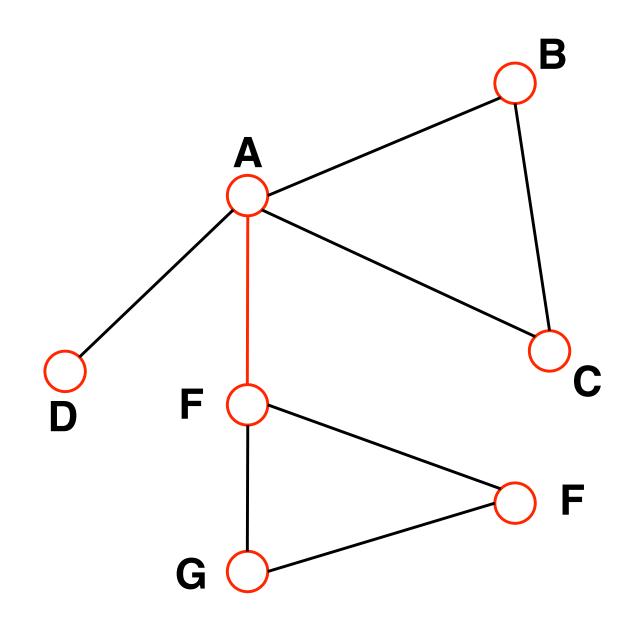
paths: summary

Average Path Length

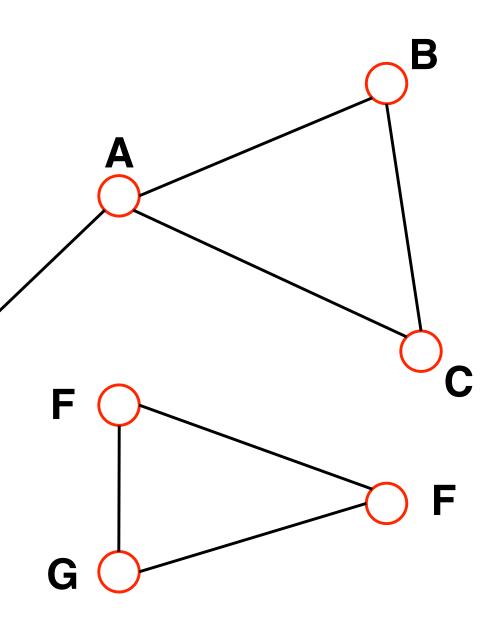


connectivity

Connected (undirected) graph: any two vertices can be joined by a path. A disconnected graph is made up by two or more connected components.



Bridge: if we erase it, the graph becomes disconnected.



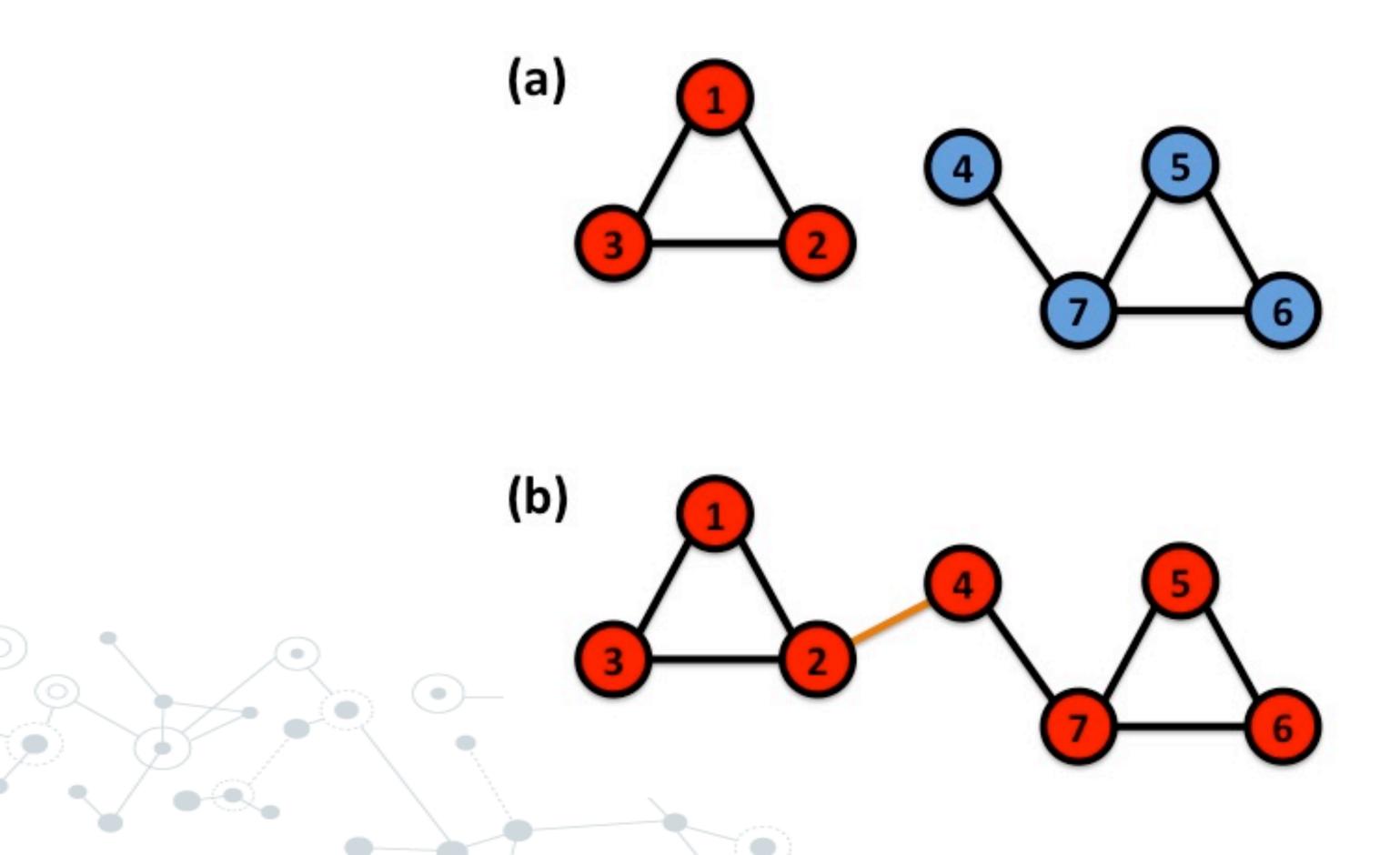
Largest Component: Giant Component

The rest: Isolates

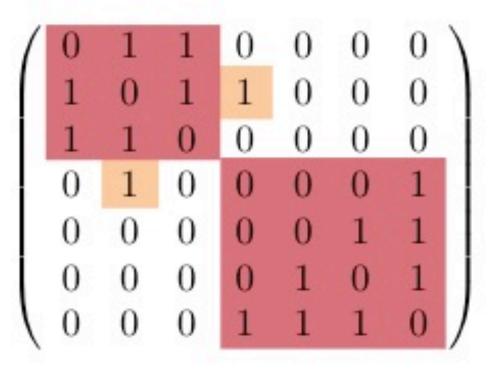


connectivity

The adjacency matrix of a network with several components can be written in a blockdiagonal form, so that nonzero elements are confined to squares, with all other elements being zero:

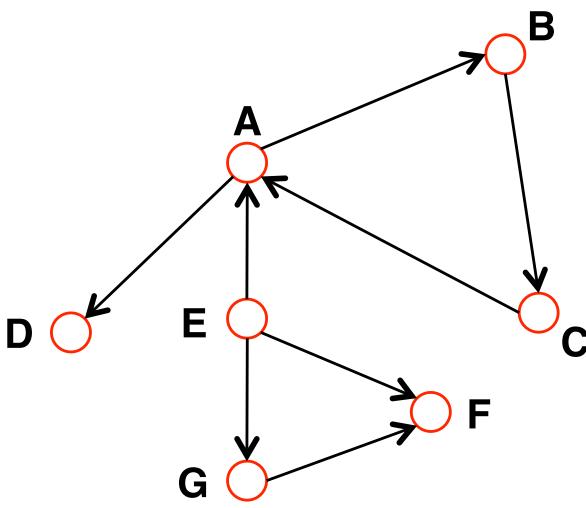


0	1	1	0	0	0	0	1
1	0	1	0	0	0	0	
1	1	0	0	0	0	0	
0	0	0	0	0	0	1	
0	0	0		0	1	1	
0	0	0	0	1	0	1	
0	0	0	1	1	1	0]
	1 1 0 0	$ \begin{array}{ccc} 1 & 0 \\ 1 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{array} $	$\begin{array}{cccc} 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$





connectivity in directed graphs E (Ε G

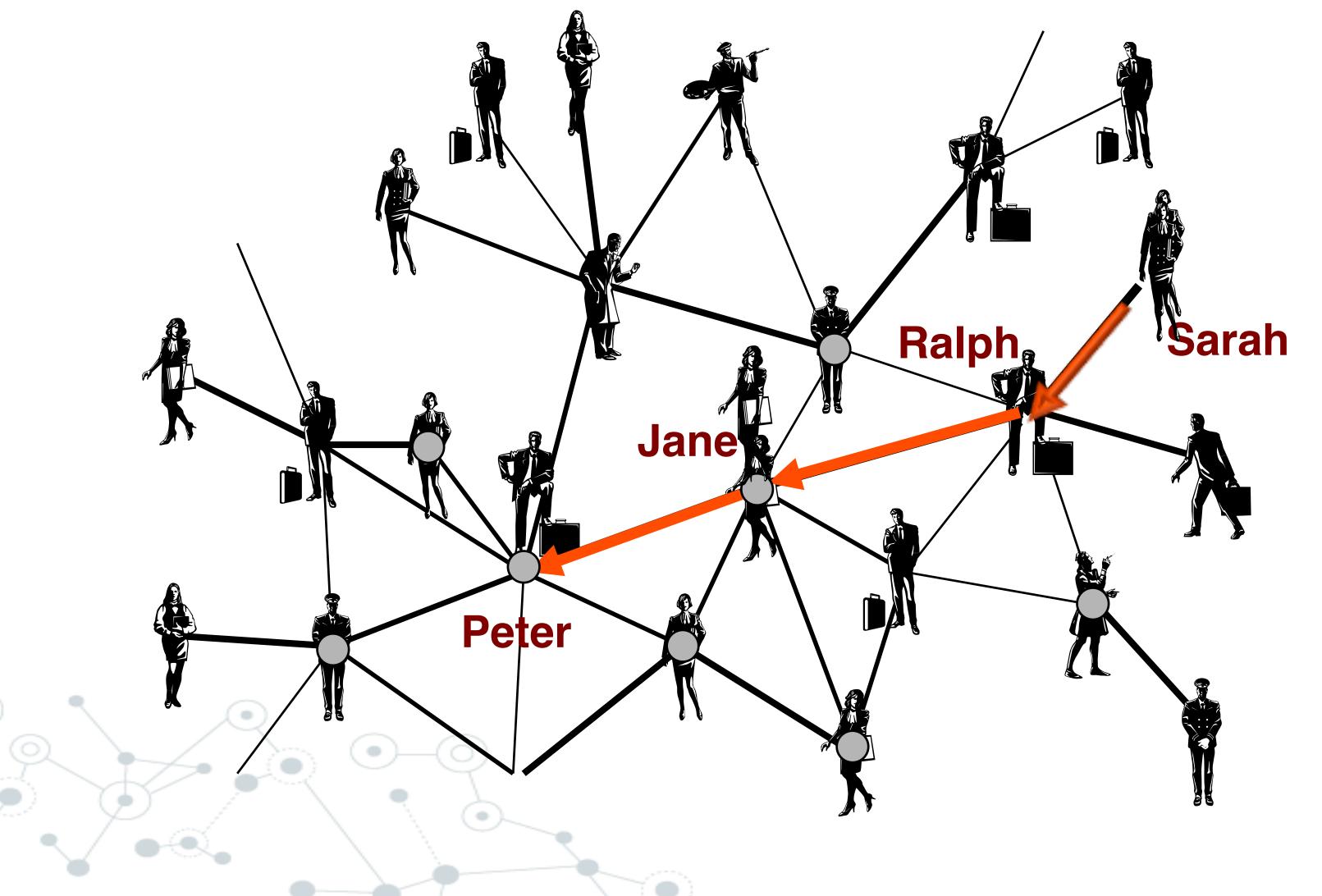


Strongly connected directed graph: has a path from each node to every other node and vice versa

Weakly connected directed graph: it is connected if we disregard the edge directions.



real world networks



Small world effect

Frigyes Karinthy, 1929 Stanley Milgram, 1967



six degrees of separation

Stanley Milgram (1967)

Two targets in Boston and Sharon, MA.

Randomly selected residents of Wichita and Omaha were asked to forward a letter to someone who is most likely to know the target person.

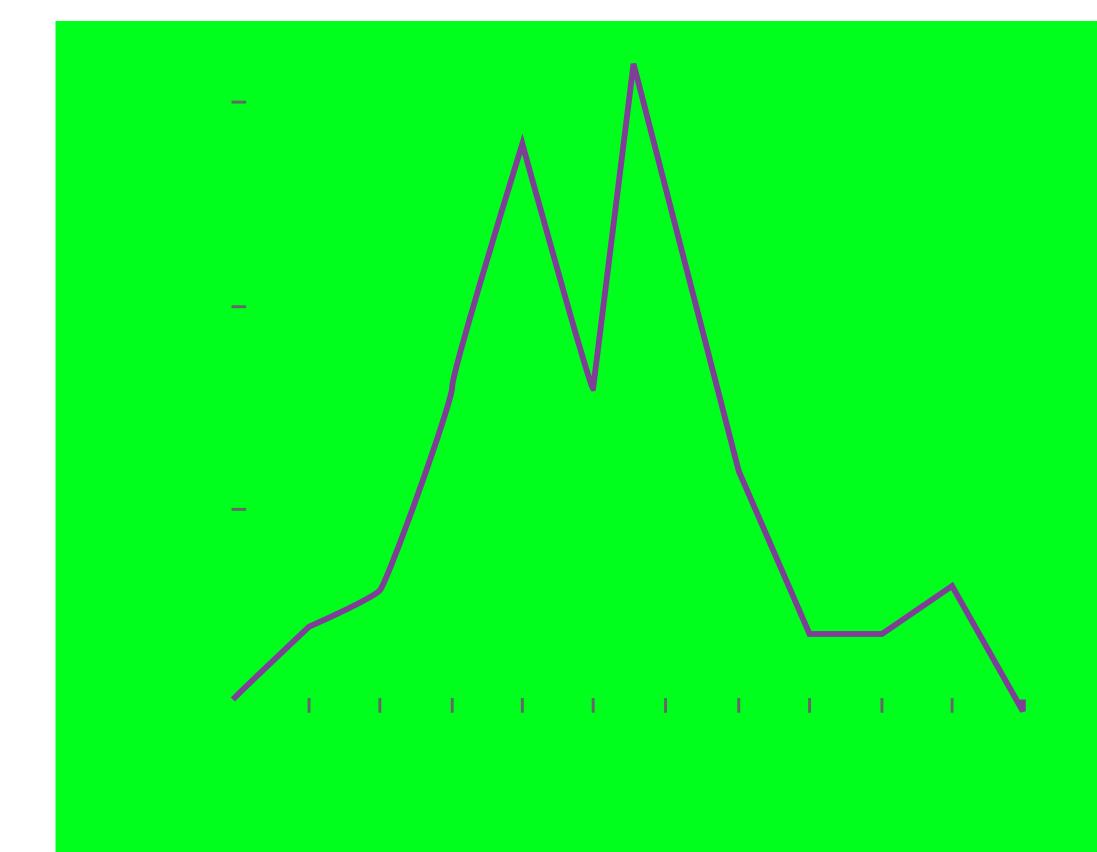


six degrees of separation

Stanley Milgram (1967)

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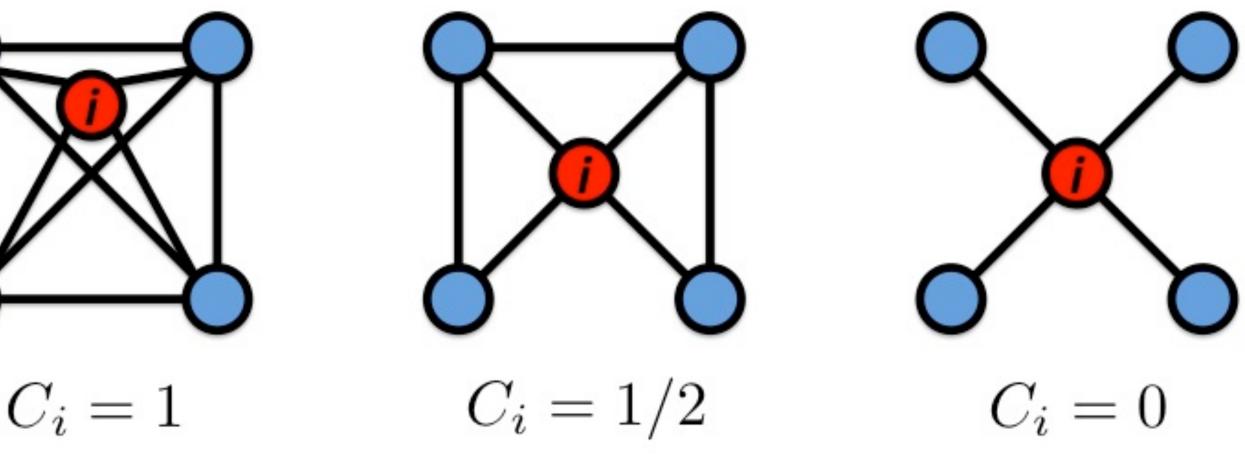
The clustering coefficient of a node captures the degree to which the neighbors of a given node link to each other, i.e. what fraction of your neighbors are connected?





 $2L_i$ $k_{i}(k_{i}-1)$

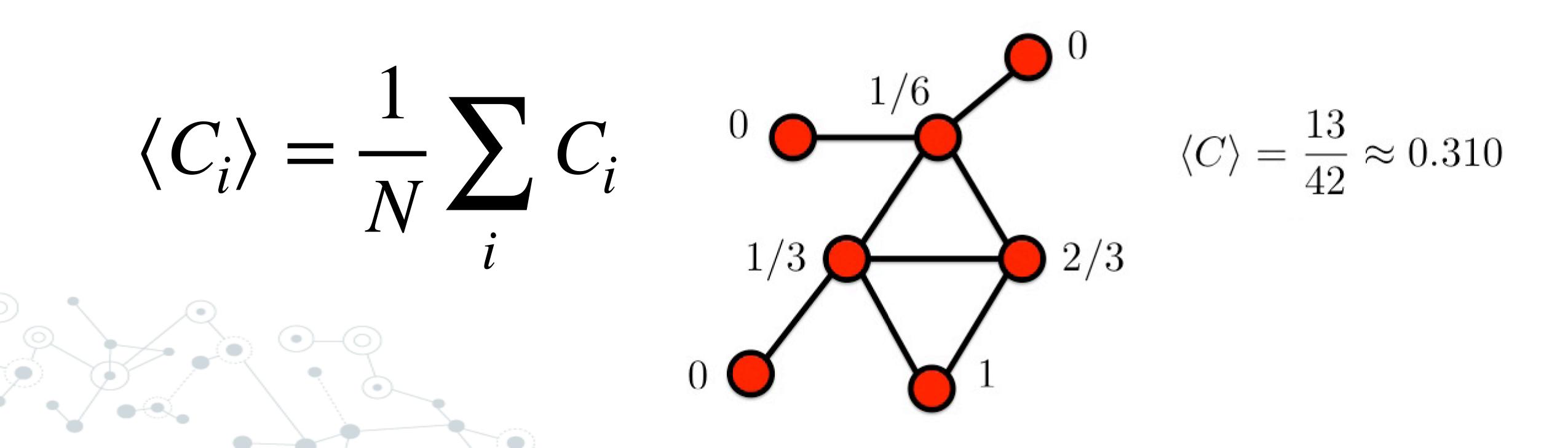
The clustering coefficient of a node captures the degree to which the neighbors of a given node link to each other, i.e. what fraction of your neighbors are connected?



Watts & Strogatz, Nature 1998.







The degree of clustering of a whole network is captured by the average clustering coefficient, representing the average of C over all nodes i = 1,...,N



$$C_{\Delta} = \frac{3 \times Nun}{Number C}$$

the global clustering coefficient measures the total number of closed triangles in a network. Indeed, L_i in the previous equation is the number of triangles that node i participates in, as each link between two neighbors of node *i* closes a triangle.

mber Of Triangles

Of Connected Triples



real world networks

 Real world networks are highly clustered

 Average clustering coefficient can have values >0.5

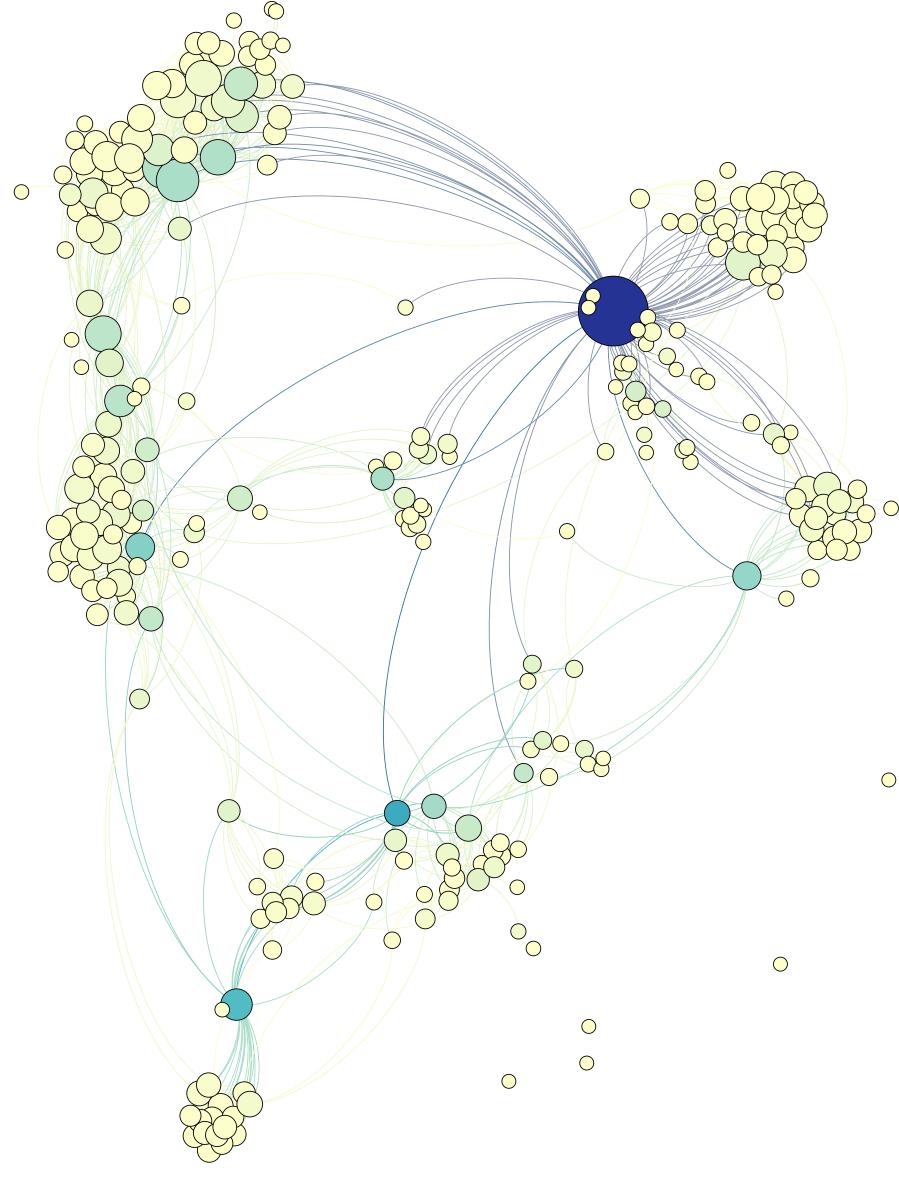
•Triadic closure in social networks is a common phenomenon



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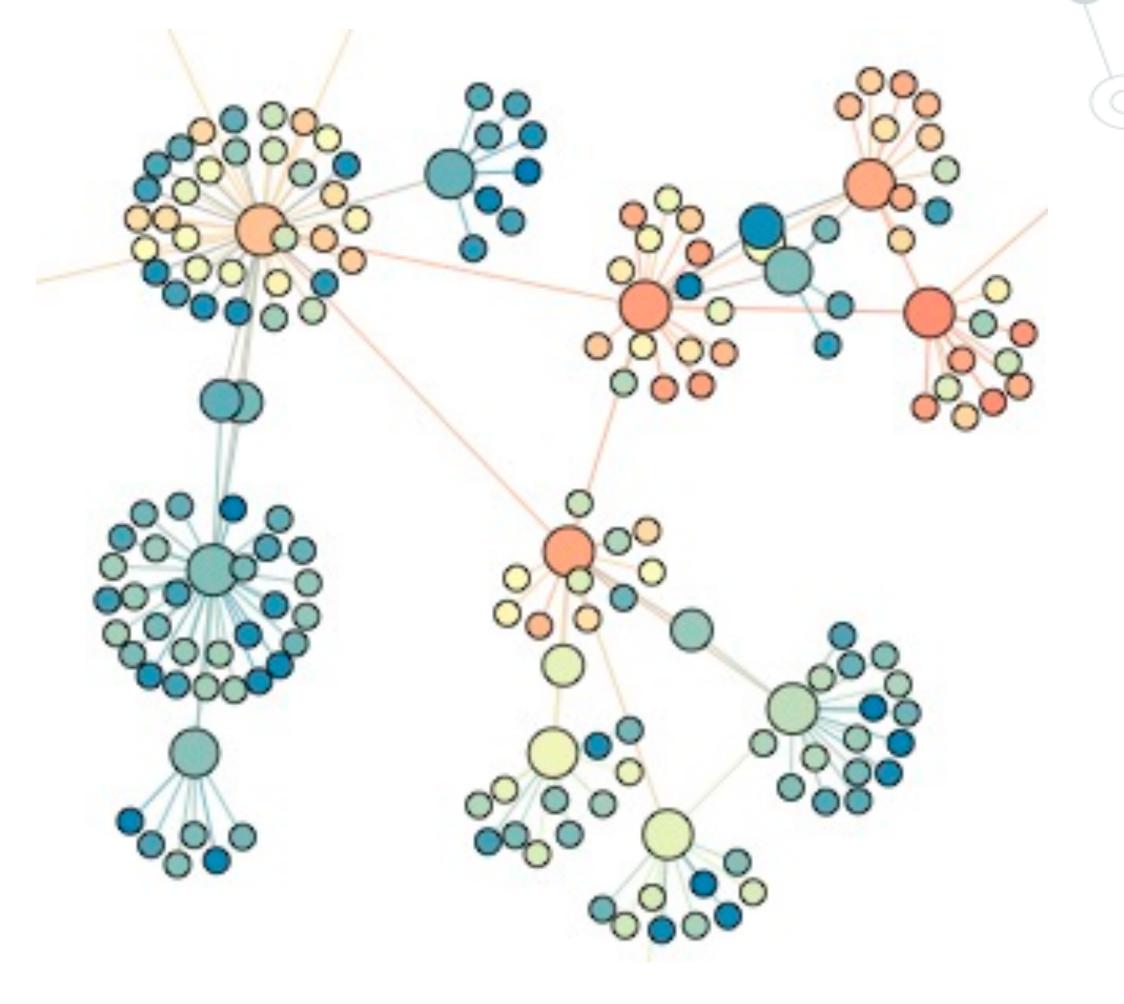


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- Degree centrality
- Closeness centrality
- Betweenness centrality
- Eigenvector centrality
- Katz centrality
- Pagerank

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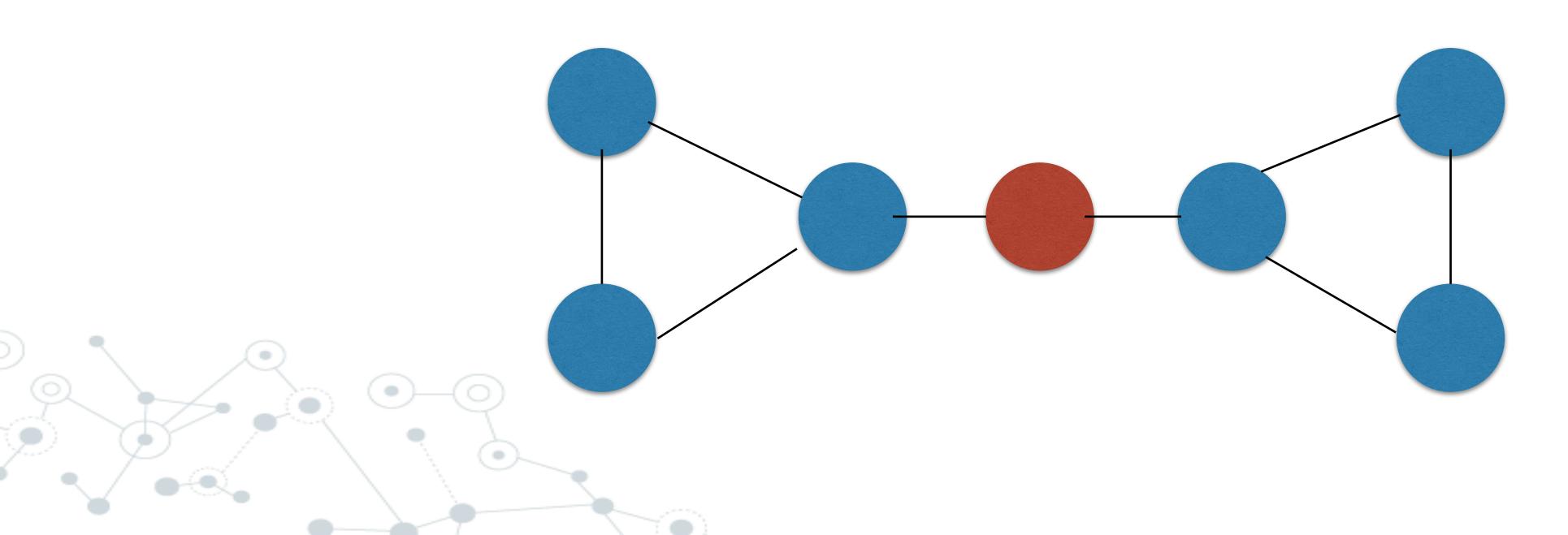






betweeness centrality

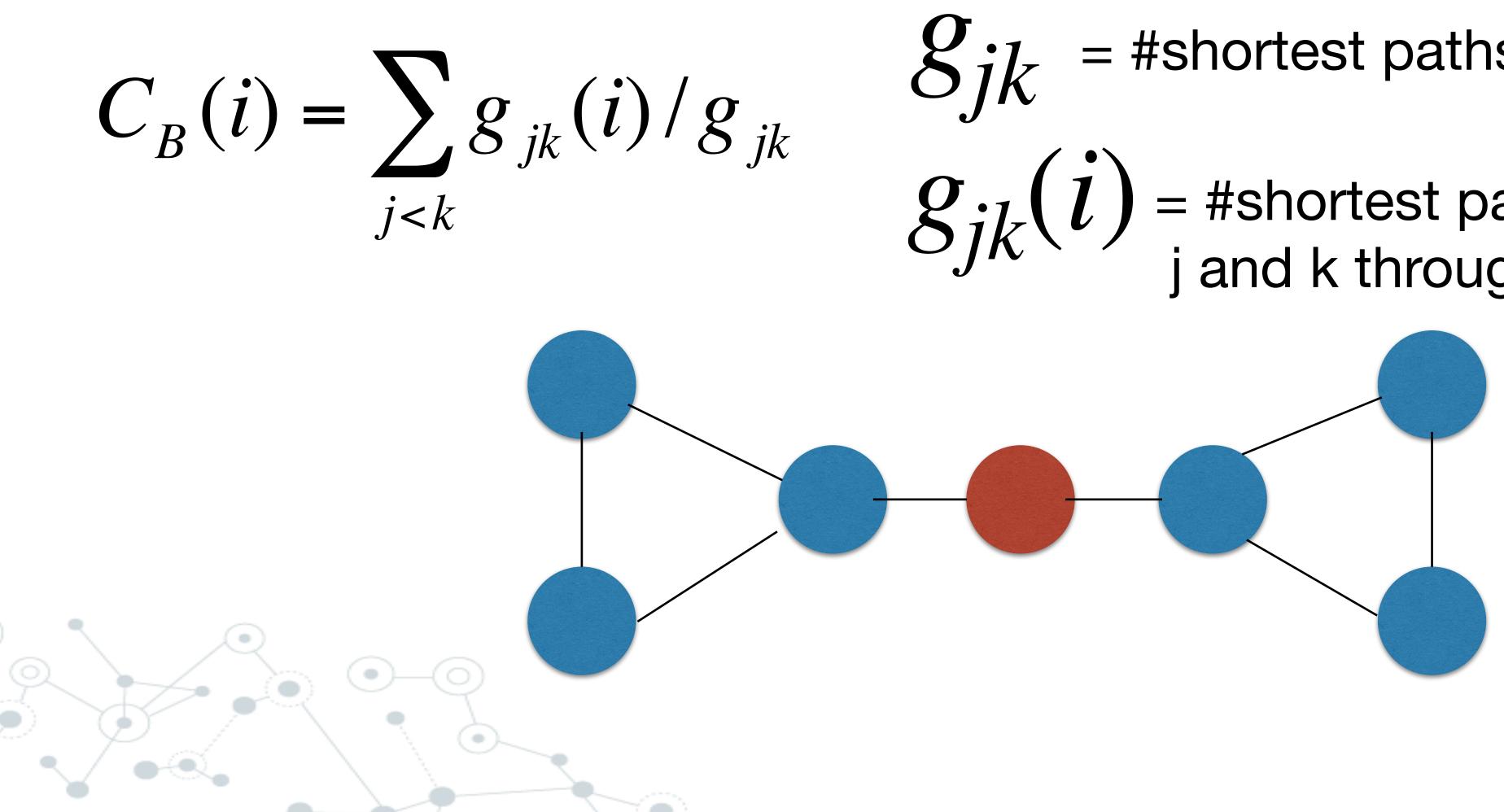
Betweeness captures a node's brokerage



intuition: how many pairs of individuals would have to go through you in order to reach one another in the minimum number of hops?



betweeness centrality



8ik = #shortest paths connecting j and k $g_{jk}(i)$ = #shortest paths connecting j and k through i



betweeness centrality

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My Facebook graph

Node size is proportional to the degree

Node color is proportional to the betweenness



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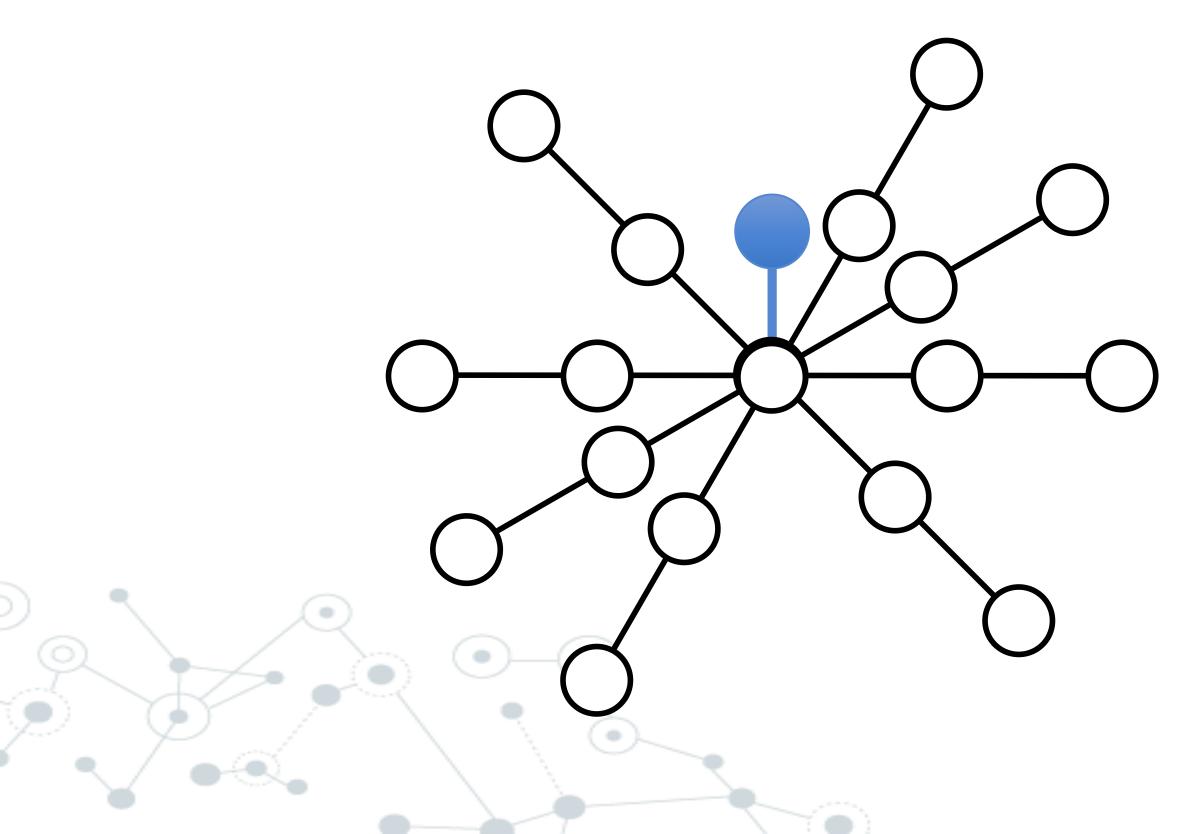
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closeness centrality

Closeness is based on the length of the average shortest path between a node and all other nodes in the network. It quantifies the reachability of a node.



 $C_{c}(i) = \left| \sum_{i=1}^{N} d(i,j) \right|^{-1}$



 ∞

Katz centrality computes the relative influence of a node within a network by measuring the number of the immediate neighbors and also all other nodes in the network that connect to the node through these immediate neighbors. Connections made with distant neighbors are, however, penalized by an attenuation factor

Katz centrality

$C_{KZ}(i) = \sum \alpha^k (A^k)_{ji}$ $k=1 \ j=1$



Katz centrality computes the relative influence of a node within a network by measuring the number of the immediate neighbors and also all other nodes in the network that connect to the node through these immediate neighbors. Connections made with distant neighbors are, however, penalized by an attenuation factor

Katz centrality

 $C_{KZ}(i) = \alpha \sum A_{ii} C_{KZ}(j)$ i = 1

