

# Advanced Algorithms and Computational Models (module A)

## Elements of graph theory

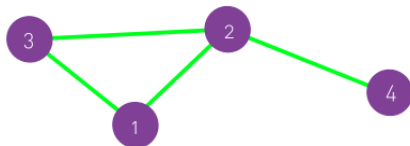
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# Degree, Average Degree and Degree Distribution

## Degree

A key property of each node is its *degree*, representing the number of links it has to other nodes

$k_i$  is the degree of the  $i^{th}$  node in the network



In this case, we have  $k_1 = 2$ ,  $k_2 = 3$ ,  $k_3 = 2$ ,  $k_4 = 1$

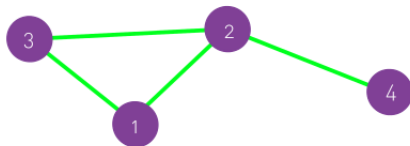
# Degree, Average Degree and Degree Distribution

## Degree

In an undirected network, the *total number of links*  $L$  can be expressed as the sum of the node degrees:

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

Here the factor  $\frac{1}{2}$  corrects for the fact that, in the sum, each link is counted twice



# Degree, Average Degree and Degree Distribution

Digression /1

## Average (mean)

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

## $n^{th}$ moment

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

# Degree, Average Degree and Degree Distribution

Digression /2

## Standard deviation

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

## Distribution of $x$

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

where

$$\sum_i p_x = 1 \text{ or } \int p_x dx = 1$$

# Degree, Average Degree and Degree Distribution

## Average Degree

For undirected networks, average degree is defined as

$$\langle k \rangle = \frac{1}{N} \sum_{i=1}^N k_i = \frac{2L}{N}$$

In directed networks we distinguish between *incoming degree*  $k_i^{in}$ , representing the number of links that point to node  $i$ , and *outgoing degree*  $k_i^{out}$ , representing the number of links that point from node  $i$  to other nodes

A node's *total degree*  $k_i$  is given by

$$k_i = k_i^{in} + k_i^{out}$$

# Degree, Average Degree and Degree Distribution

## Degree Distribution

The *degree distribution*  $p_k$  provides the probability that a randomly selected node in the network has degree  $k$ . Since  $p_k$  is a probability, it must be normalized, i.e.

$$\sum_{i=1}^{\infty} p_k = 1$$

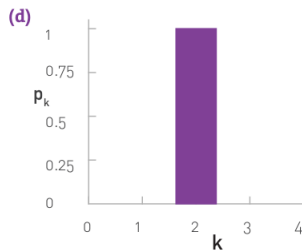
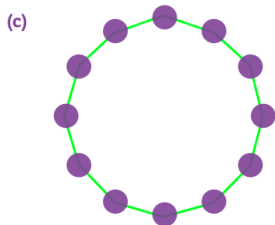
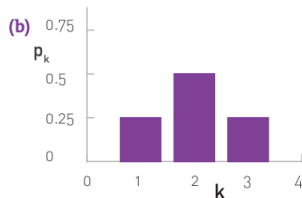
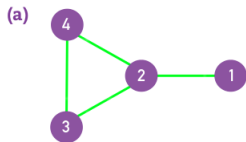
For a network with  $N$  nodes, the degree distribution is the normalized histogram given by

$$p_k = \frac{N_k}{N}$$

where  $N_k$  is the number of degree- $k$  nodes.

# Degree, Average Degree and Degree Distribution

## Degree Distribution





# Degree, Average Degree and Degree Distribution

## Degree Distribution

- The degree distribution has assumed a central role in network theory following the discovery of scale-free networks.
- The calculation of most network properties requires to know  $p_k$
- For example, the average degree of a network can be written as:

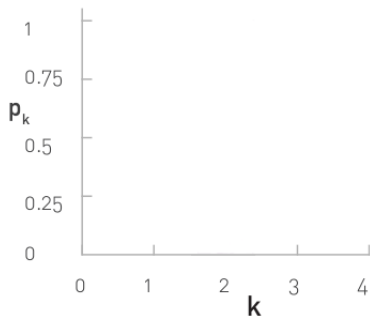
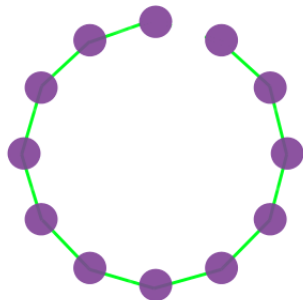
$$\langle k \rangle = \sum_{k=0}^{\infty} k p_k$$

- Another reason is that the precise functional form of  $p_k$  determines many network phenomena, from network robustness to the spread of viruses

# Degree, Average Degree and Degree Distribution

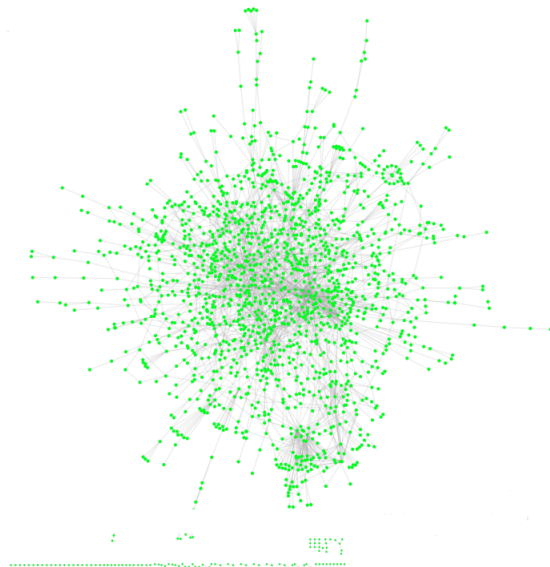
## Degree Distribution

A simple exercise:



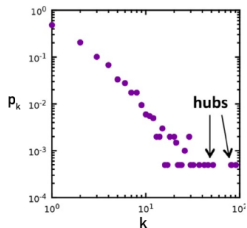
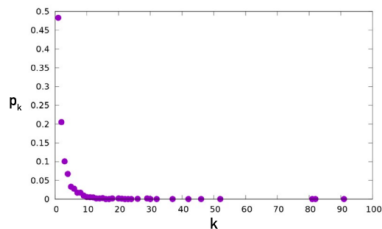
# Degree, Average Degree and Degree Distribution

## Degree Distribution



# Degree, Average Degree and Degree Distribution

## Degree Distribution



# Adjacency Matrix

- A complete description of a network requires to keep track of its links
- The simplest way to achieve this is to provide a complete list of the links
- For mathematical purposes it is better to represent a network through its adjacency matrix
- The *adjacency matrix* of a directed network of  $N$  nodes has  $N$  rows and  $N$  columns
- For directed networks the sums over the rows and columns of the adjacency matrix provide the incoming and outgoing degrees, that is

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

# Adjacency Matrix

- The number of nonzero elements of the adjacency matrix is  $2L$ , or twice the number of links
- Indeed, an undirected link connecting two nodes  $i$  and  $j$  appears in two entries:

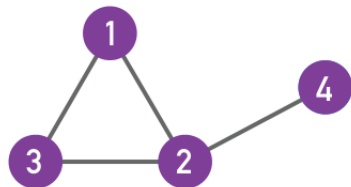
$$A_{ij} = A_{ji} = 1$$

## Adjacency Matrix

$$A_{ij} = \begin{matrix} & A_{11} & A_{12} & A_{13} & A_{14} \\ A_{21} & A_{22} & A_{23} & A_{24} \\ A_{31} & A_{32} & A_{33} & A_{34} \\ A_{41} & A_{42} & A_{43} & A_{44} \end{matrix}$$

# Adjacency Matrix

## Undirected Network



$$A_{ij} = \begin{matrix} & \begin{matrix} 1 & 2 & 3 & 4 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \end{matrix} & \begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \end{matrix}$$

$$k_2 = \sum_{j=1}^4 A_{2j} = \sum_{i=1}^4 A_{i2} = 3$$

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

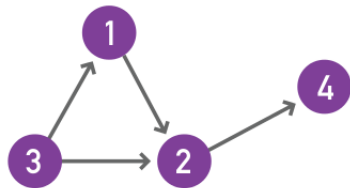
$$L = \frac{1}{2} \sum_{i,j=1}^N A_{ij}$$

$$\langle k \rangle = \frac{2L}{N}$$



# Adjacency Matrix

## Directed Network



$$A_{ij} = \begin{matrix} & \begin{matrix} 1 & 2 & 3 & 4 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \end{matrix} & \begin{bmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \end{matrix}$$

$$k_2^{in} = \sum_{j=1}^4 A_{2j} = 2 \quad k_2^{out} = \sum_{i=1}^4 A_{i2} = 1$$

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

$$L = \sum_{i,j=1}^N A_{ij}$$

$$\langle k^{in} \rangle = \langle k^{out} \rangle = \frac{L}{N}$$

## Real Networks are Sparse

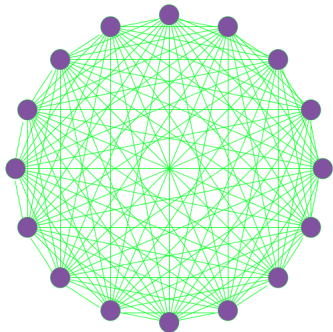
- In real networks, the number  $N$  of nodes and  $L$  of links can vary widely
- For example, the neural network of the worm *Caenorhabditis Elegans*, whose nervous system has been completely mapped, has  $N = 302$  neurons (nodes)
- In contrast, the human brain is estimated to have about  $N = 10^{11}$  neurons
- The genetic network of a human cell has about 20000 genes (nodes)
- The social network consists of  $N = 7 \times 10^9$  individuals
- The WWW is estimated to have  $N > 10^{12}$  documents

## Real Networks are Sparse

- In a network of  $N$  nodes, the number of links can change between  $L = 0$  and  $L_{max}$ , where

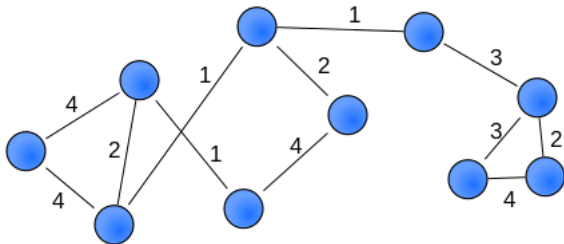
$$L_{max} = \frac{N(N-1)}{2}$$

is the total number of links present in a *complete graph* of size  $N$



## Weighted Networks

- In many applications it is necessary to study *weighted networks*, where each link  $(i, j)$  has a unique weight  $w_{ij}$
- For example, in mobile call networks the weight can represent the total number of minutes two individuals talk with each other on the phone, or the total number of calls

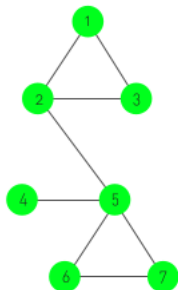


# Bipartite Networks

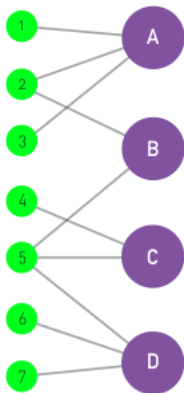
- A *bipartite network* is a network whose nodes can be divided into two disjoint sets  $U$  and  $V$  such that each link connects a  $U$ -node to a  $V$ -node
- Two *projections* can be generated for each bipartite network. The first connects two  $U$ -nodes if they are linked to the same  $V$ -node in the bipartite representation. The second projection connects the  $V$ -nodes by a link if they connect to the same  $U$ -node

# Bipartite Networks

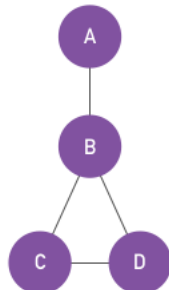
PROJECTION U U



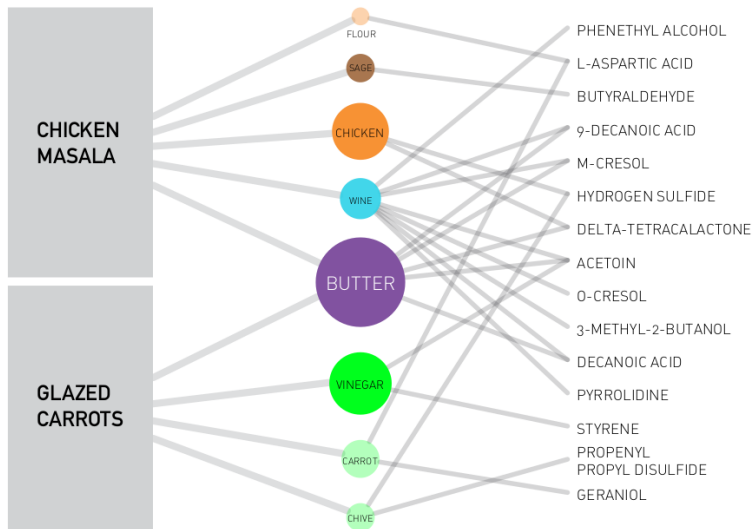
U V



PROJECTION V V

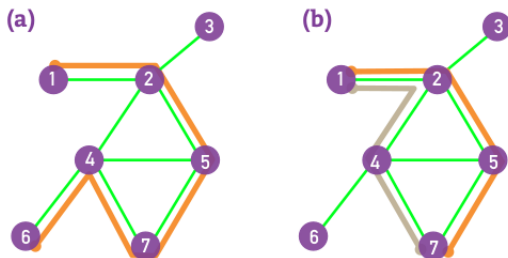


# Bipartite Networks



# Paths and Distances

- In networks, the concept of physical distance is meaningless
- For example, two web pages may reside on computers physically very distant but have a link to each other
- In networks, physical distance is replaced by *path length*. A *path* is a route that runs along the links of the network. The path length is the number of links the path contains





# Paths and Distances

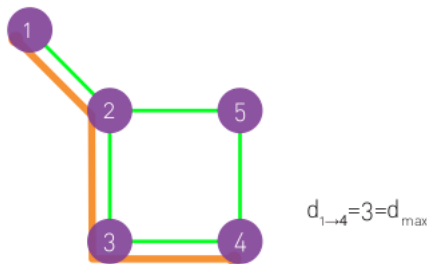
## Shortest Path

- The shortest path between nodes  $i$  and  $j$  is the path with the fewest number of links
- The shortest path is often called the *distance* between nodes  $i$  and  $j$  and is denoted as  $d_{ij}$
- We can have multiple shortest paths of the same length between a pair of nodes
- In an undirected network,  $d_{ij} = d_{ji}$ , i.e. the distance between node  $i$  and  $j$  is the same as the distance between node  $j$  and  $i$
- In a directed network, the existence of a path from node  $i$  to node  $j$  does not guarantee the existence of a path from  $j$  to  $i$

# Paths and Distances

## Shortest Path

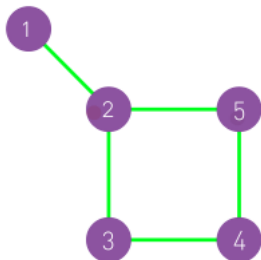
- The *diameter* of a network, denoted by  $d_{max}$ , is the maximum shortest path in the network. It is the largest distance recorded between any pair of nodes



# Paths and Distances

## Shortest Path

- The *average path length*, denoted by  $\langle d \rangle$  is the average distance between all pairs of nodes in the network.



$$\begin{aligned}\langle d \rangle = & (d_{1 \rightarrow 2} + d_{1 \rightarrow 3} + d_{1 \rightarrow 4} + d_{1 \rightarrow 5} + \\ & + d_{2 \rightarrow 3} + d_{2 \rightarrow 4} + d_{2 \rightarrow 5} + \\ & + d_{3 \rightarrow 4} + d_{3 \rightarrow 5} + \\ & + d_{4 \rightarrow 5}) / 10 = 1.6\end{aligned}$$

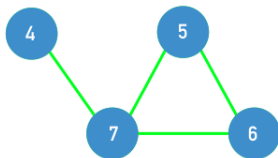
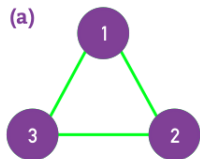
# Connectedness

- Directly related to path and distances is the concept of *connectedness*
- In an undirected network, nodes  $i$  and  $j$  are *connected* if there is a path between them. They are *disconnected* if such a path does not exist, in which case we have  $d_{ij} = \infty$
- A network is connected if **all** pairs of nodes in the network are connected
- A network is disconnected if there is **at least** one pair with  $d_{ij} = \infty$
- If a network is disconnected, its subnetworks are called *components* or *clusters*

# Connectedness

## Disconnected Network

(a)



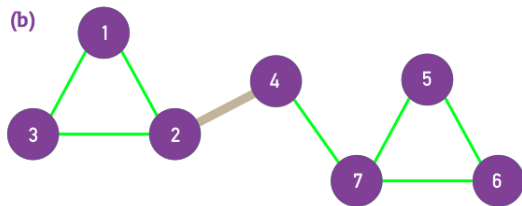
$$\begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 \end{pmatrix}$$

# Connectedness

## Connected Network

- If a network consists of two components, a properly placed link can connect them, making the network connected. Such a link is called *bridge*

(b)


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

# Clustering Coefficient

- The clustering coefficient captures the degree to which the neighbours of a given node link to each other
- For a node  $i$  with degree  $k_i$ , the local clustering coefficient is defined as

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

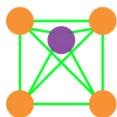
where  $L_i$  represents the number of links between the  $k_i$  neighbours of node  $i$ .

# Clustering Coefficient

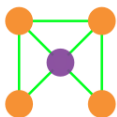
$C_i$  is the probability that two neighbours of a node link to each other. It measures the network's local density

$C_i$  is between 0 and 1:

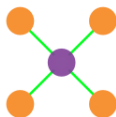
- If  $C_i = 0$ , none of the neighbours of node  $i$  link to each other
- If  $C_i = 1$ , the neighbours of node  $i$  form a complete graph, they all link to each other



$$C_i=1$$



$$C_i=1/2$$



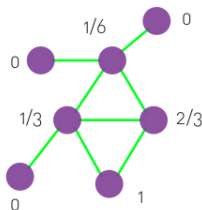
$$C_i=0$$



# Clustering Coefficient

- The degree of clustering of a whole network is captured by the *average clustering coefficient*,  $\langle C \rangle$ , representing the average of  $C_i$  over all nodes  $i = 1, \dots, N$

$$\langle C \rangle = \frac{1}{N} \sum_{i=1}^N C_i$$



$$\langle C \rangle = \frac{13}{42} \approx 0.310$$

$$C_{\Delta} = \frac{3}{8} = 0.375$$