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Social Network Analysis

A.Y. 23/24

Communication Strategies

Graphs

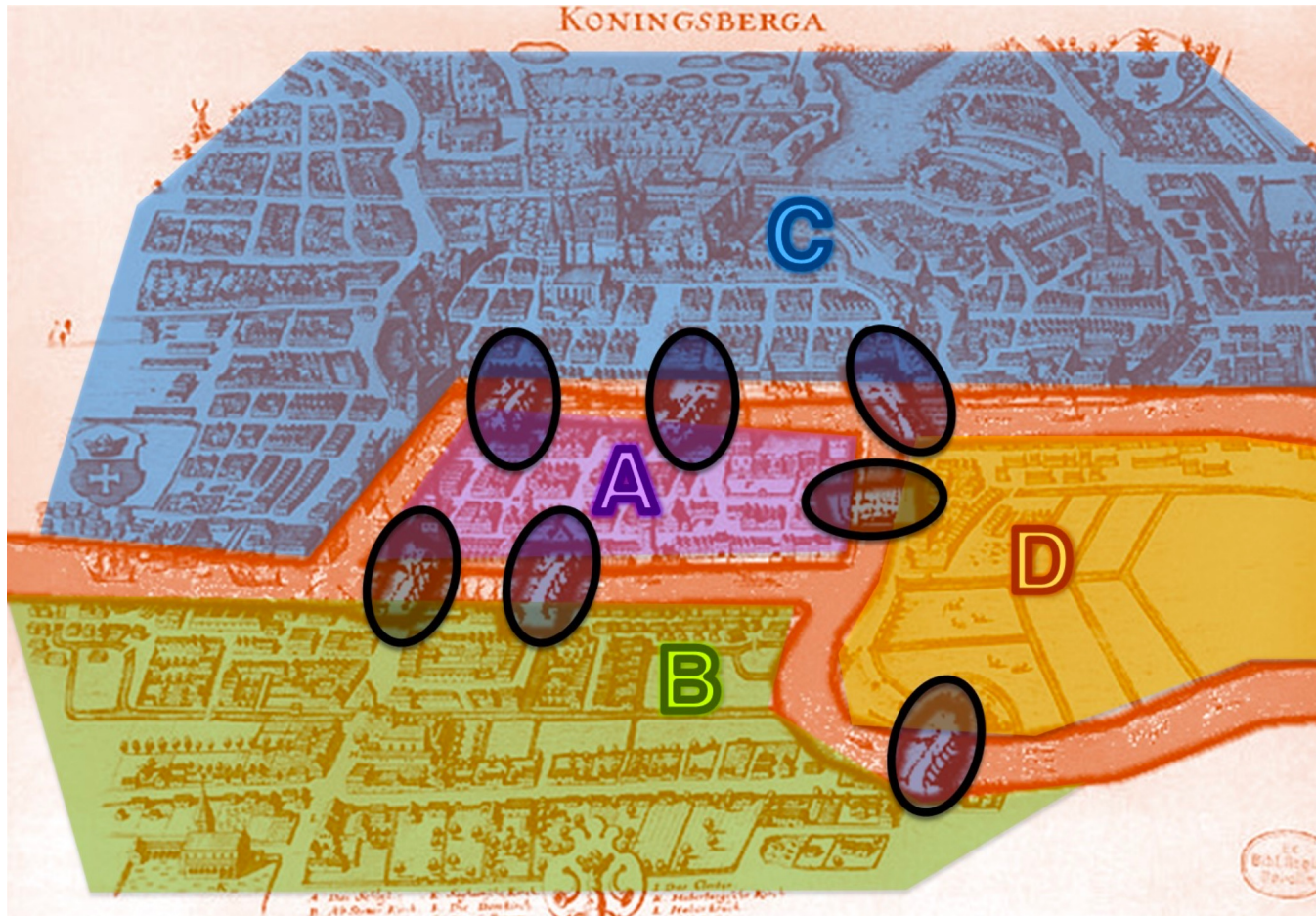
an introduction



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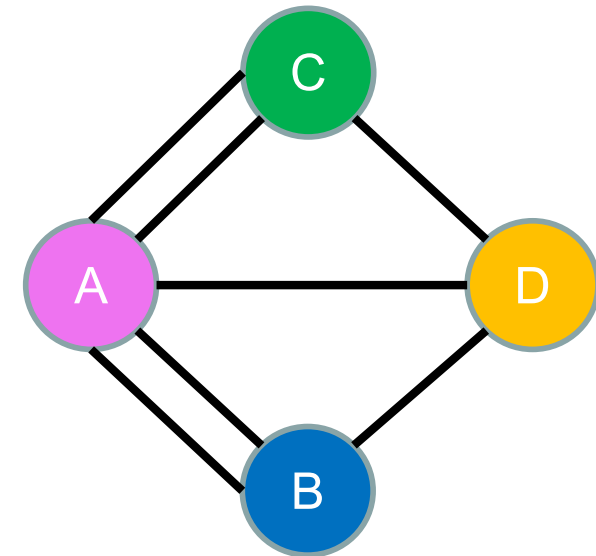
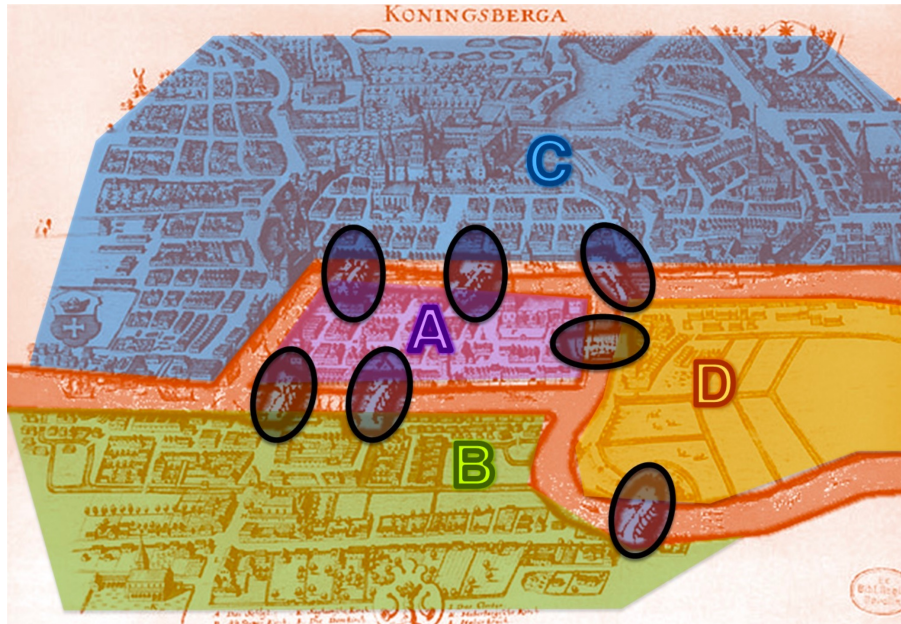
Euler and the 7 bridges of Königsberg

(Prussia, 1736) today Kaliningrad



How to walk through the city by crossing each bridge only once?

Networks as graphs



Graph $G(\mathcal{V}, \mathcal{E})$: network

□ Vertices (set \mathcal{V}): nodes, people, concepts

□ Edges (set \mathcal{E}): links, relations, associations

↑
mathematics

↑
technology

↑
social
psychology

↑
social
cognition



Directed versus undirected

- ❑ A connection relationship can have a privileged direction or can be mutual
- ❑ Either a **directed** or an **undirected** link

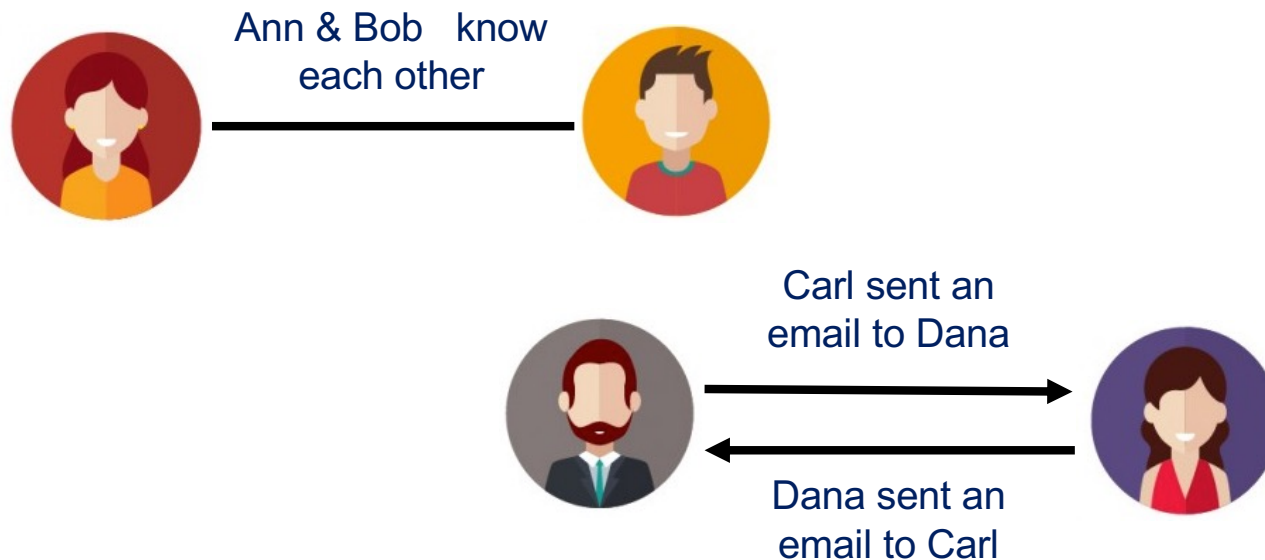


- ❑ If the network has only (un)directed links, it is also called itself (un)directed network
- ❑ Certain networks can have both types



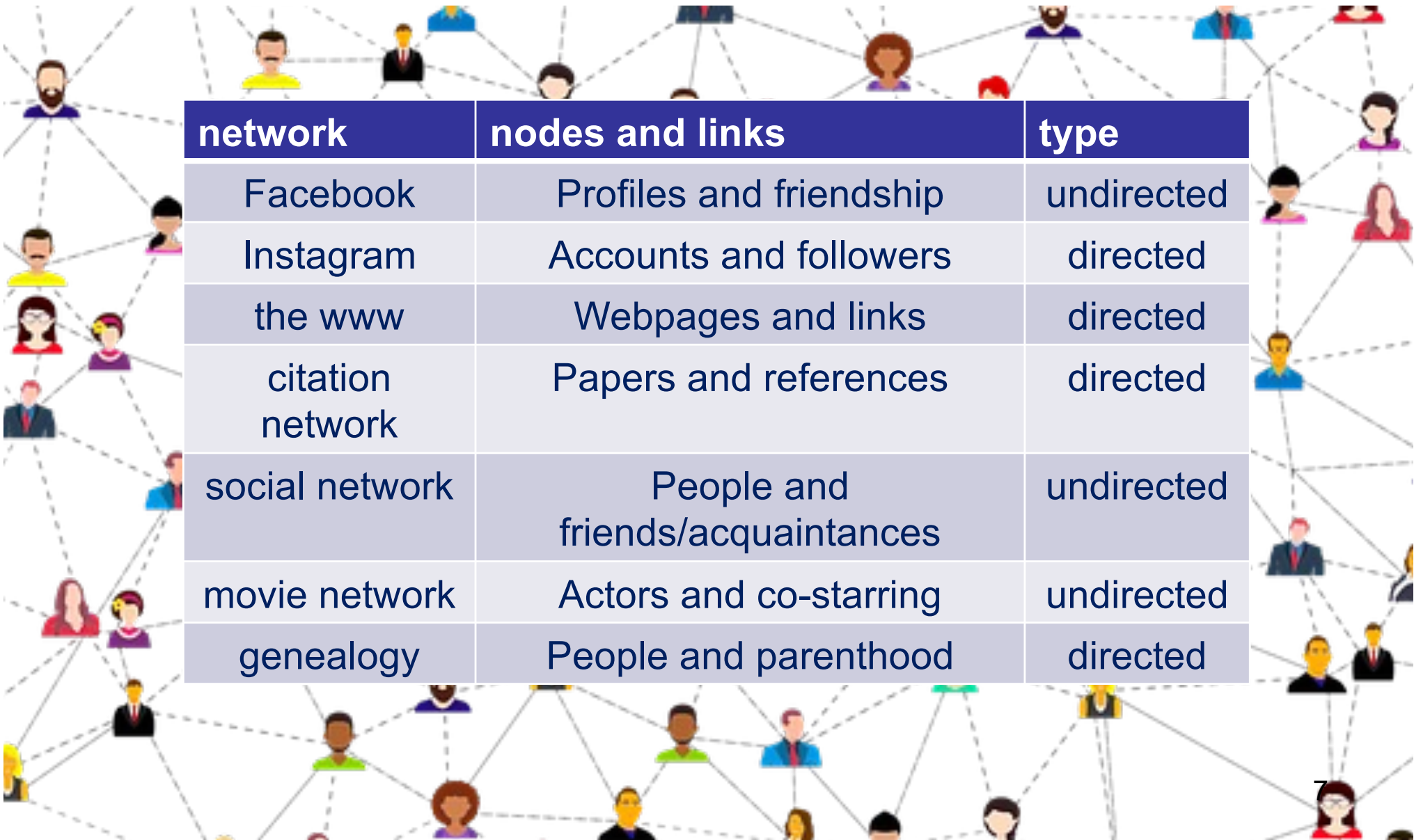
Directed versus undirected

- ❑ At first glance **undirected** → **directed** by duplicating links, but not necessarily quite the same though





Some examples



network	nodes and links	type
Facebook	Profiles and friendship	undirected
Instagram	Accounts and followers	directed
the www	Webpages and links	directed
citation network	Papers and references	directed
social network	People and friends/acquaintances	undirected
movie network	Actors and co-starring	undirected
genealogy	People and parenthood	directed

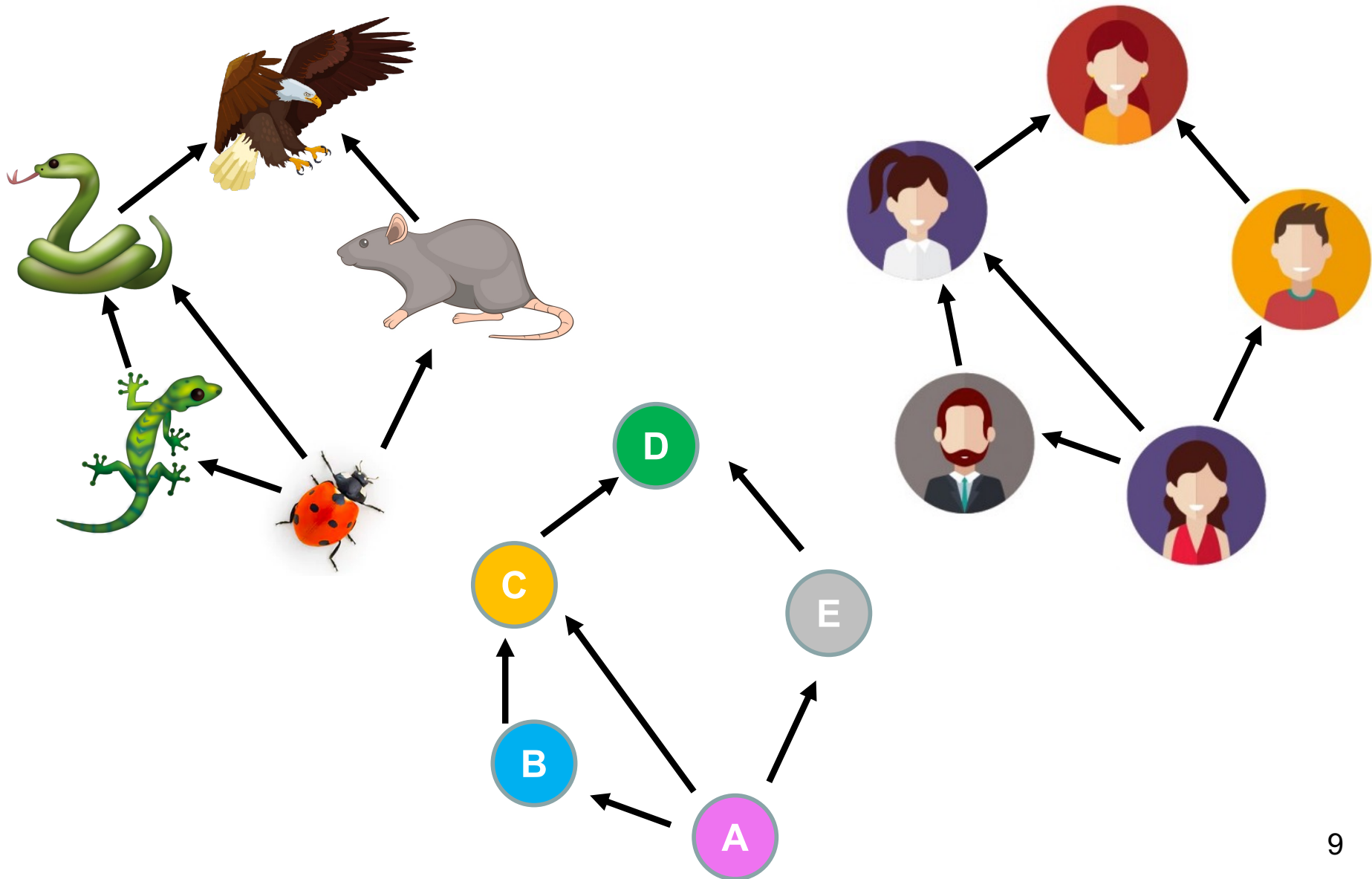


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Can U think of other social networks?

network	nodes and links	type
X	Accounts & follows	directed
WhatsApp	People & messages	directed
WhatsApp	People and groupchats	undirected
TikTok	Accounts & likes or comments to posts/ joining a livestream	directed
Universities		
TikTok		
Pinterest, YouTube		
Pinterest, YouTube		
Movies		
Ask		
LinkedIn		

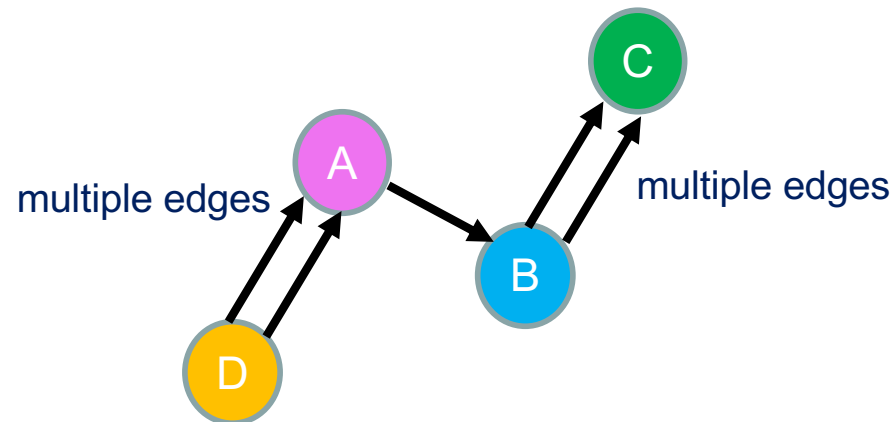
Generality of representation



Graph representations

visual plot, adjacency matrix, edge list

- ❑ Multi-graphs (or pseudo-graphs)
Some network representations require **multiple** links (e.g., number of citations from one author to another)

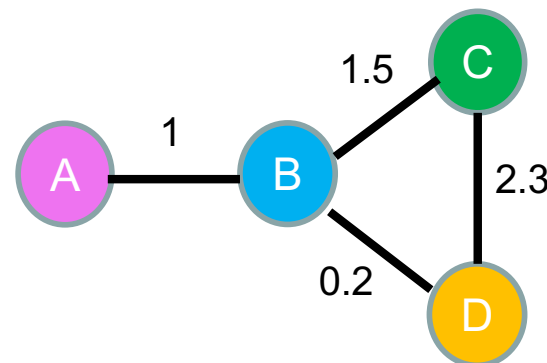




□ Weighted graph

Sometimes a **weight** is associated to a link, e.g., to underline that the links are not identical (strong/weak relationships)

Can be seen as a generalization of multi-graphs (weight = # of links)



e.g., **strength of a tie**

0.2 = weak (acquaintances)

1 = strong (friends)

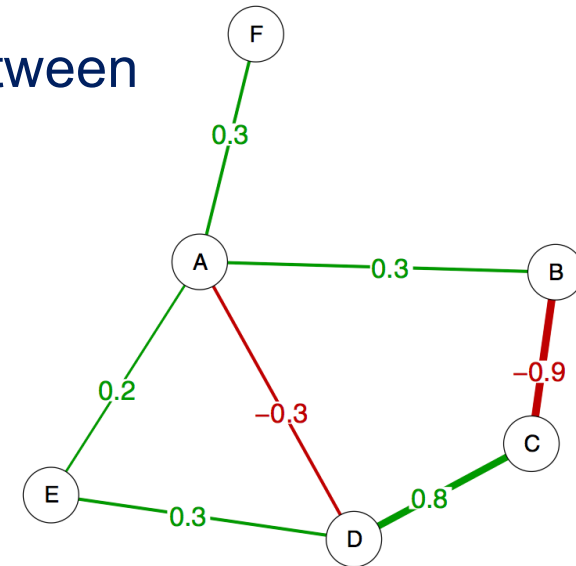
1.5 = stronger (close friends)

2.3 = very strong (best friends)

□ Edges can have signed values

positive if there is an agreement between nodes

negative if there's a disagreement



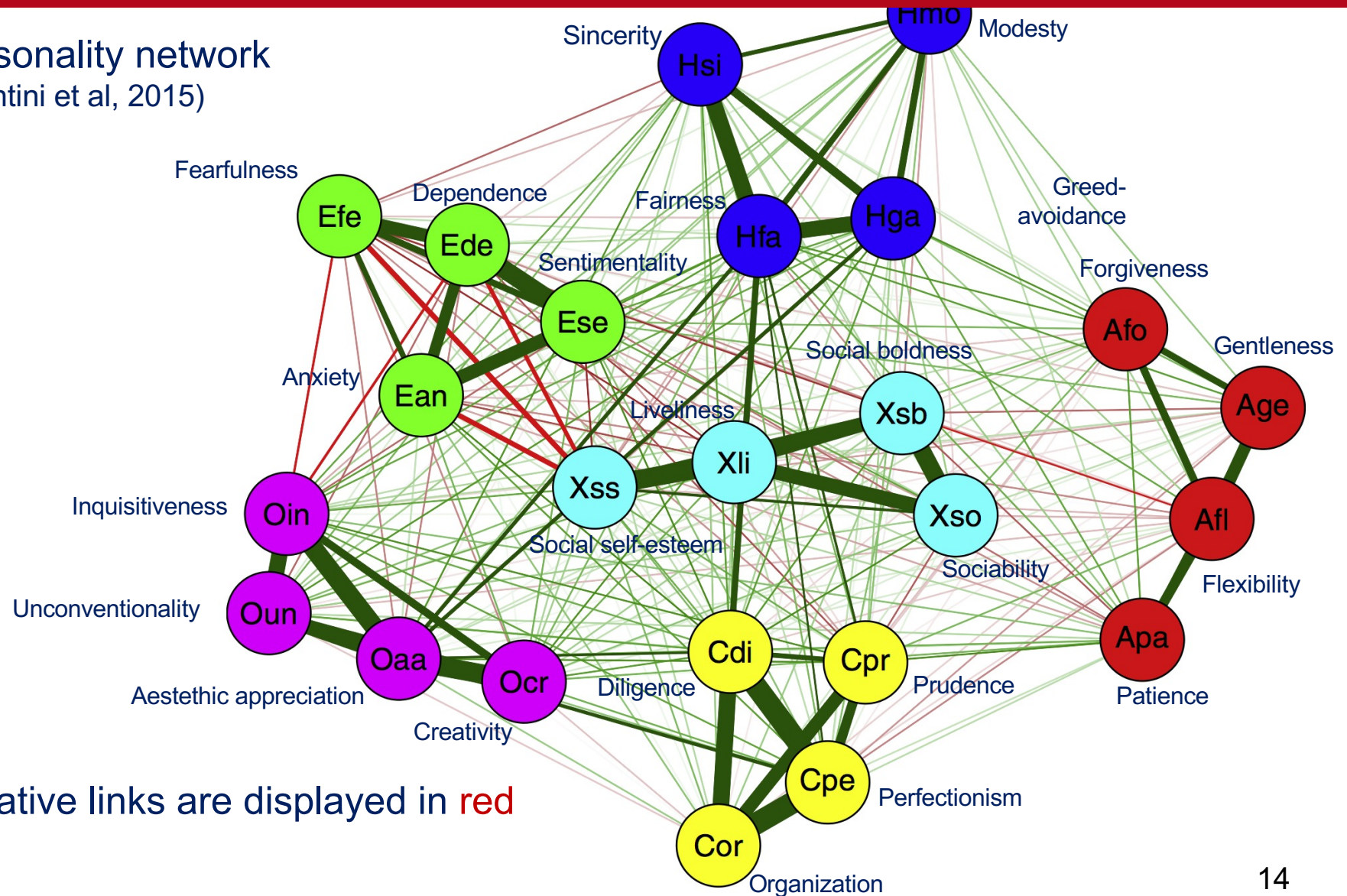
□ This is typical of correlation networks

correlation = a measure of similarity

□ More difficult to handle

Signed graph example

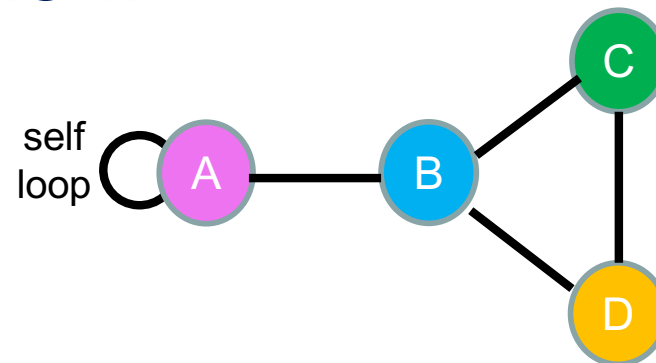
A personality network
(Costantini et al, 2015)



Negative links are displayed in **red**



- ❑ In many networks nodes do not interact with themselves
- ❑ To account for self-interactions, we add **loops** to represent them



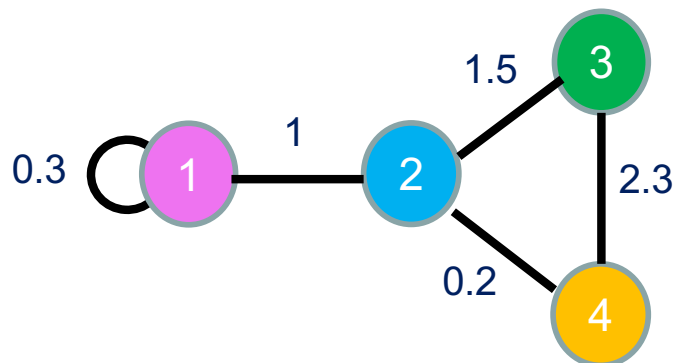


□ An adjacency matrix $A = [a_{ij}]$ associated to graph \mathcal{G} has

i is the row index

j is the column index

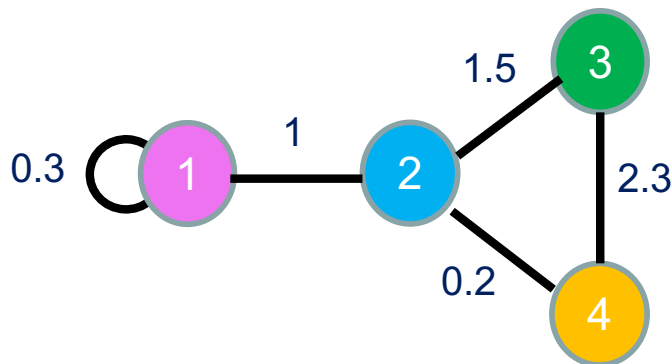
entries $a_{ij} = 0$ if nodes i and j are **not connected**
if nodes i and j are **connected** then $a_{ij} \neq 0$



$$A = \begin{bmatrix} 0.3 & 1 & 0 & 0 \\ 1 & 0 & 1.5 & 0.2 \\ 0 & 1.5 & 0 & 2.3 \\ 0 & 0.2 & 2.3 & 0 \end{bmatrix}$$

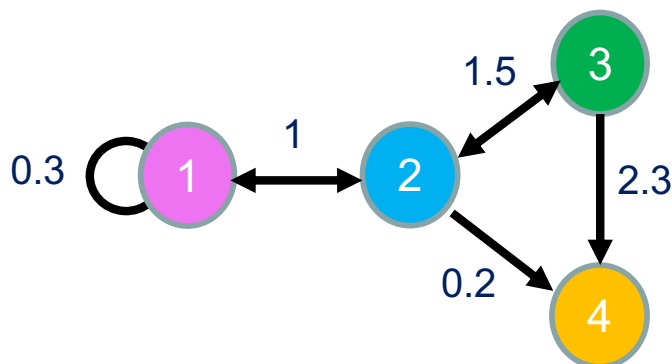
Annotations:
- "this is a_{12} " points to the value 1 in row 1, column 2.
- "row 1" points to the first row of the matrix.
- "column 2" points to the second column of the matrix.

□ Undirected graph = **symmetric** matrix



$$A = \begin{bmatrix} 0.3 & 1 & 0 & 0 \\ 1 & 0 & 1.5 & 0.2 \\ 0 & 1.5 & 0 & 2.3 \\ 0 & 0.2 & 2.3 & 0 \end{bmatrix}$$

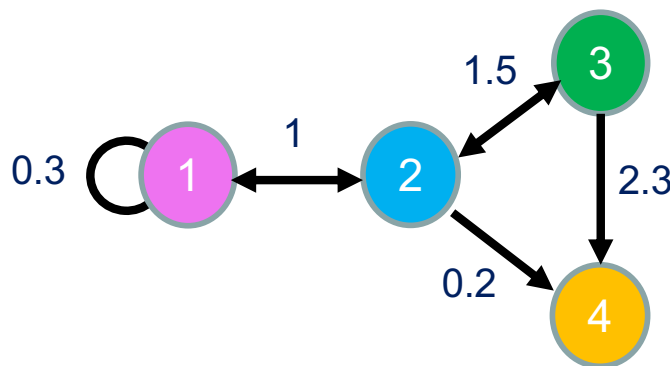
□ Directed graph = **asymmetric** matrix



$$A = \begin{bmatrix} 0.3 & 1 & 0 & 0 \\ 1 & 0 & 1.5 & 0 \\ 0 & 1.5 & 0 & 0 \\ 0 & 0.2 & 2.3 & 0 \end{bmatrix}$$



- The weight a_{ij} is associated to
 i th row
 j th column
directed edge $j \rightarrow i$ starting from node j and leading to node i



$$A = \begin{bmatrix} 0.3 & 1 & 0 & 0 \\ 1 & 0 & 1.5 & 0 \\ 0 & 1.5 & 0 & 0 \\ 0 & 0.2 & 2.3 & 0 \end{bmatrix}$$

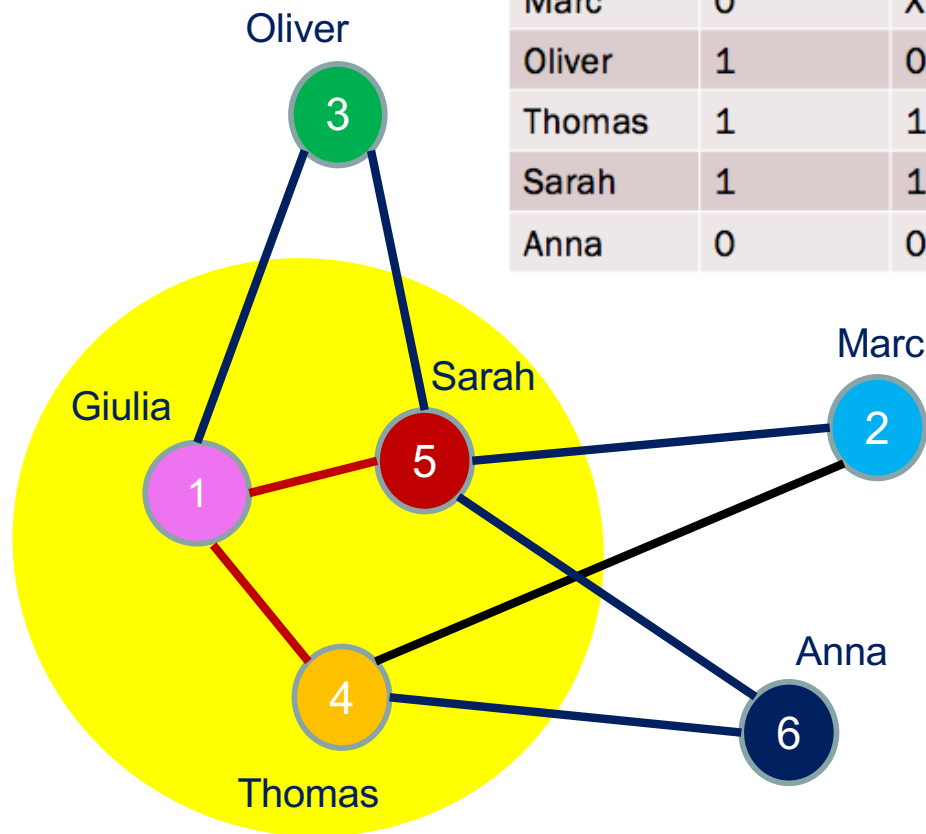
Labels for matrix elements: a_{24} (top-right), a_{34} (middle-right), a_{42} (bottom-left), a_{43} (bottom-middle).



An example

which of these representations do you like best?

	Giulia	Marc	Oliver	Thomas	Sarah	Anna
Giulia	X					
Marc	0	X				
Oliver	1	0	X			
Thomas	1	1	0	X		
Sarah	1	1	1	0	X	
Anna	0	0	0	1	1	x



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

which of these representations do you like best?



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Graph plots may carry relevant info...

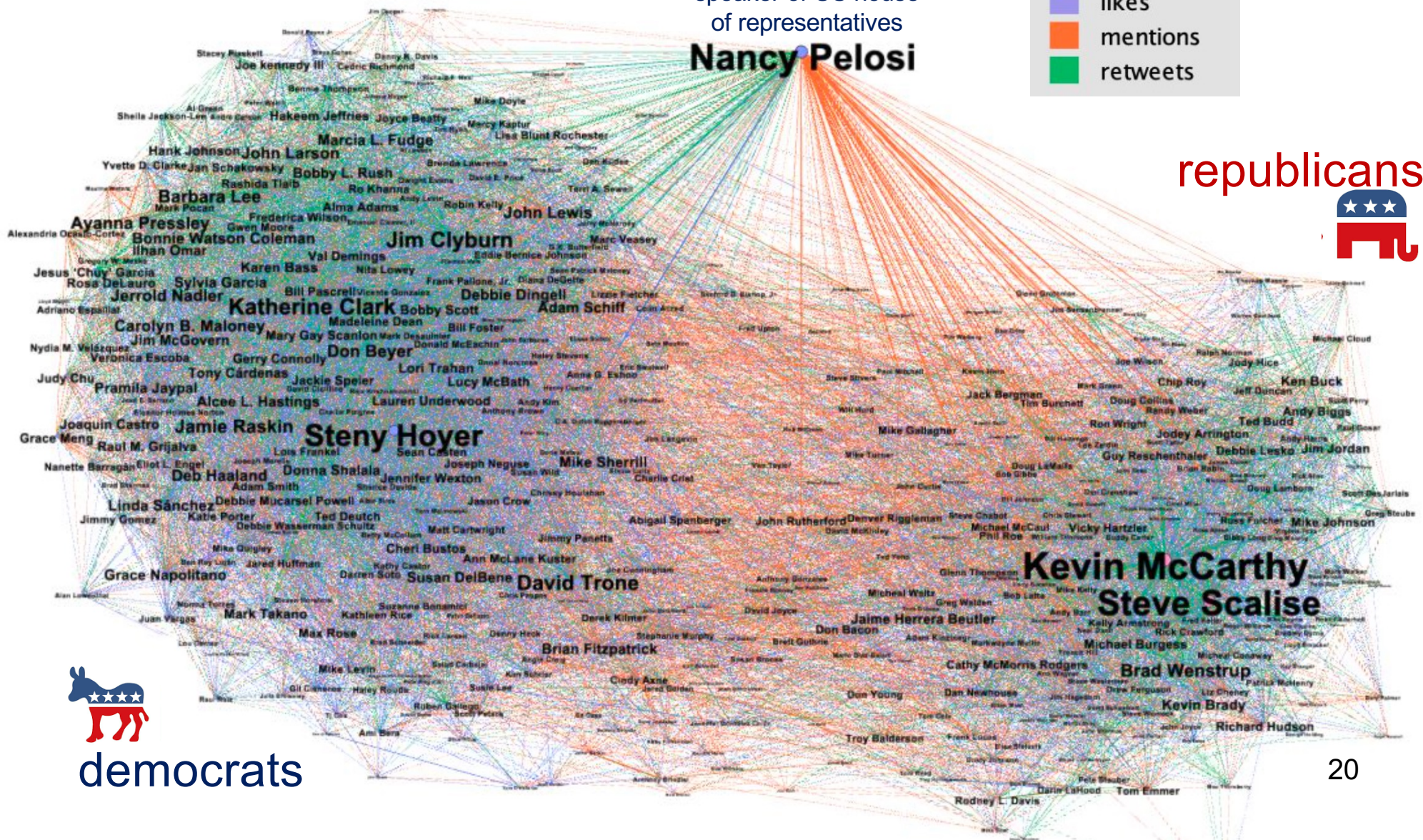
US republicans and democrats interactions on Twitter (2020)

speaker of US house
of representatives

Nancy Pelosi

- likes
- mentions
- retweets

republicans



democrats



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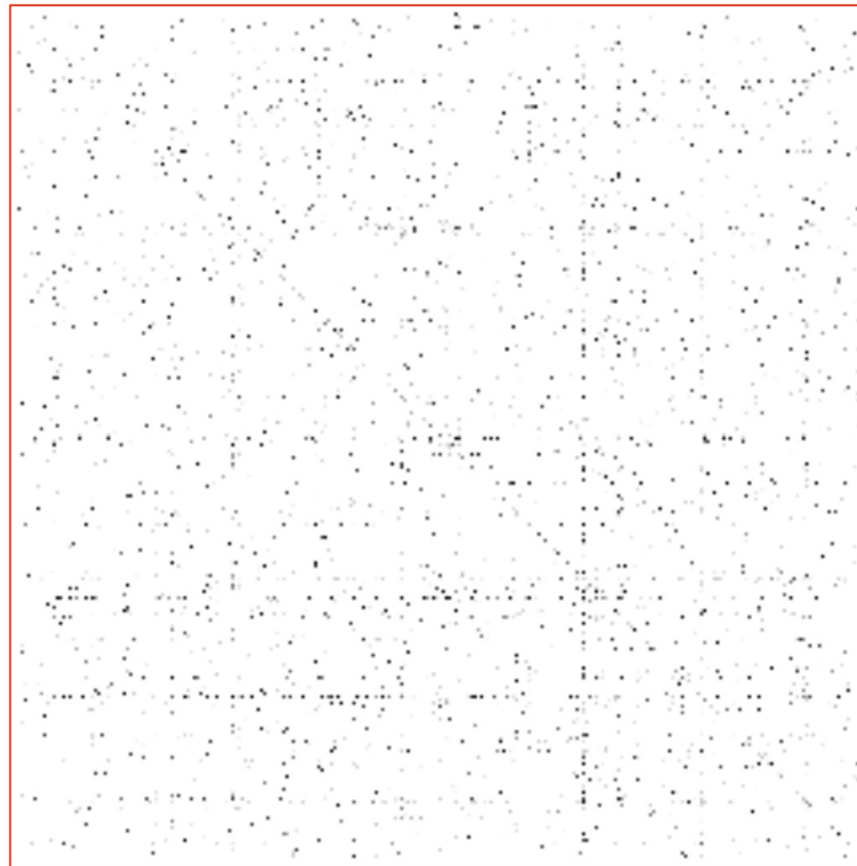
... or may not!

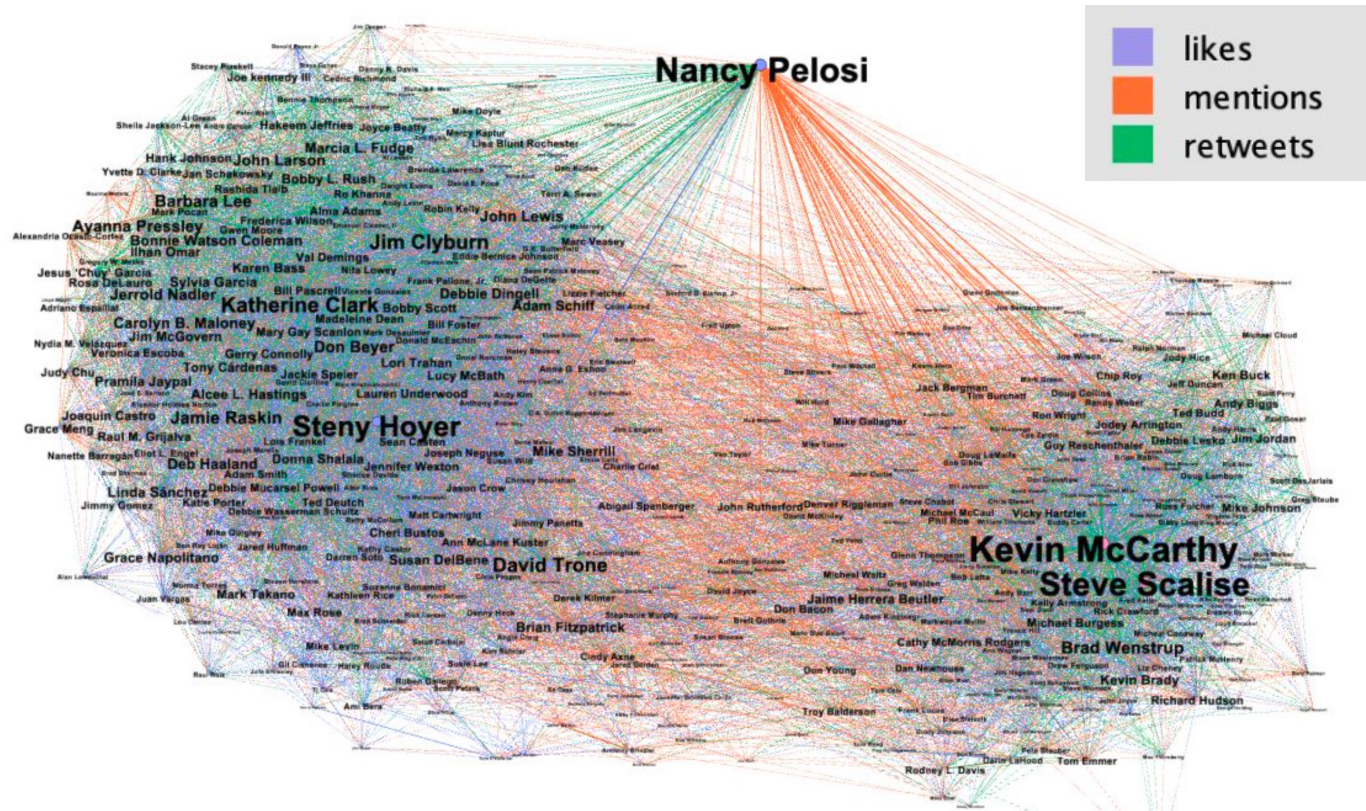




- The adjacency matrix is typically sparse
good for tractability !

A =





described by a **set** of adjacency matrices A_ℓ
e.g., one for likes, one for mentions, and one for retweets



□ So, what's the take-away so far?



Storing network data

adjacency matrix versus edge list

adjacency matrix

$A =$

0	0	1	1	1	0
0	0	0	1	1	0
1	0	0	0	1	0
1	1	0	0	0	1
1	1	1	0	0	1
0	0	0	1	1	0

N^2 entries

edge list

L entries

- 1 → 3
- 1 → 4
- 1 → 5
- 2 → 4
- 2 → 5
- 3 → 5
- 4 → 6
- 5 → 6

Which one do U think is better?

Distances in graphs

and related concepts



□ Path

a sequence of interconnected nodes (meaning each pair of nodes adjacent in the sequence are connected by a link)

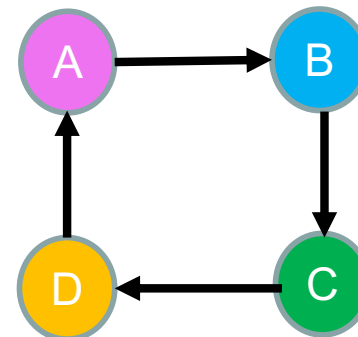


□ Path length

of links involved in the path (if the path involves n nodes then the path link is $n-1$)

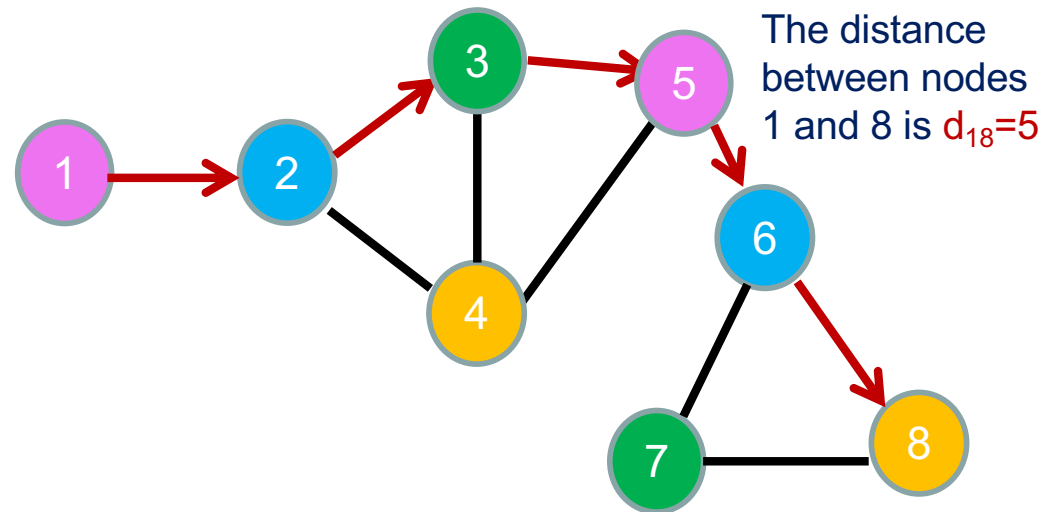
□ Cycle

path where starting and ending nodes coincide



□ Shortest path (between any two nodes)

the path with the minimum length, which is called the **distance**



it is **not** unique!

□ Diameter (of the network)

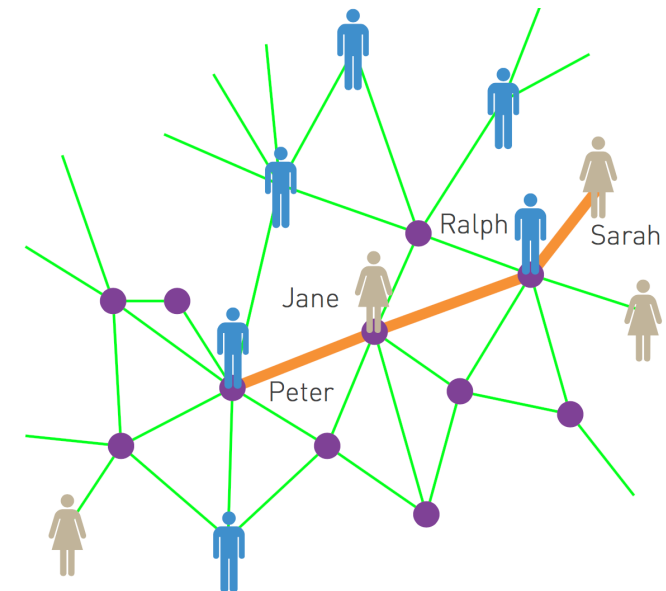
the highest distance in the network

The diameter is $d=5$

□ Average path length

average distance between all nodes pairs (apply an algorithm to all node couples, and take the average)

- In real networks distance between two randomly chosen nodes is generally short
- Milgram [1967]: *6 degrees of separation*

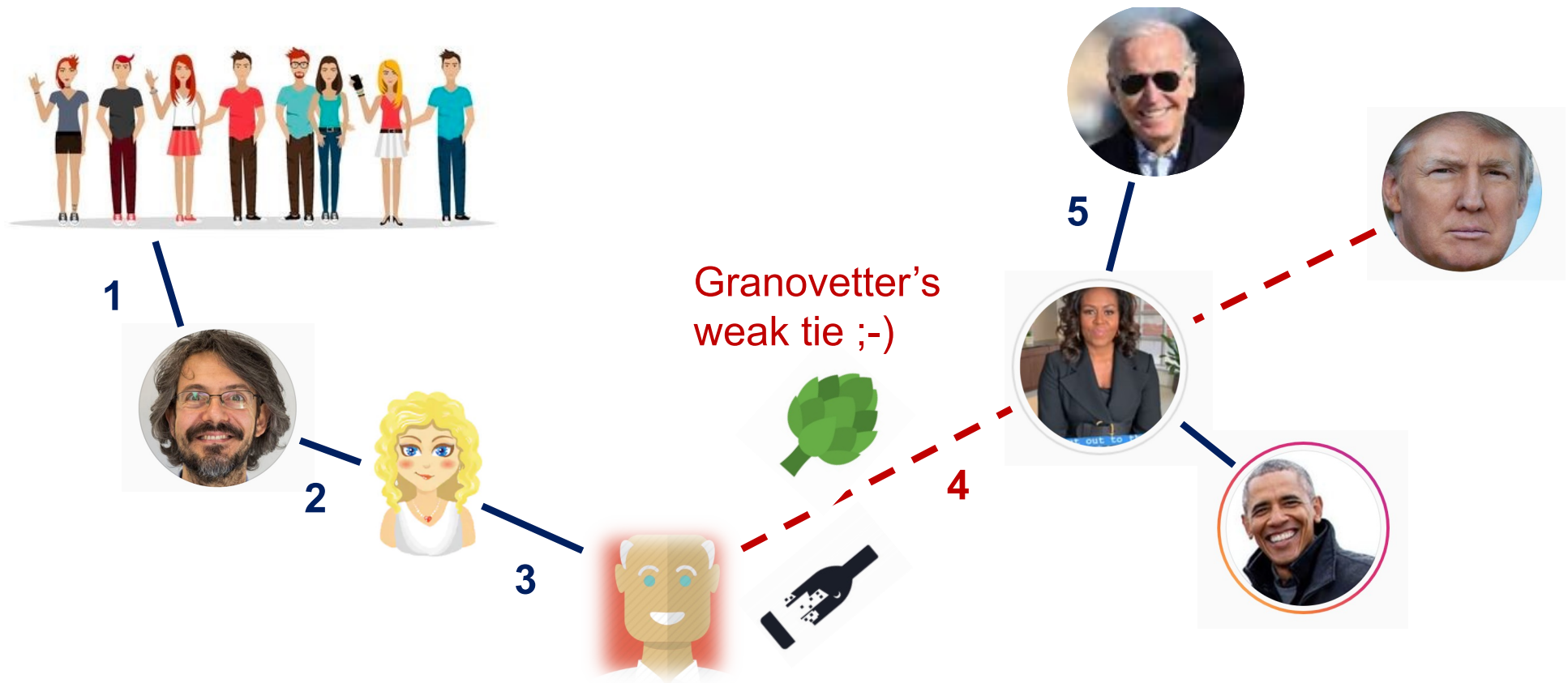


- What does this mean?
We are more connected than we think



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Small world we and the US presidents



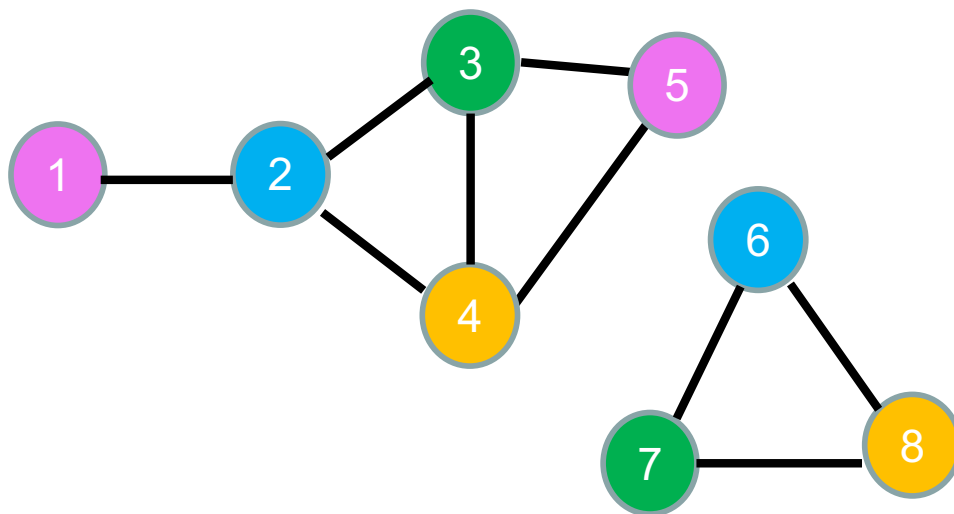
❑ Connected graph (undirected)

for all couples (i,j) there exists a path connecting them

if **disconnected**, we count the # of connected components
(e.g., use BFS and iterate)

❑ Giant component (the biggest one)

❑ Isolates (the other ones)



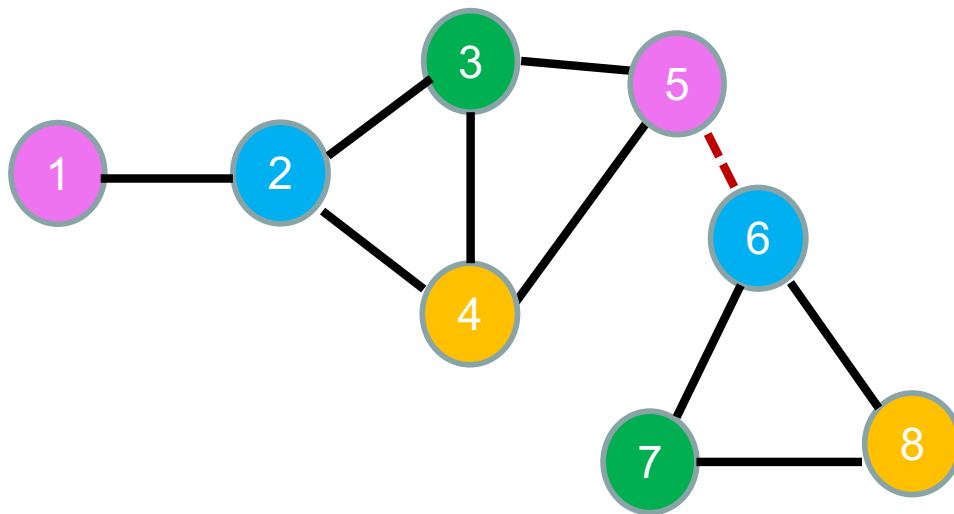
$A =$

0	1	0	0	0	0	0	0	0
1	0	1	1	0	0	0	0	0
0	1	0	1	1	0	0	0	0
0	1	1	0	1	0	0	0	0
0	0	1	1	0	0	0	0	0
0	0	0	0	0	0	1	1	1
0	0	0	0	0	1	0	1	0
0	0	0	0	0	1	1	0	0

block-diagonal matrix

□ A **bridge** is a link between two connected components

its removal would make the network disconnected



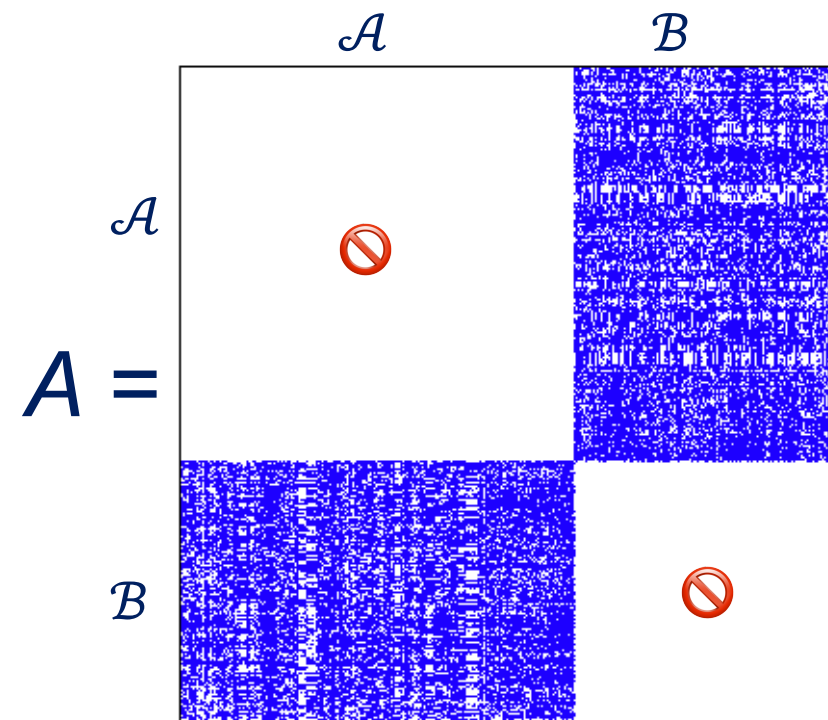
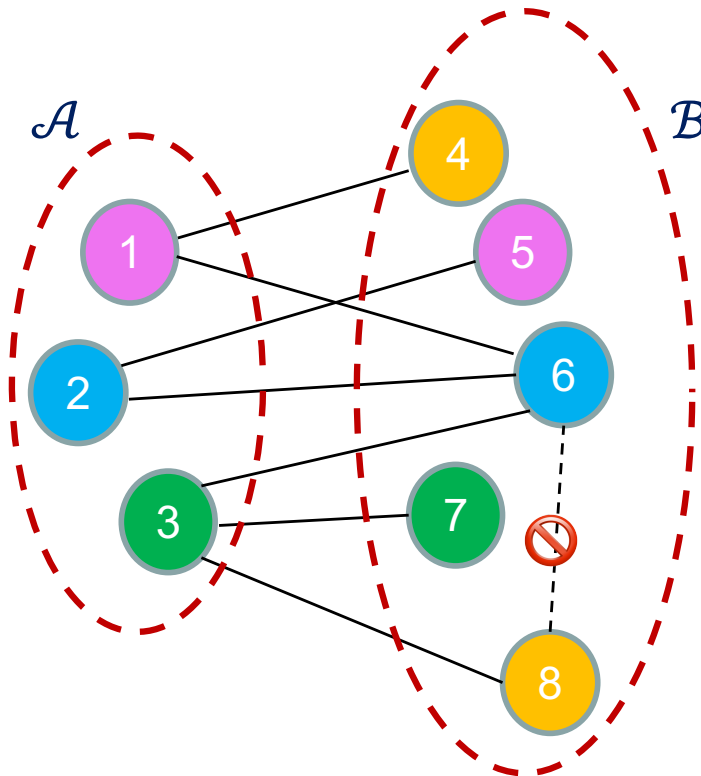
$A =$

0	1	0	0	0	0	0	0	0
1	0	1	1	0	0	0	0	0
0	1	0	1	1	0	0	0	0
0	1	1	0	1	0	0	0	0
0	0	1	1	0	1	0	0	0
0	0	0	0	1	0	1	1	1
0	0	0	0	0	1	0	1	1
0	0	0	0	0	1	1	0	0

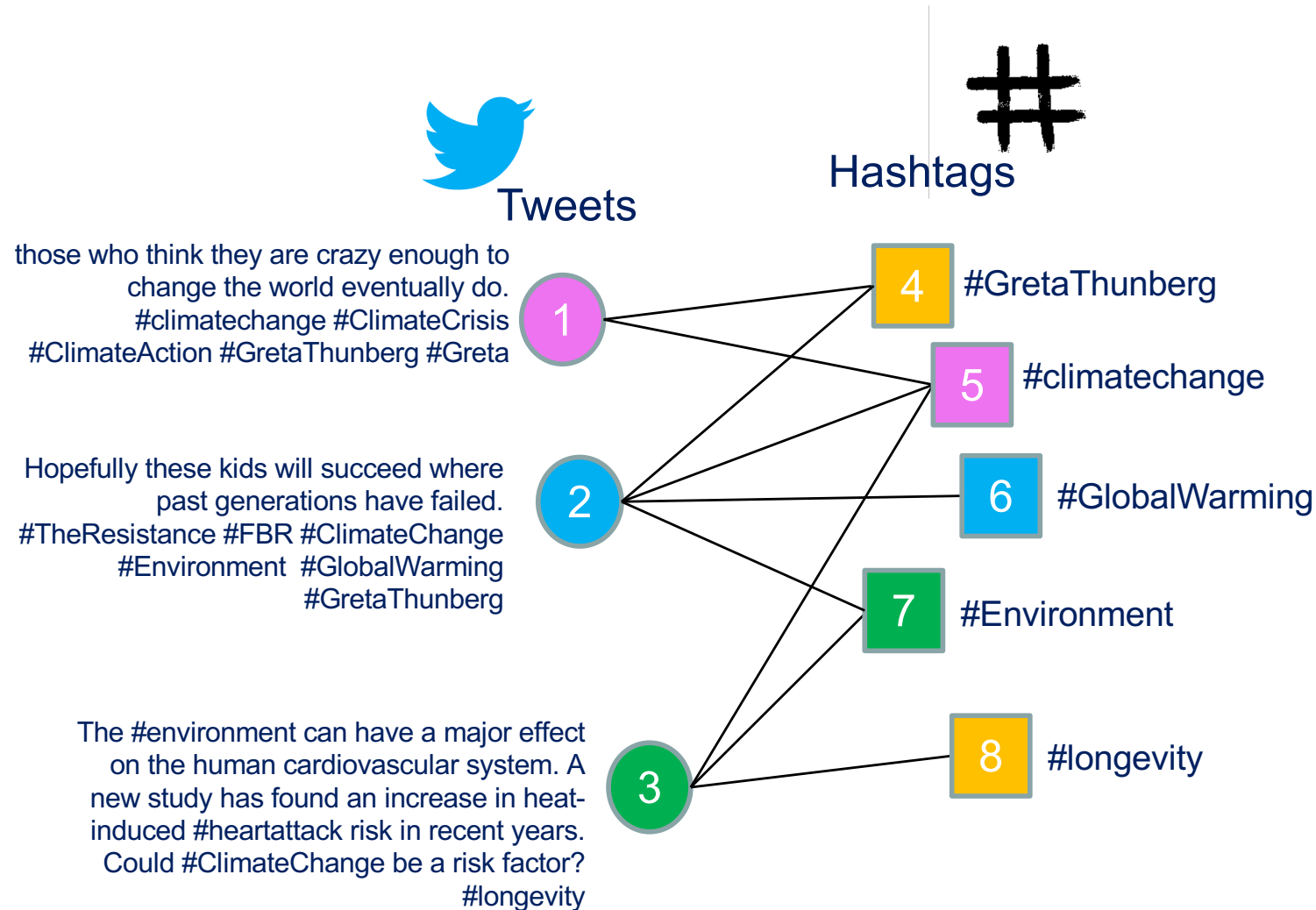
Bipartite graphs

and semantic networks

- Connections are available only between the groups \mathcal{A} and \mathcal{B}



Bipartite graph example





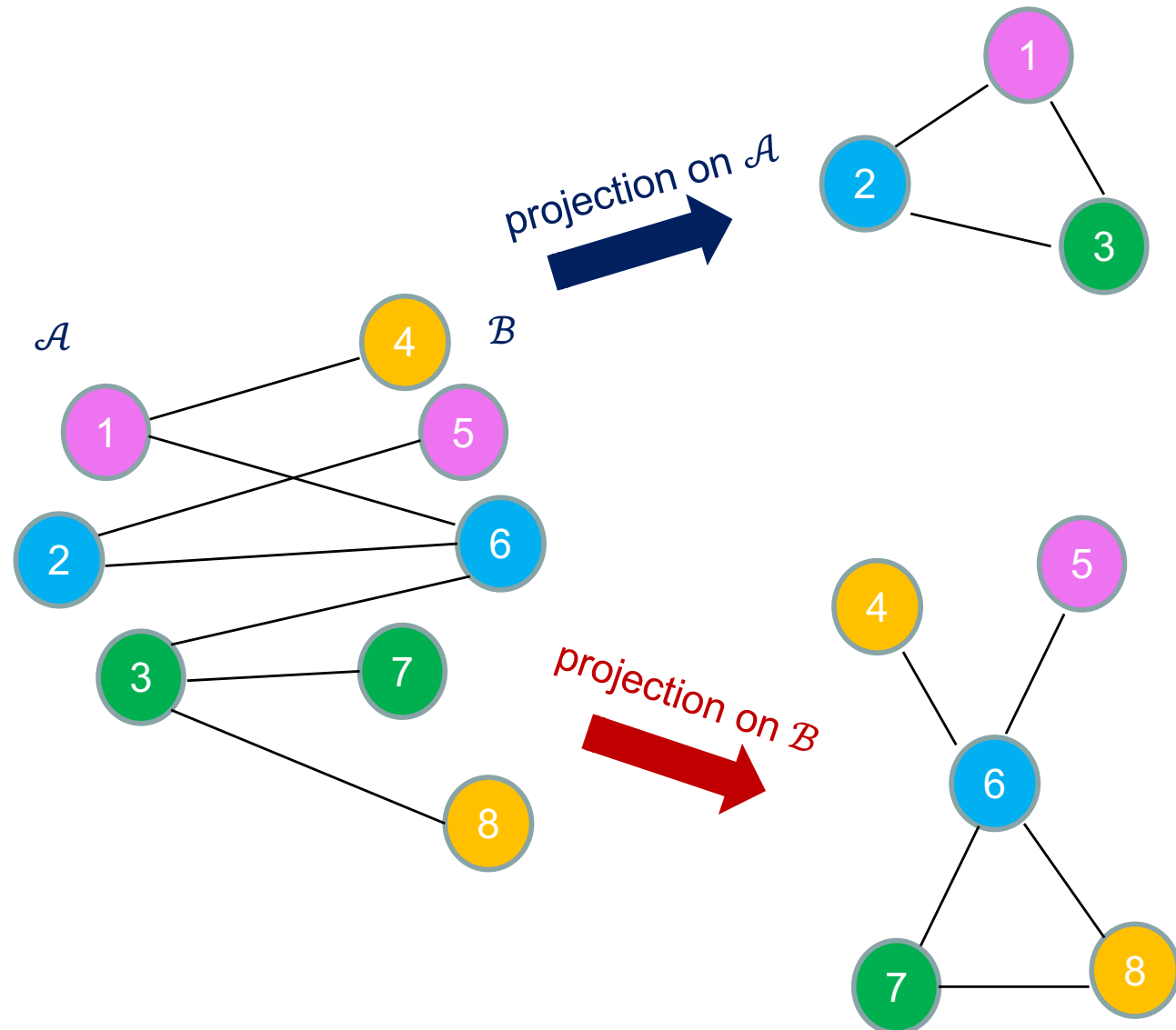
- ❑ Bipartite graphs represent **memberships**/relationships, e.g., groups (\mathcal{A}) to which people (\mathcal{B}) belong

examples: movies/actors, classes/students, conferences/authors

- ❑ We can build separate networks (**projections**) for \mathcal{A} and \mathcal{B} (sometimes this is useful)

in the **movies/actors** example being linked can be interpreted in two ways: “**actors in the same movie**” (projection on \mathcal{B}), or “**movies sharing the same actor**” (projection on \mathcal{A})

Abstract example



Nodes are linked
if they have a
common
neighbour in \mathcal{B}

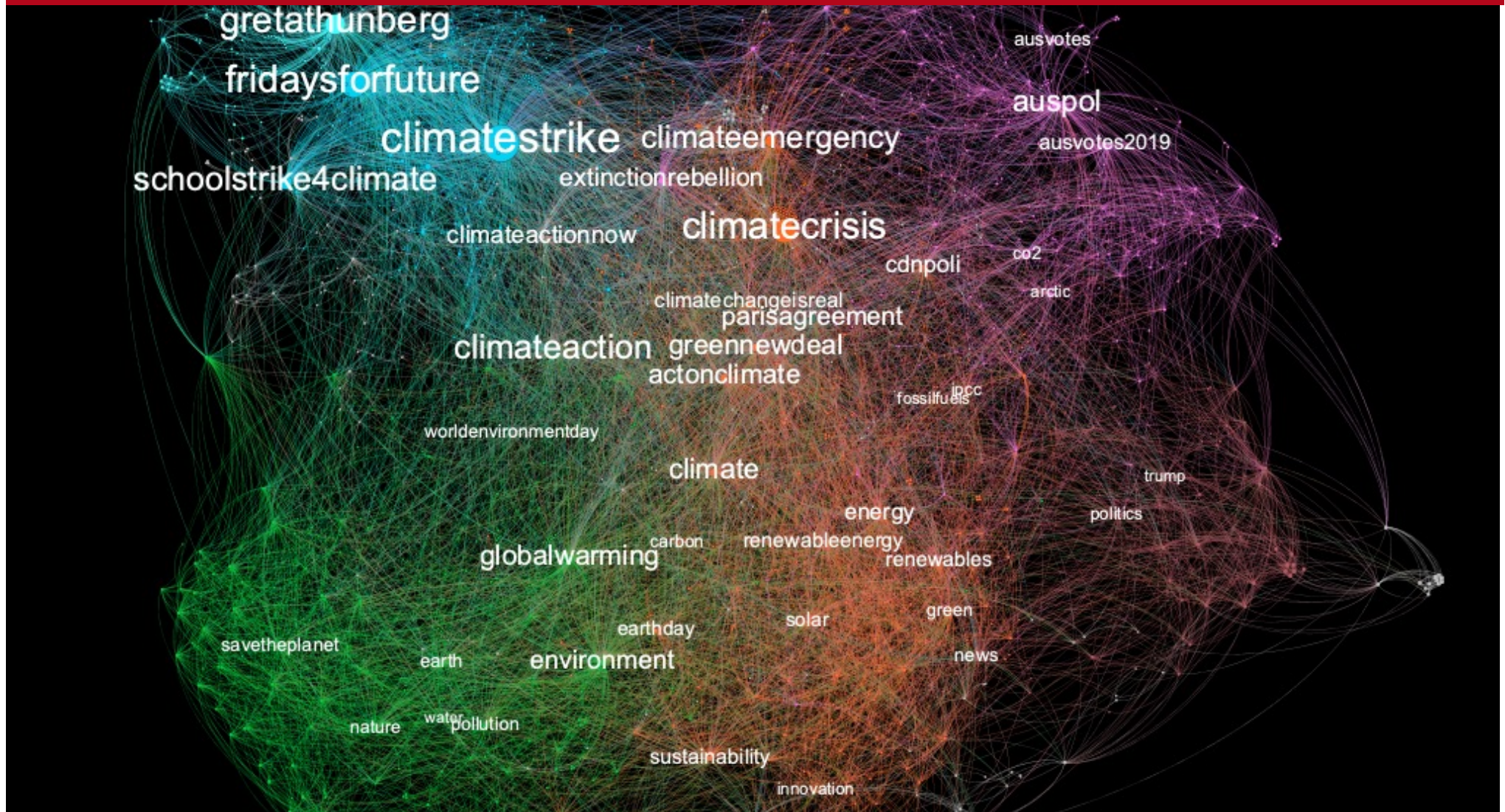
PS: we say that
nodes i and j have a
common neighbour k
if both i and j are
connected to k

Nodes are linked
if they have a
common
neighbour in \mathcal{A}



Projection on a semantic network

#hashtags that appear in the same tweet are linked





- ❑ (un)Directed graphs
- ❑ Weighted and signed graphs
- ❑ Adjacency matrix & edge list
- ❑ Distances
- ❑ Giant component, isolates, bridges
- ❑ Bipartite graphs & projections

Degree centrality

a first approach to node importance



Centrality

From Wikipedia, the free encyclopedia

For the statistical concept, see [Central tendency](#).

In [graph theory](#) and [network analysis](#), indicators of **centrality** identify the most important [vertices](#) within a graph.

Applications include identifying the most influential person(s) in a [social network](#), key infrastructure nodes in the [Internet](#) or [urban networks](#), and [super-spreaders](#) of disease. Centrality concepts were first developed in [social network analysis](#), and many of the terms used to measure centrality reflect their [sociological](#) origin.^[1] They should not be confused with [node influence metrics](#), which seek to quantify the influence of every node in the network.



[Degree centrality](#) [\[edit \]](#)

Main article: [Degree \(graph theory\)](#)

[PageRank centrality](#) [\[edit \]](#)

Main article: [PageRank](#)

[Betweenness centrality](#) [\[edit \]](#)

Main article: [Betweenness centrality](#)

[Eigenvector centrality](#) [\[edit \]](#)

Main article: [Eigenvector centrality](#)

[Closeness centrality](#) [\[edit \]](#)

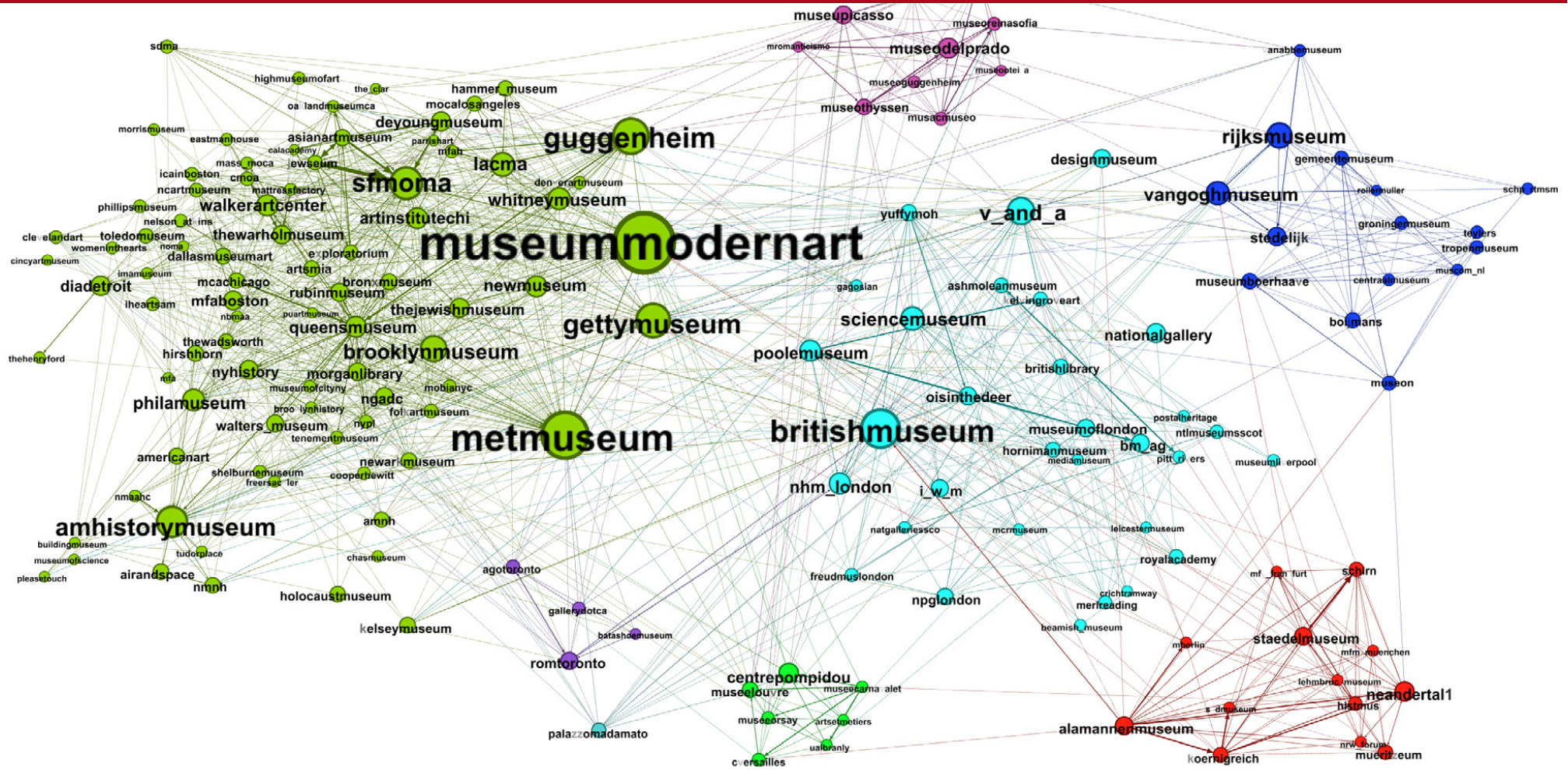
Main article: [Closeness centrality](#)



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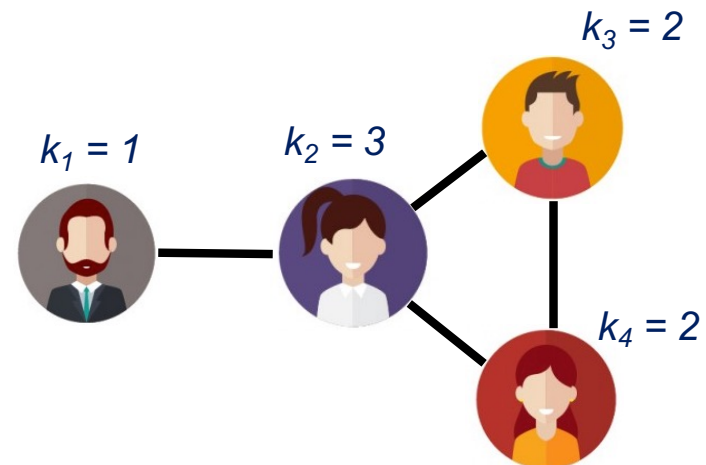
An example of node centrality

museums network



□ The **degree** k_i of node i in an **undirected** networks is

the # of links i has to other nodes, or
the # of nodes i is linked to

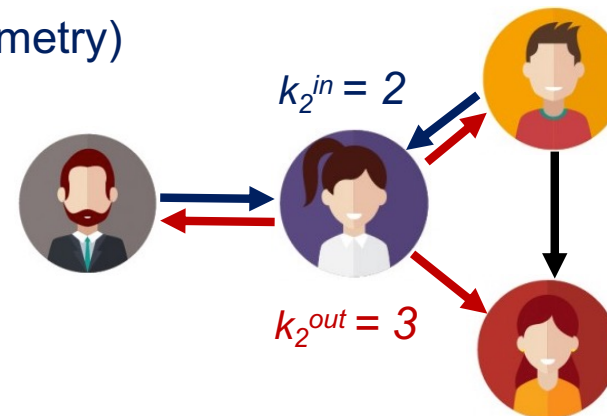


The **average** degree is

$$\langle k \rangle = \sum_i k_i / N = (1+3+2+2)/4 = 2$$

- For **directed** networks we distinguish between
in-degree k_i^{in} = # of entering links
out-degree k_i^{out} = # of exiting links

(undirected: $k_i^{in} = k_i^{out}$ due to the symmetry)



The **average** degree is

$$\begin{aligned} \langle k \rangle &= \sum k_i^{out} / N = (1+3+2+0)/4 \\ &= \sum k_i^{in} / N = (1+2+1+2)/4 \\ &= 3/2 \end{aligned}$$

- ❑ A social-capital measure of **cohesion**
- ❑ In-degree = importance as an **Authority**
- ❑ Out-degree = importance as a **Hub**

In www:

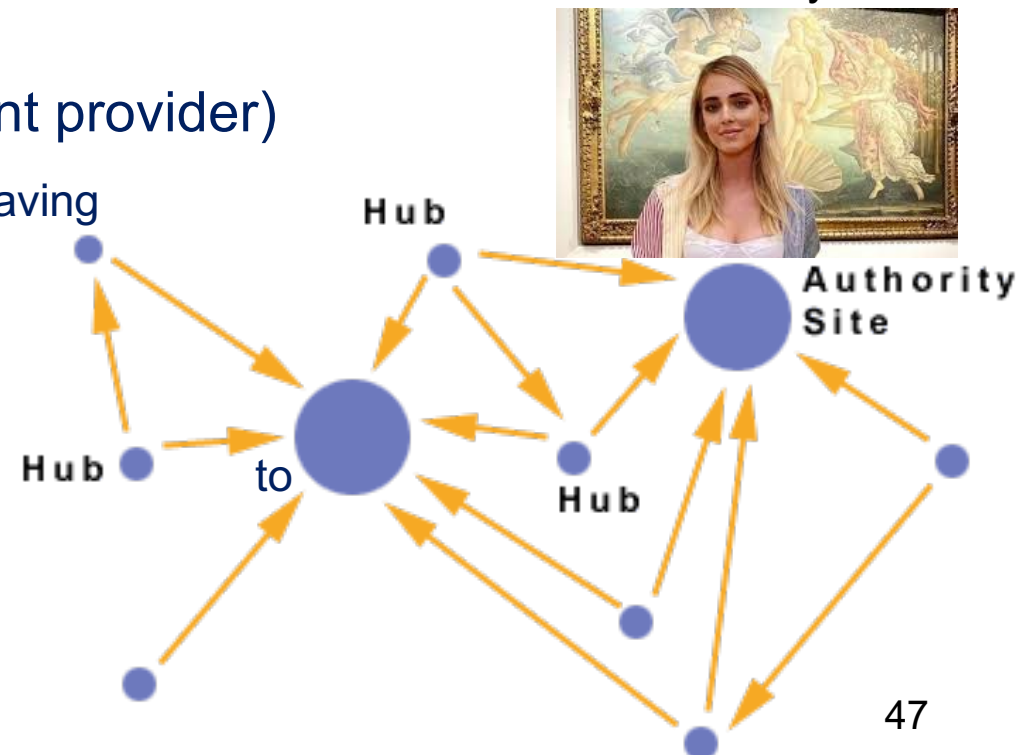
- ❑ **Authorities** (quality as a content provider)

nodes that contain useful information, or having a high number of edges pointing to them (e.g., course homepages)

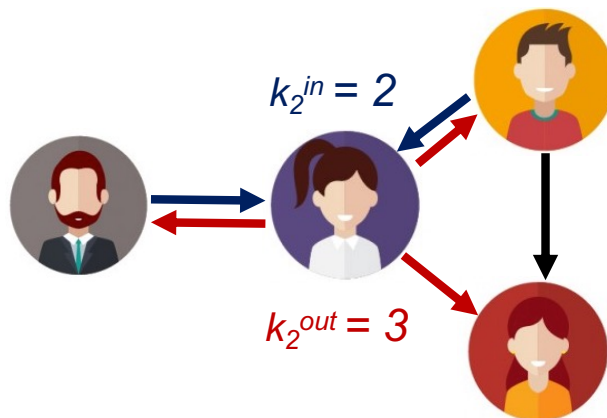
- ❑ **Hubs** (quality as an expert)

trustworthy nodes, or nodes that link many authorities (e.g., course bulletin)

an influencer:
authority or hub?



- The in (out) degree can be obtained by **summing** the adjacency matrix over rows (columns)



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

$k_2^{in} = 2$

$k_2^{out} = 3$



Real networks are sparse

- The maximum degree is $N-1$
- In real networks $\langle k \rangle \ll N-1$

NETWORK	N	L	$\langle k \rangle$
Internet	192,244	609,066	6.34
WWW	325,729	1,497,134	4.60
Mobile Phone Calls	36,595	91,826	2.51
Email	57,194	103,731	1.81
Science Collaboration	23,133	93,439	8.08
Actor Network	702,388	29,397,908	83.71
Citation Network	449,673	4,689,479	10.43

Visualizing degree centrality

how to get useful insights on centrality



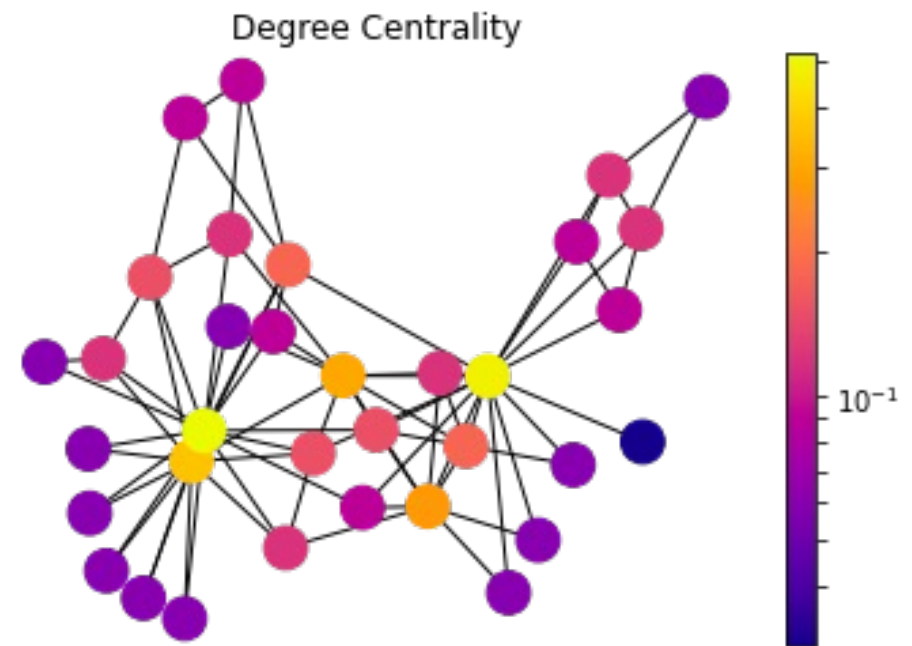
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Graphical representations of degree centrality

by size



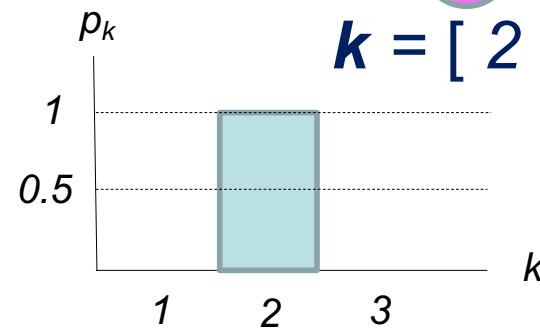
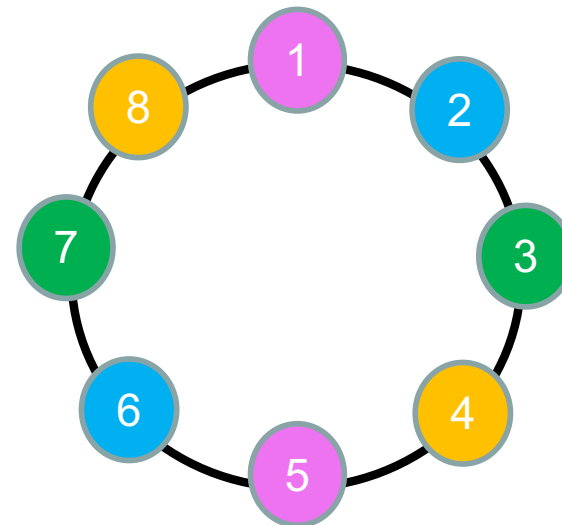
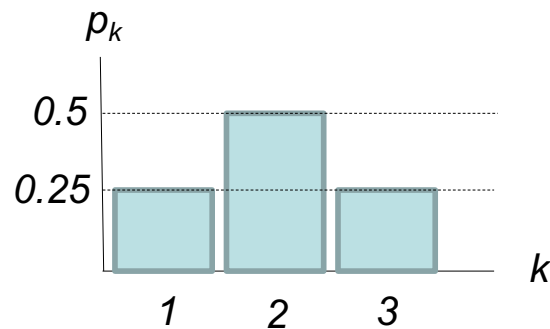
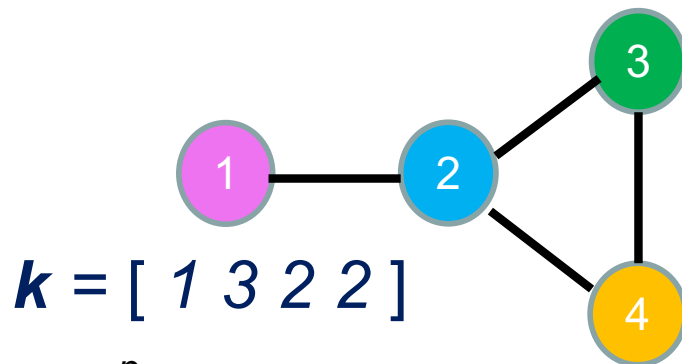
by colour



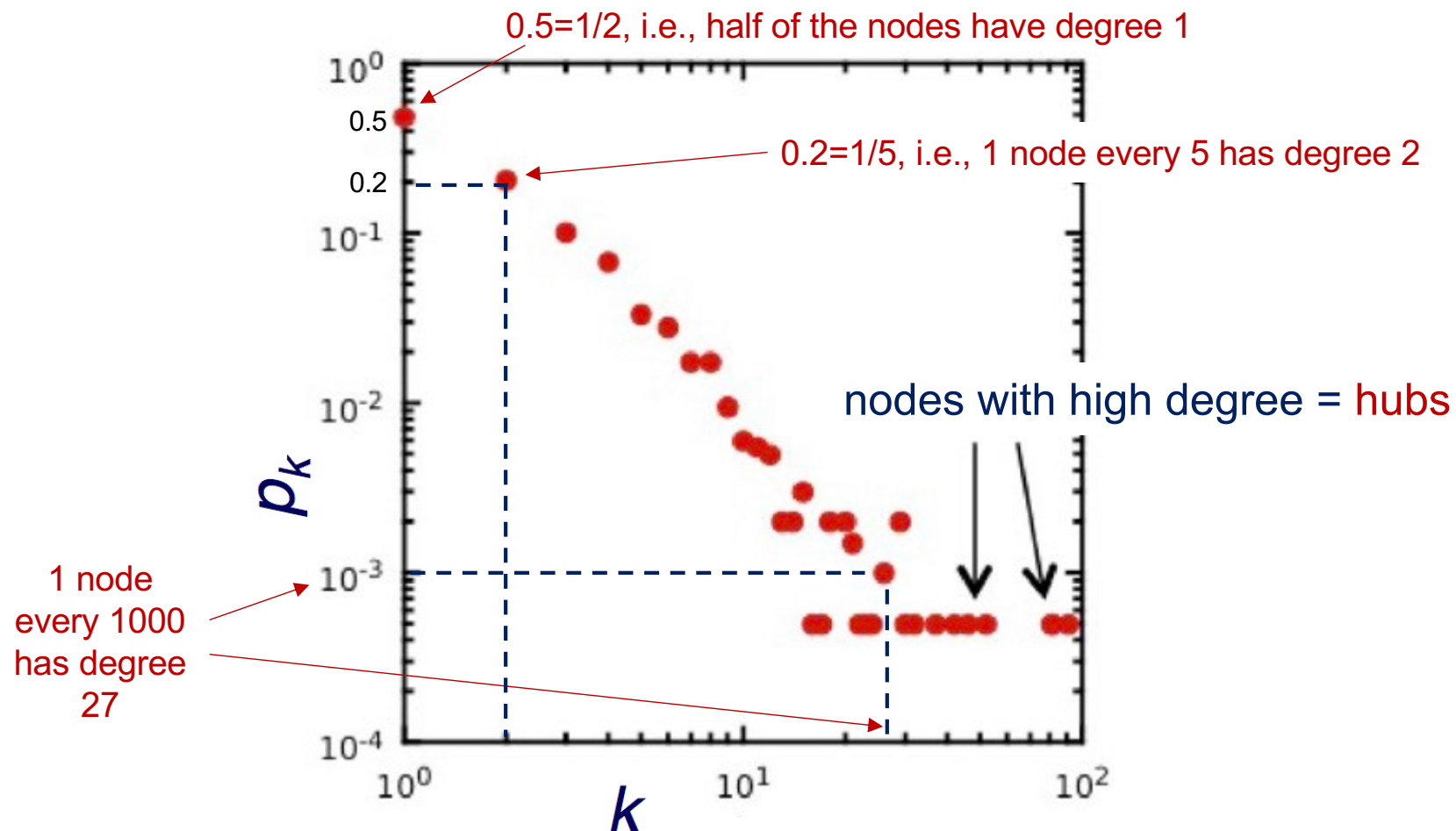


Degree distribution

- ✓ a probability distribution p_k
- ✓ p_k = the **fraction** of nodes that have degree equal to k
- ✓ p_k = # of nodes with degree k , divided by N



- In real (large) networks, degrees have a large range \rightarrow log representation

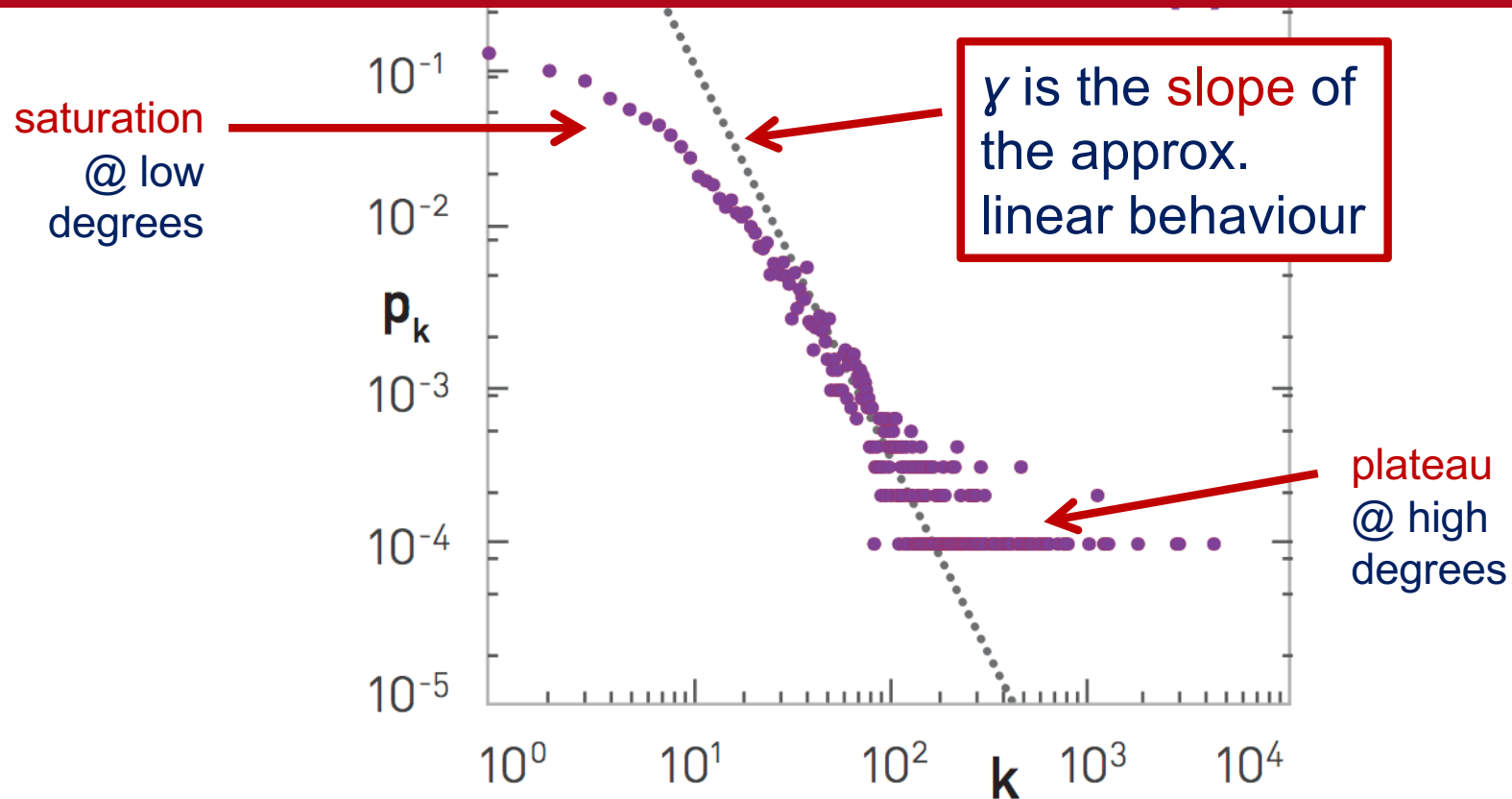


Scale-free networks

those that follow a power-law

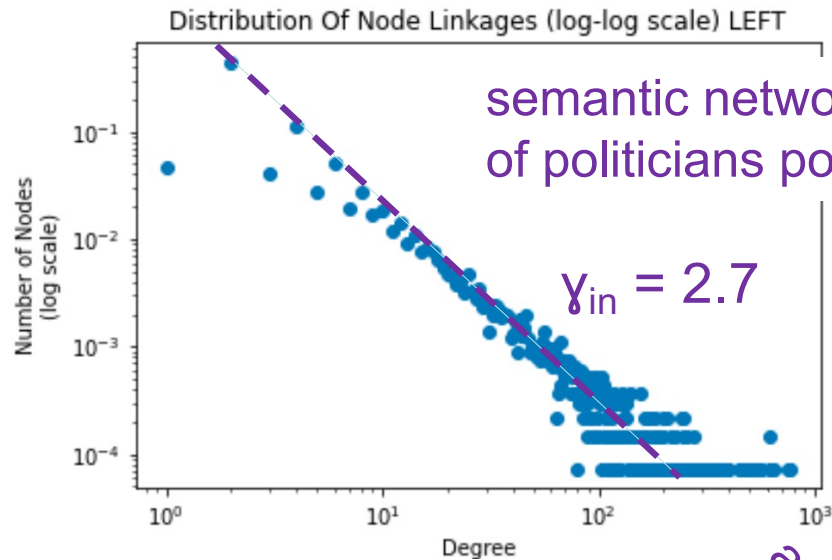


The power law typical of social networks

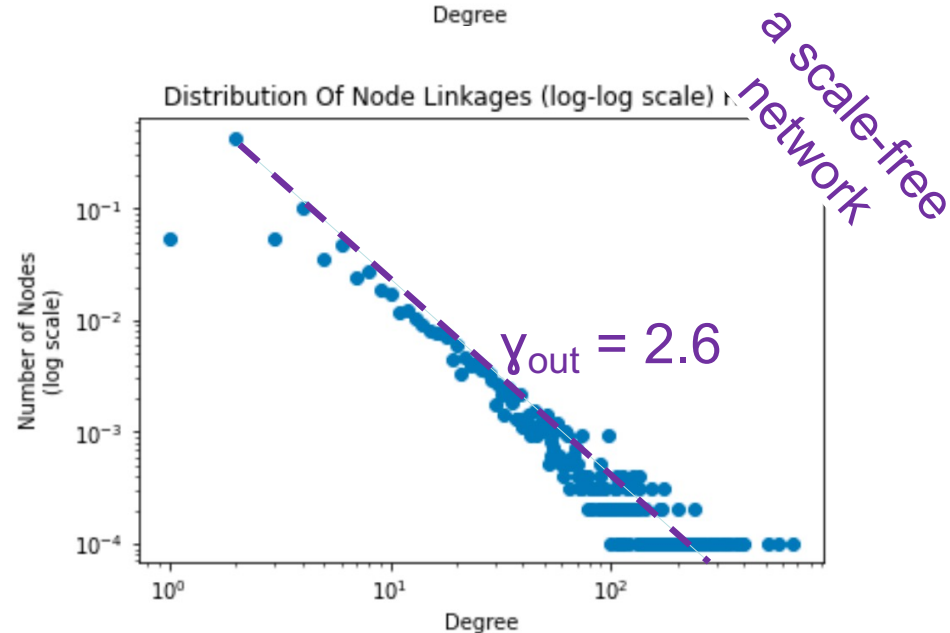
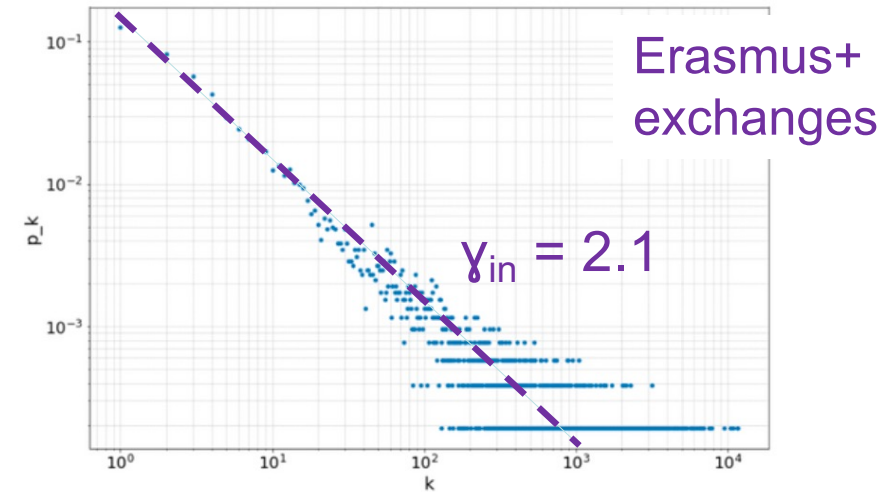


Why the name **power-law**? Because the (approx.) linear behaviour in the log domain ensures

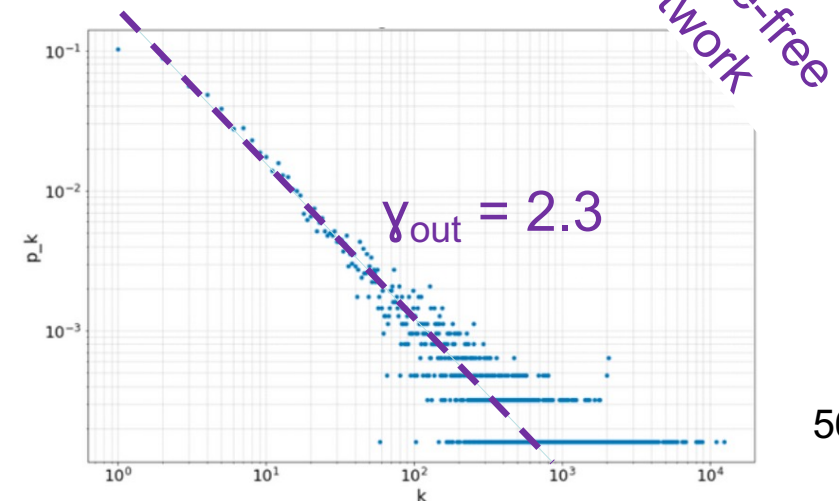
$$\ln(p_k) = c - \gamma \cdot \ln(k) \quad \rightarrow \quad p_k = C k^{-\gamma}$$



In Degrees Distribution



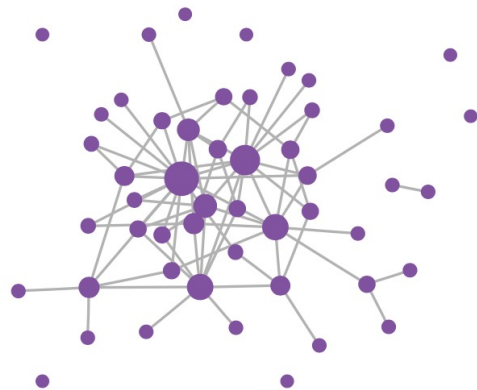
Out Degrees Distribution





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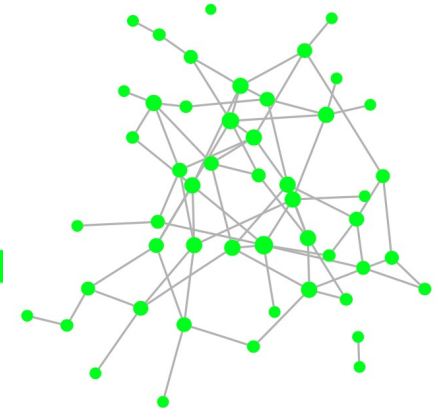
The ultra-small-world of scale-free networks



Ultra small world
large hubs

SCALE-FREE
REGIME

Small world
hubs not
significantly large



RANDOM
REGIME

Indistinguishable
from a random network

WWW (OUT)
EMAIL (OUT)
ACTOR
WWW (IN)

2



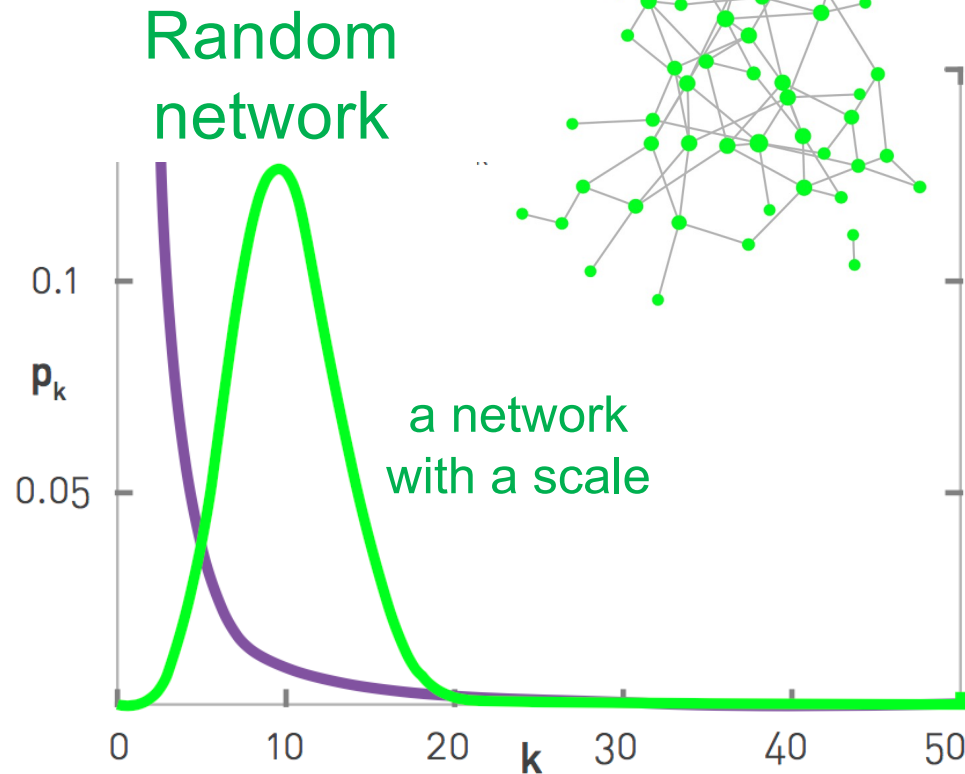
3

CITATION (IN)

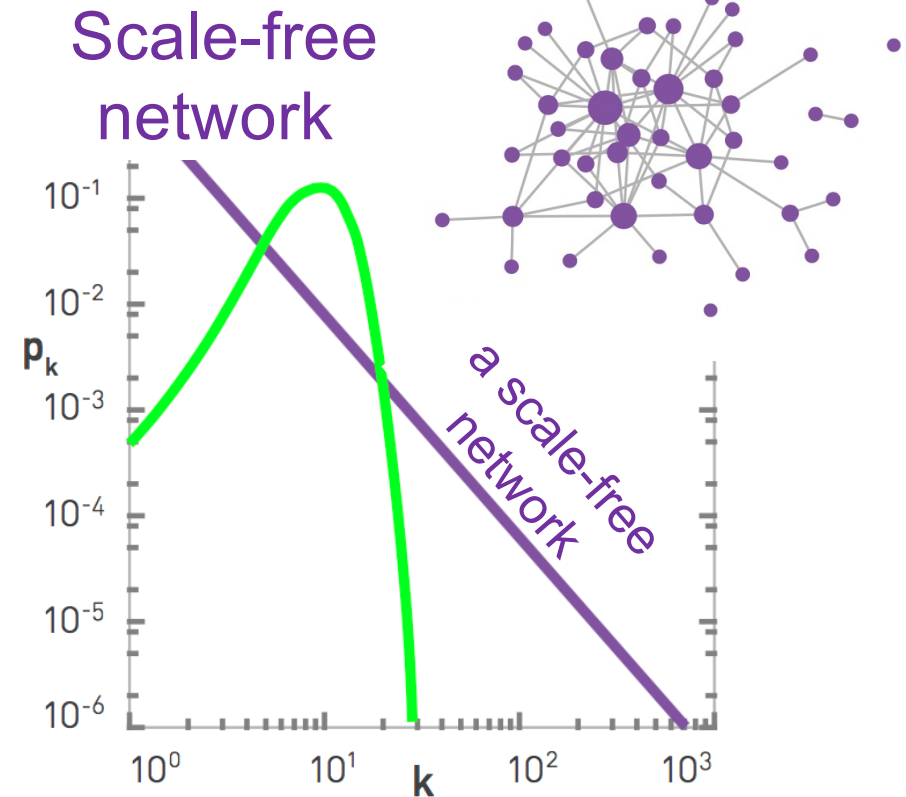
COLLABORATION
INTERNET
EMAIL (IN)

γ , the slope

Scale-free networks versus random networks



- Randomly wired network
- Has smaller hubs
- Needs a linear plot



- Power-law network
- Has big hubs
- Needs a log-log plot



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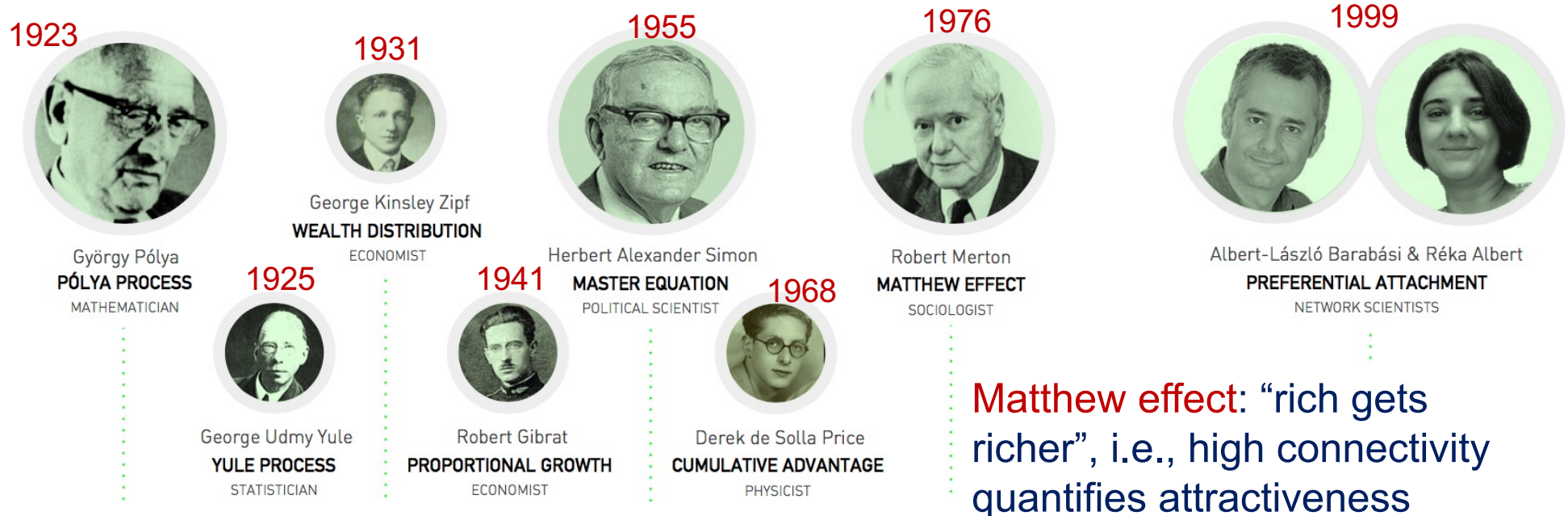
Preferential attachment

a simple concept that (partially) explains the power-law

Nodes link to the **more connected** nodes

e.g., think of www

This idea has a long history





□ Citation network

researchers decide what papers to read and cite by
“**copying**” **references** from papers they have read →
papers with more citations are more likely to be cited

□ Social network

the more acquaintances an individual has, the higher
the chance of getting new friends, i.e., we “**copy**” the
friends of friends → difficult to get friends if you have
none

□ Semantic network

does the model apply here?



❑ There is an innate ability of a node to **attract** links
just a quality assessment of the individual

❑ Otherwise oldest nodes would have an inherent advantage and cannot be defeated (*first mover's advantage*), which is in contrast with intuition and evidence

e.g., Altavista [1990] → Google [2000] → Facebook [2011] → Instagram [202?]

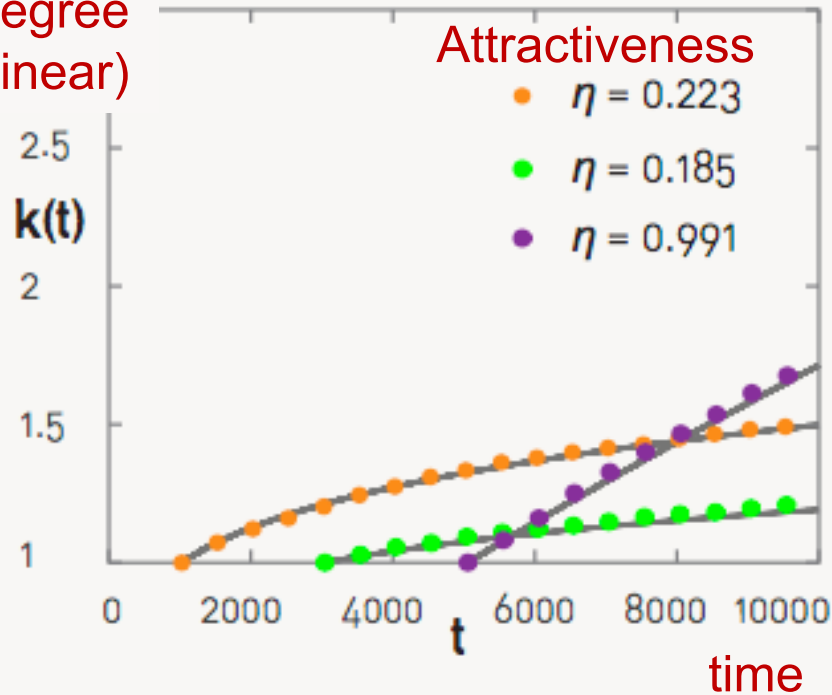
e.g., #parisagreement [2018] → #fridays4future [2019]



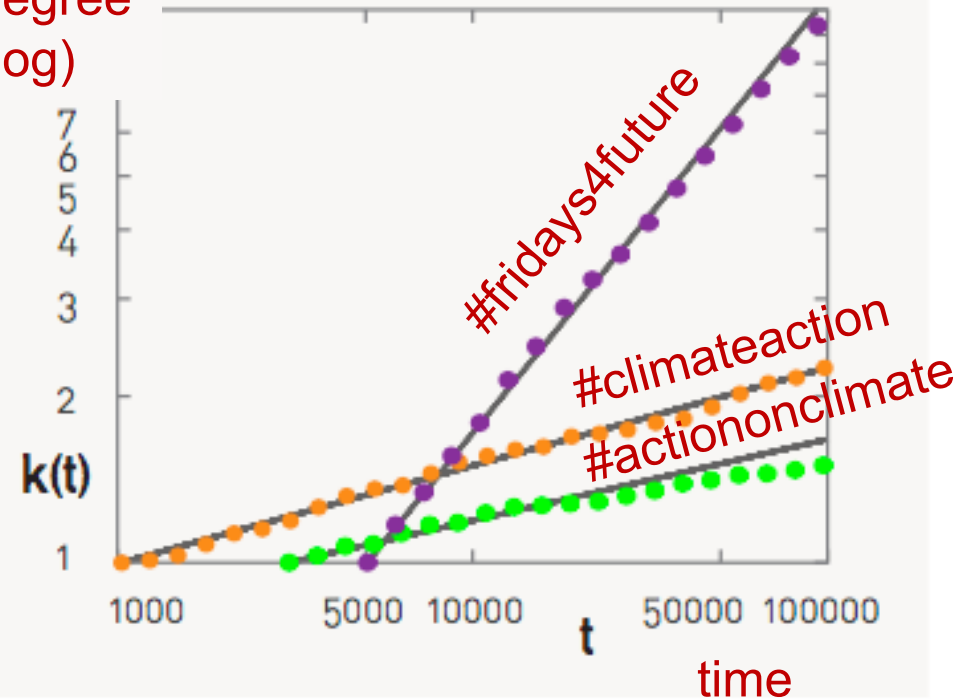
Attractiveness

a visual example

node
degree
(linear)



node
degree
(log)



η_i can be measured by data scientists !



- ☐ Degree, degree distribution, loglog plot
- ☐ Authorities and hubs
- ☐ Power law, scale-free networks
- ☐ Slope, Ultra-small-world regime
- ☐ Preferential attachment
- ☐ Attractiveness