

# Social Network Analysis

## #12 Homophily

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# Homophily



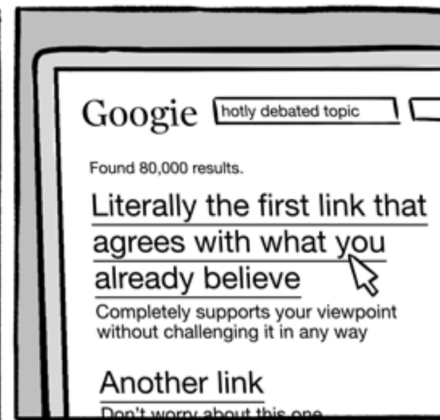
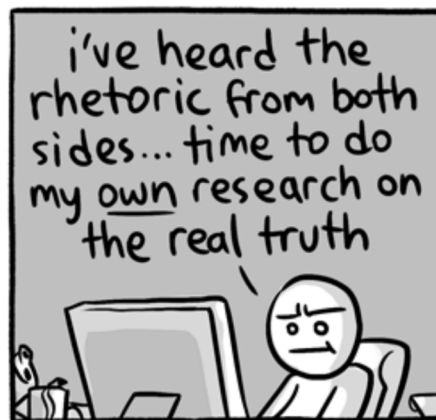
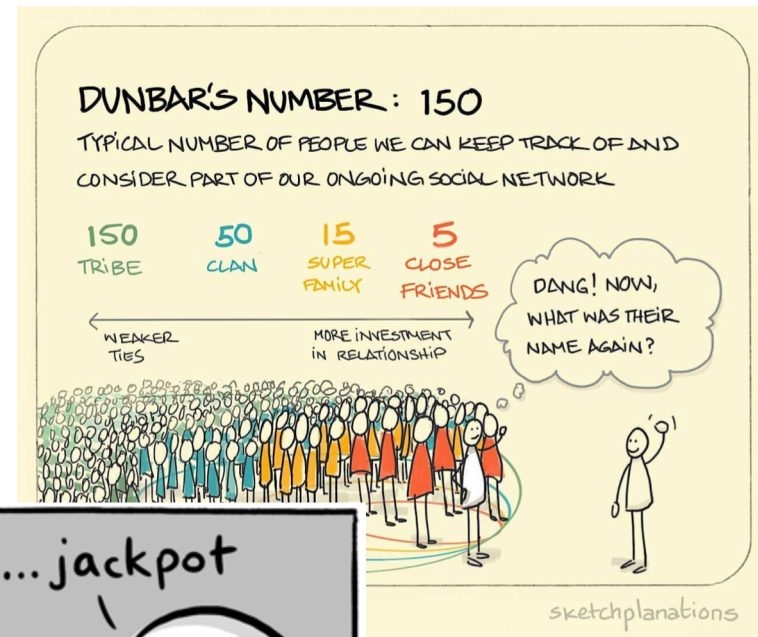
# Humans and social media

We have access to an unlimited amount of information, but we follow a **limited** number of sources

Because we are...

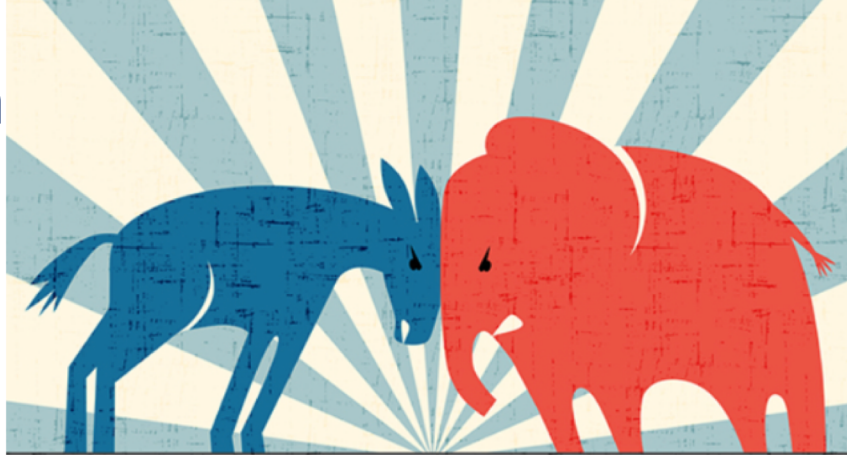
**Bounded**

**Biased**



# Effects on online behaviour

Polarization



Homophily



Selective exposure

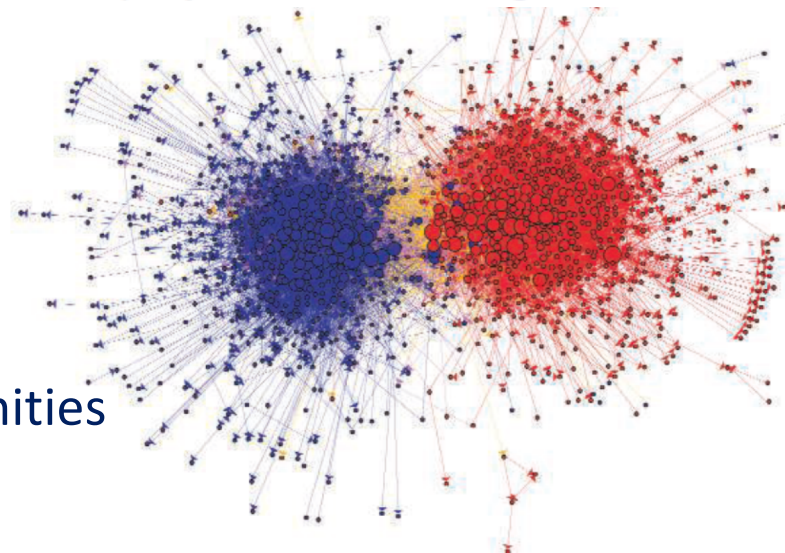


# Homophily

## Homophily

From Wikipedia, the free encyclopedia

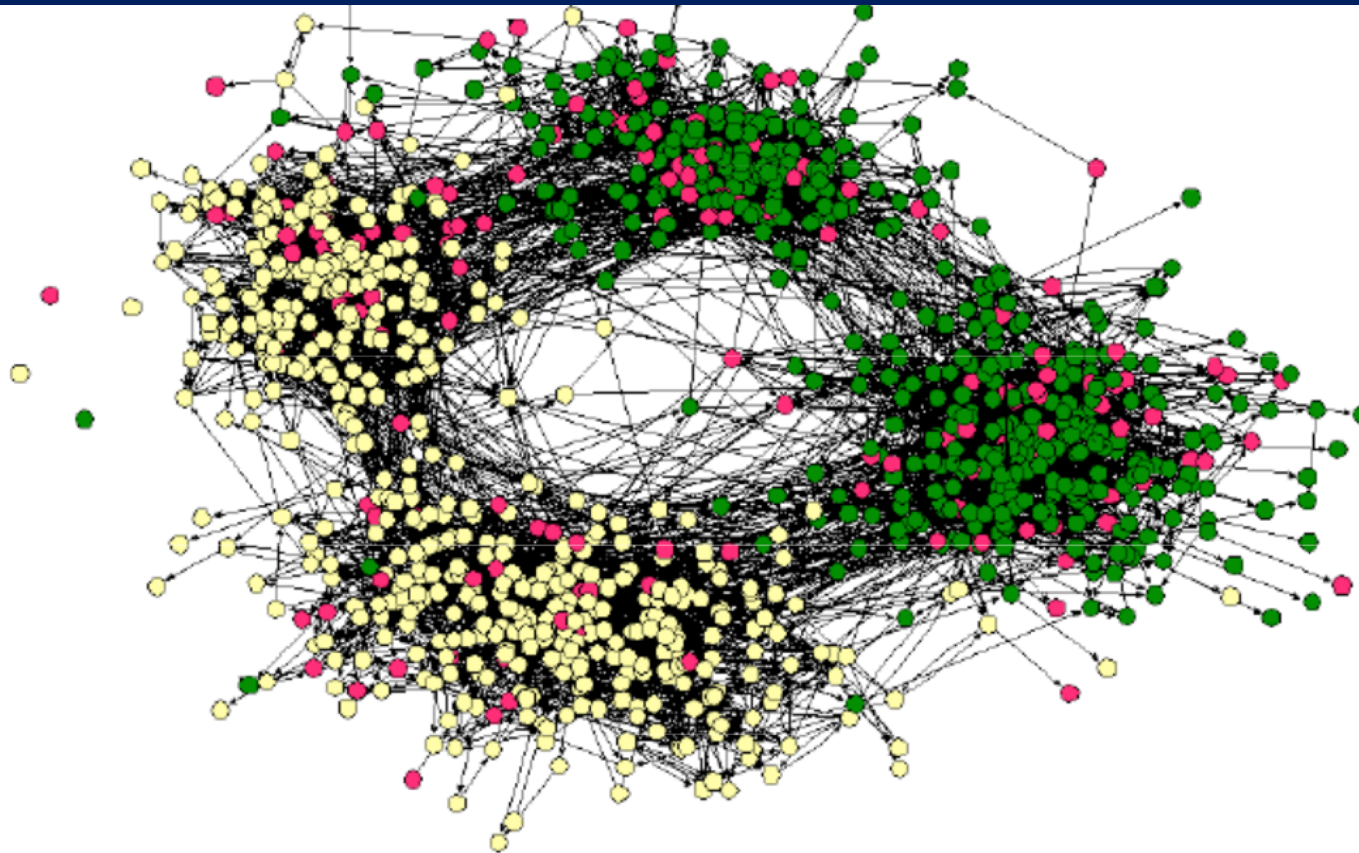
**Homophily** (from *Ancient Greek*: *homou*, 'together' + *philē*, 'friendship, love') is the tendency of individuals to associate and bond with similar others, as in the proverb "birds of a feather flock together."<sup>[1]</sup> The presence of homophily has been discovered in a vast array of network studies: over 100 studies have observed homophily in some form or another, and they establish that similarity is associated with connection.<sup>[2]</sup> The categories on which homophily occurs include **age**, **gender**, **class**, and organizational role.



Political blog communities



# Homophily at action: racial segregation

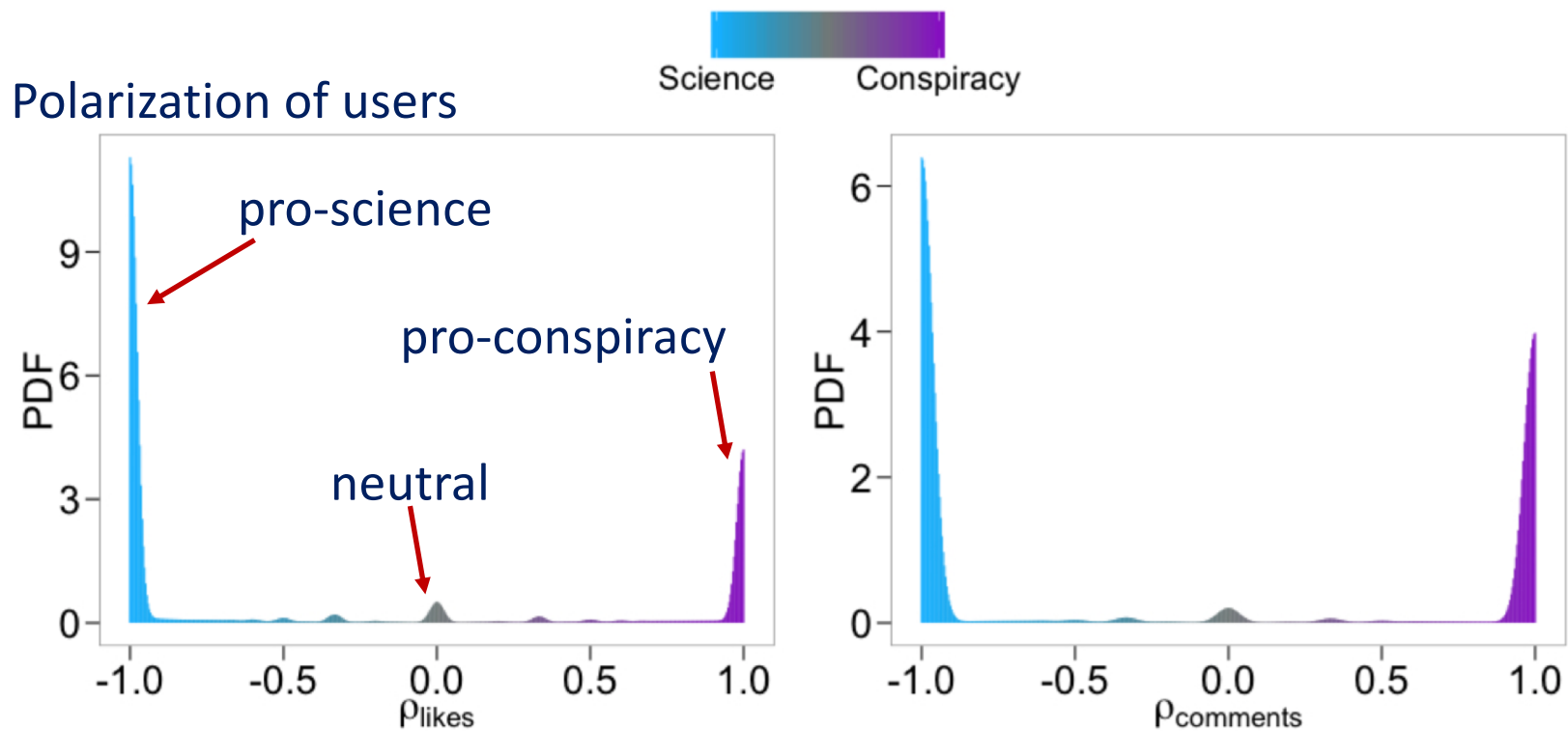


(Easley and Kleinberg, 2010)

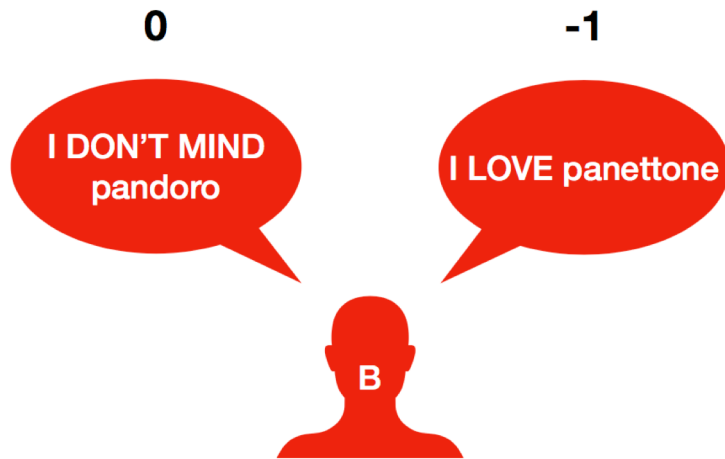
Figure 4.1: Homophily can produce a division of a social network into densely-connected, homogeneous parts that are weakly connected to each other. In this social network from a town's middle school and high school, two such divisions in the network are apparent: one based on race (with students of different races drawn as differently colored circles), and the other based on friendships in the middle and high schools respectively [304].

# Polarization

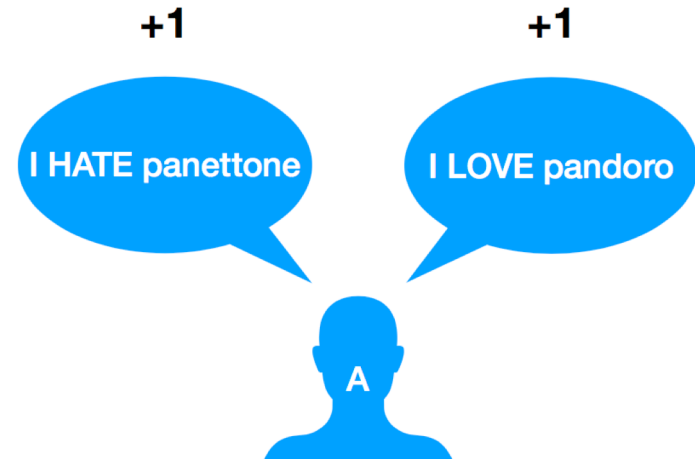
The extreme **segregation** of users into homogeneous communities based on their opinion on a controversial topic



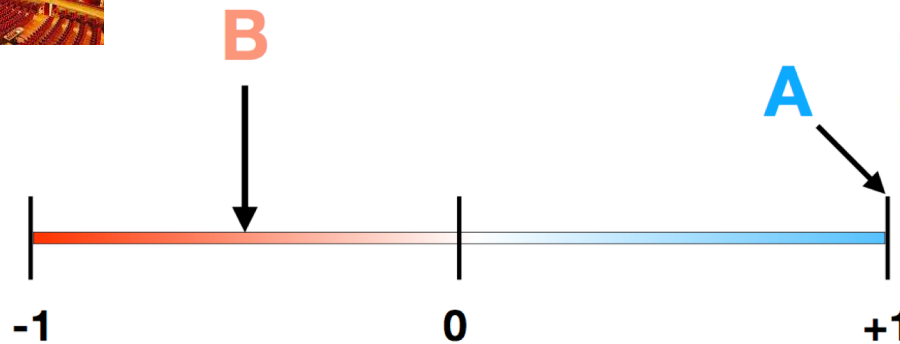
# Users' leaning



B leaning= -0.5



A leaning= +1

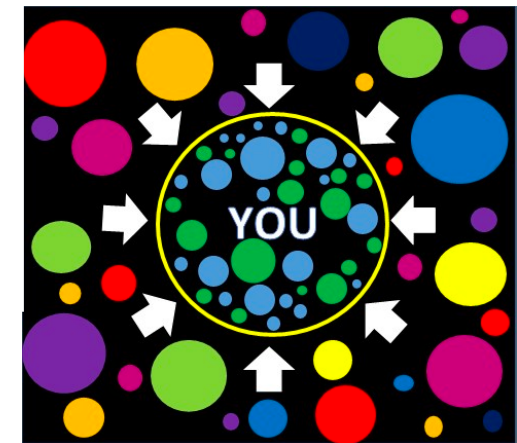


# Eco chambers

## Echo chamber (media)

From Wikipedia, the free encyclopedia

In **news media**, an **echo chamber** is a metaphorical description of a situation in which **beliefs** are amplified or reinforced by communication and repetition inside a closed system and insulates them from rebuttal.<sup>[1]</sup> By visiting an "echo chamber", people are able to seek out information that reinforces their existing views, potentially as an unconscious exercise of **confirmation bias**. This may increase social and **political polarization** and **extremism**.<sup>[2]</sup> The term is a metaphor based on the acoustic **echo chamber**, where sounds **reverberate** in a hollow enclosure. Another emerging term for this echoing and homogenizing effect on the Internet within social communities, such as Facebook, Instagram, Twitter, Reddit, etc; is **cultural tribalism**.<sup>[3]</sup>

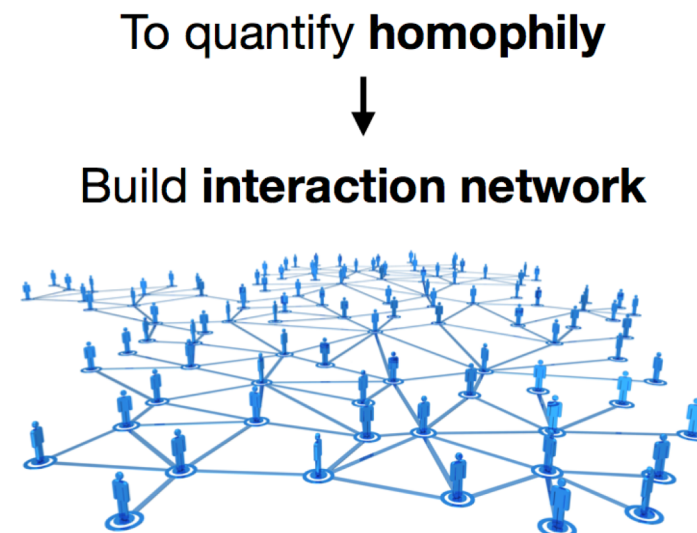
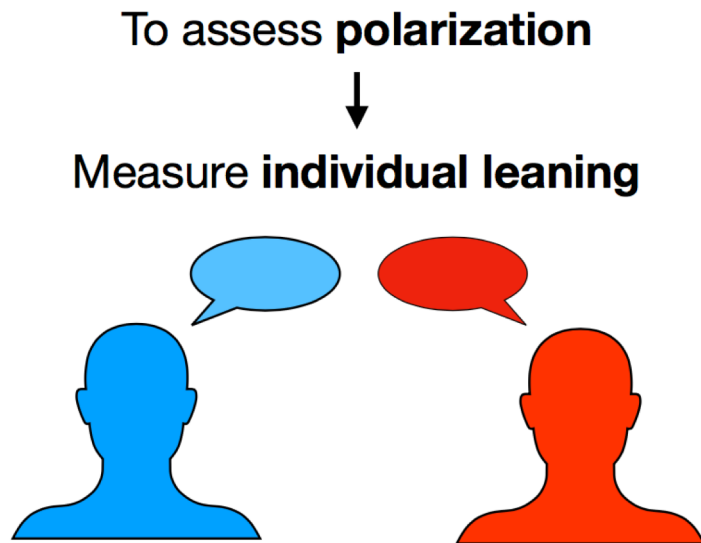


# Definition of echo-chamber

Cinelli, Morales, Galeazzi, Quattrociocchi, Starnini (2020)  
Echo chambers on social media: A comparative analysis  
<https://arxiv.org/pdf/2004.09603.pdf>

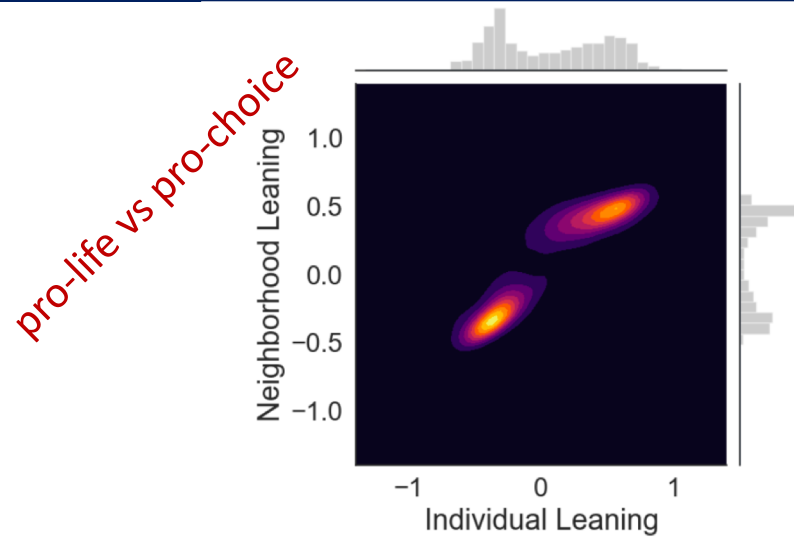
Coexistence of

- ❑ opinion **polarization** with respect to a controversial topic
- ❑ **homophily** in interactions

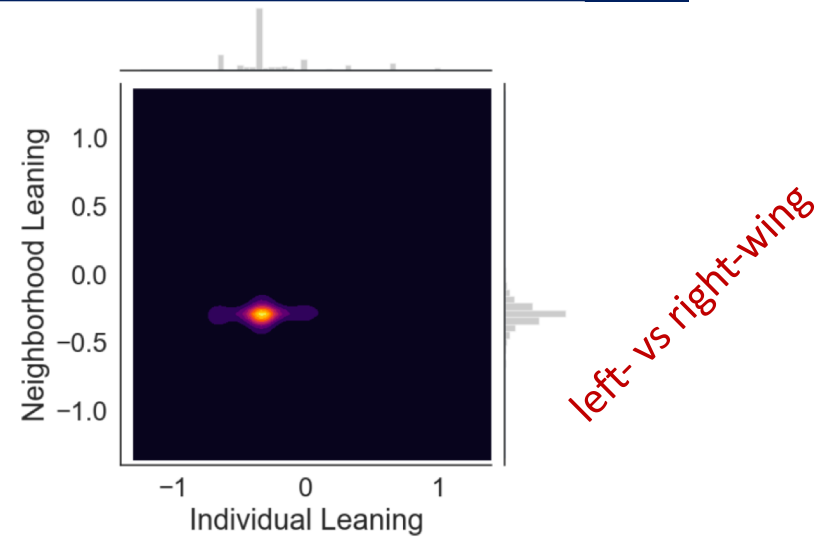




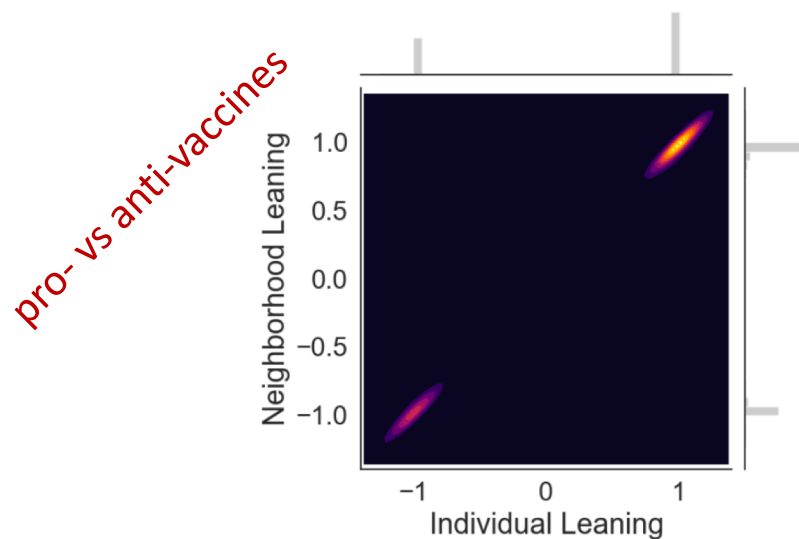
# Echo-chamber effect in social networks



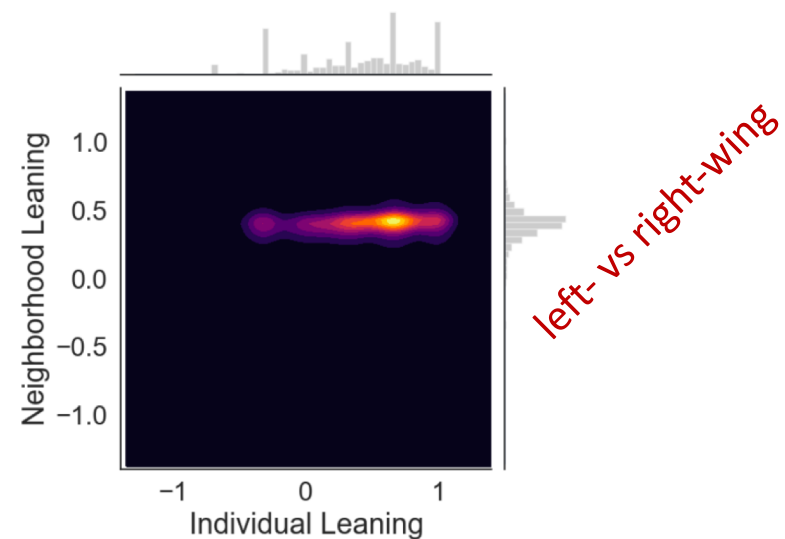
(a) Twitter



(b) Reddit



(c) Facebook



(d) Gab

# Filter bubbles

## Filter bubble

From Wikipedia, the free encyclopedia

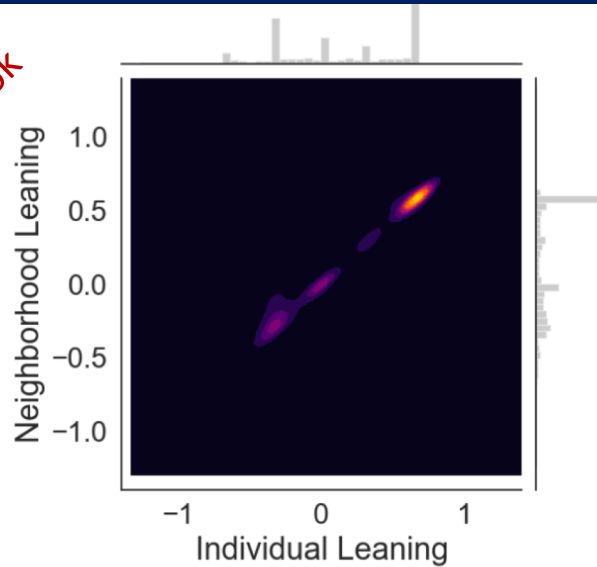
A **filter bubble** – a term coined by internet activist [Eli Pariser](#) – is a state of intellectual isolation<sup>[1]</sup> that allegedly can result from [personalized searches](#) when a website [algorithm](#) selectively guesses what information a user would like to see based on information about the user, such as location, past click-behavior and search history.<sup>[2][3][4]</sup> As a result, users become separated from information that disagrees with their viewpoints, effectively isolating them in their own cultural or ideological bubbles.<sup>[5]</sup> The choices made by these algorithms are not transparent.<sup>[6]</sup>



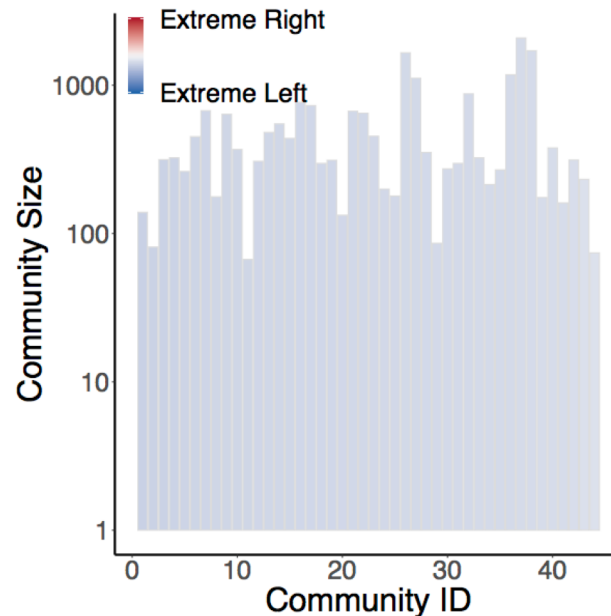
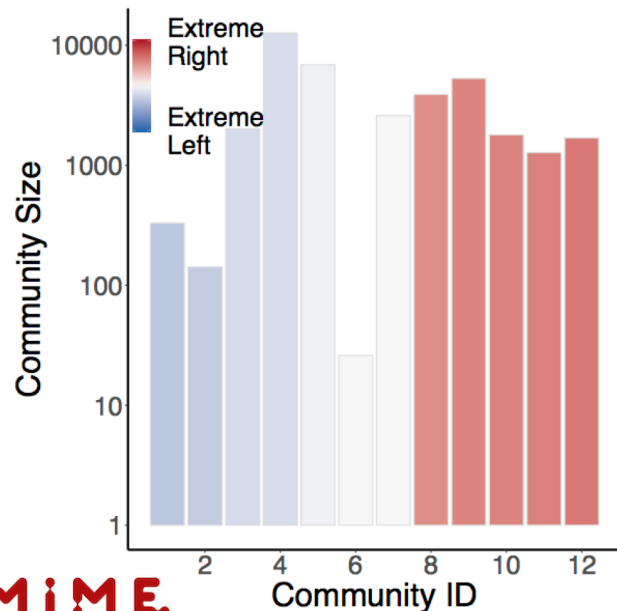
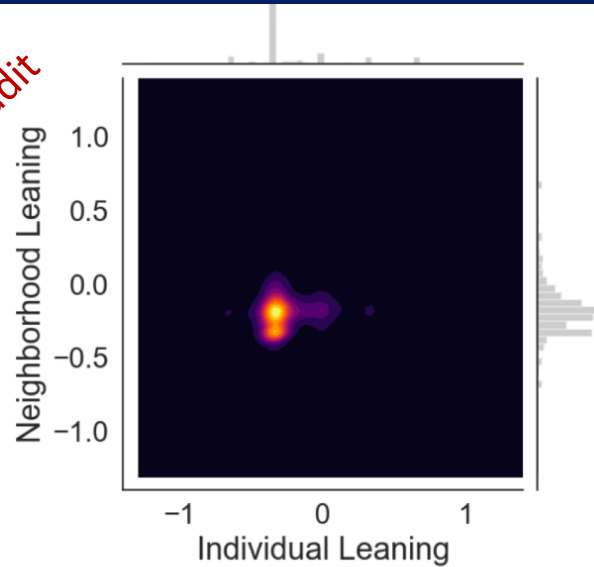
The term was coined by internet activist [Eli Pariser](#) circa 2010

# Political leaning

FaceBook



Reddit



MIME

- ❑ Same Topic: **News**
- ❑ Same leaning assigned to **news sources**
- ❑ Different platforms: Facebook has a strong **social feeding algorithm**, Reddit has not
- ❑ Different characteristics: Facebook shows **segregation** among groups with different leaning, Reddit has one group

# Polarization in pro-life/pro-choice networks

Lejla Dzanko, Giulia Rizzoli, Sanja Milijanovic, Sara Shena, Lara Malin Schwarz  
IP3 2019/20

# Background

Abortion is one of the most controversial topics in social public, political and scientific debates in different disciplines

Often debates result in reforms of the law → USA 2019

Two movements:

- ❑ **Pro-Life**: every human (embryo) has the right to live; abortion is murder → goal to ban it
- ❑ **Pro-Choice**: every woman should have the right to decide what to do with her body on her own → goal to keep abortion safe and legal

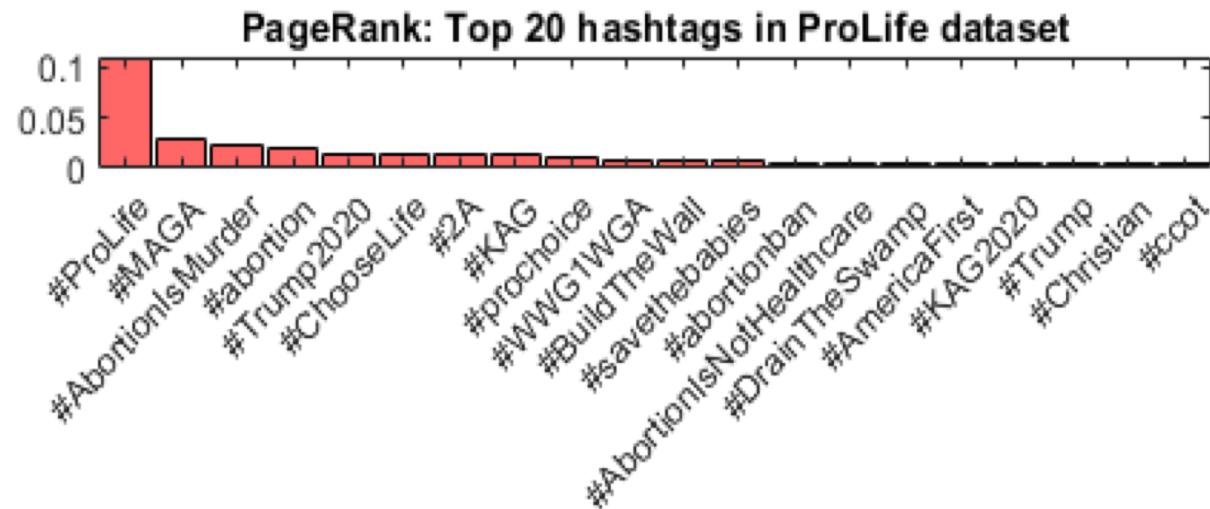
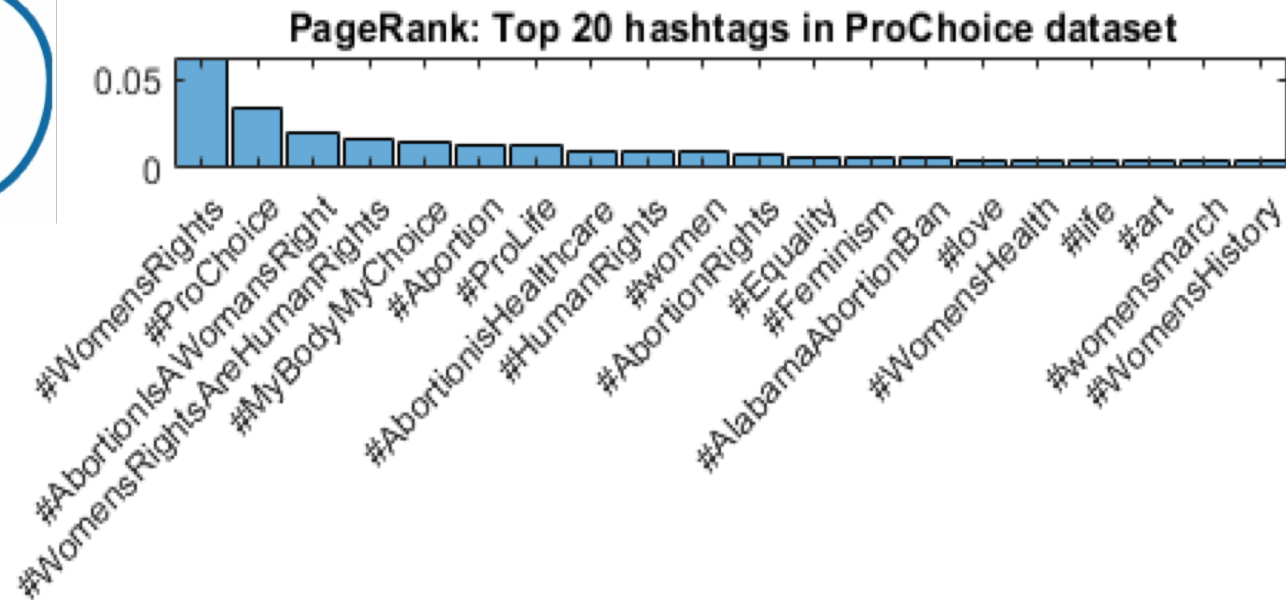


# Data collection

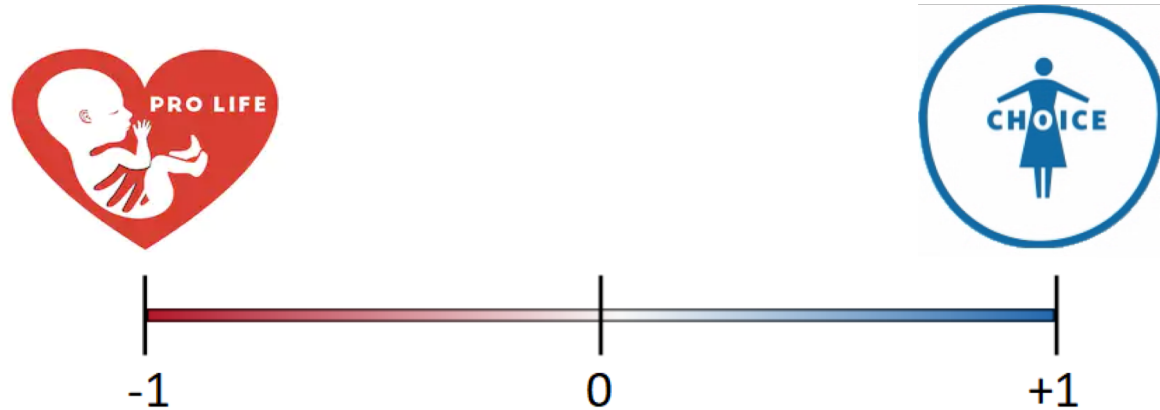


Pro-Choice	Pro-Life
#prochoice #mybodymychoice #abortionishealthcare #abortionisawomansright #abortionrights #abortionismurder #abortionsupportnetwork #proabortion	#prolife #savethebabies #babiesarehuman #chooselife #abortionban #abortionismurder #lovethemboth #whywemarch

# PageRank centrality



# Hashtag polarization



- Measure of hashtags centralities among the two dataset
- Extract which **opinion** an hashtag holds

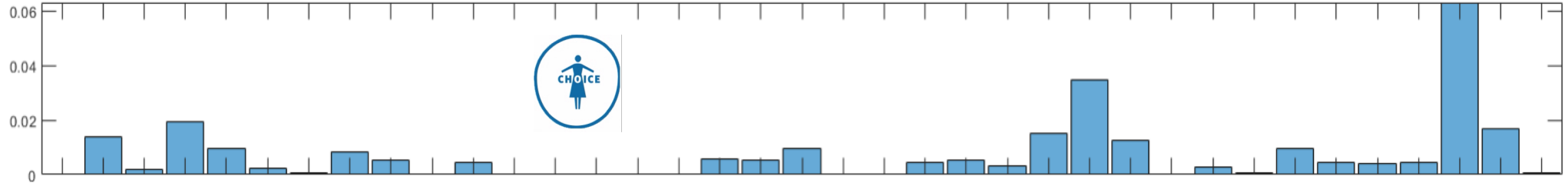
$$P_i = \frac{W_{pc_i} - W_{pl_i}}{W_{pc_i} + W_{pl_i}}$$

← Prestige mapping

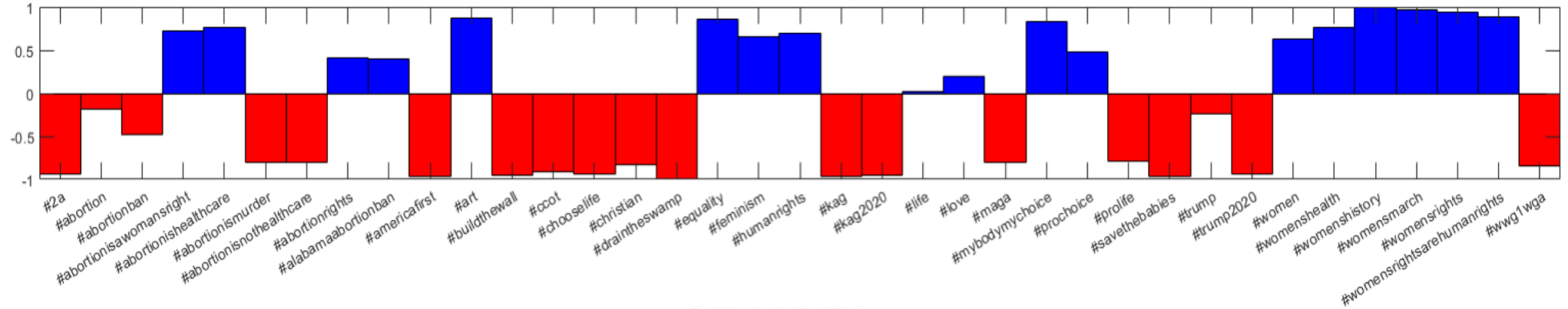


# Hashtag polarization

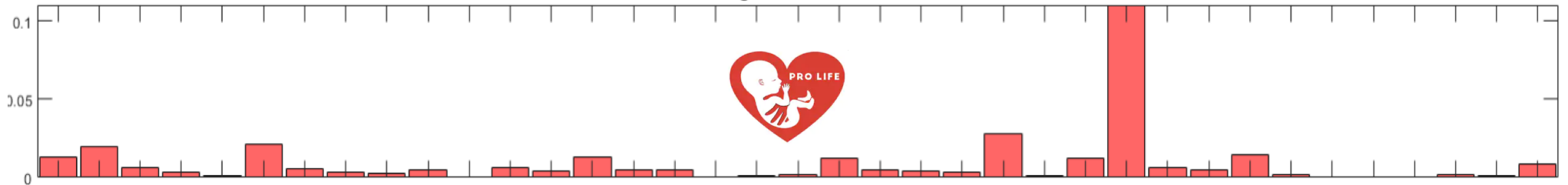
Ranking in the ProChoice dataset



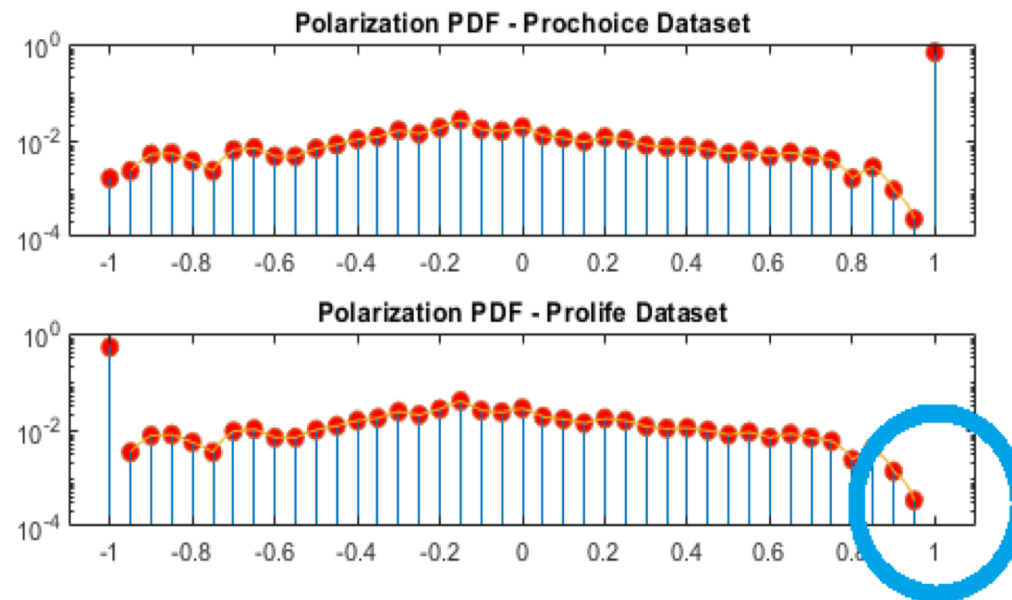
Polarization level



Ranking in the ProLife dataset



# Polarization effects



Absence of a debate?

# Assortativity (degree homophily)

A.L. Barabási, Network science, <http://barabasi.com/networksciencebook>

Ch.7 “Degree correlation”

# Correlation between hubs

- In some networks, hubs frequently **connect** with other hubs

e.g., celebrity dating, actor networks



- In other cases hubs **avoid** connections with other hubs

e.g., metabolic graphs, food webs (predators tend to differentiate their diet)

# Assortativity

- ❑ **Assortative** network: high degree nodes connect with each other avoiding low degree nodes (tend to cliques)
- ❑ **Disassortative** network: opposite trend, hubs tend to avoid each other
- ❑ **Neutral** network: one with random wiring, i.e., aside from the (marginal) degree distribution of nodes, there is no correlation

# Assortativity

(dis)**assortativity** in sociology quantifies homophily in social networks, e.g., effects like:

- Rich people tend to be friends with each other
- People with the same education tend to hang out together

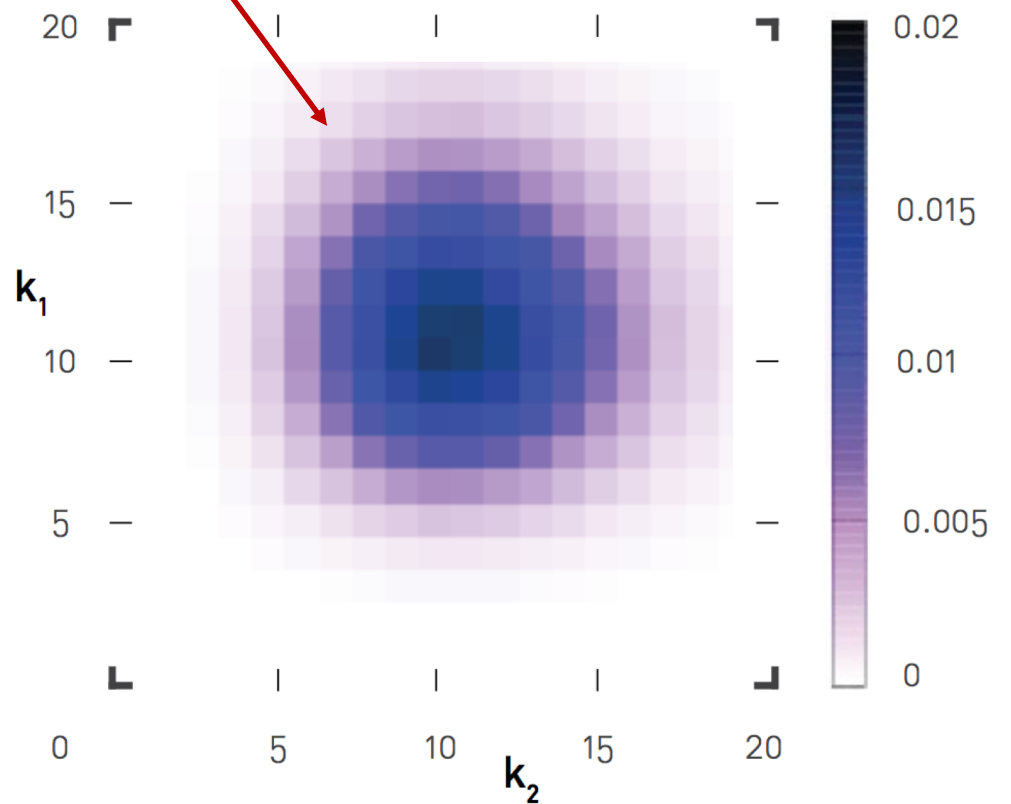
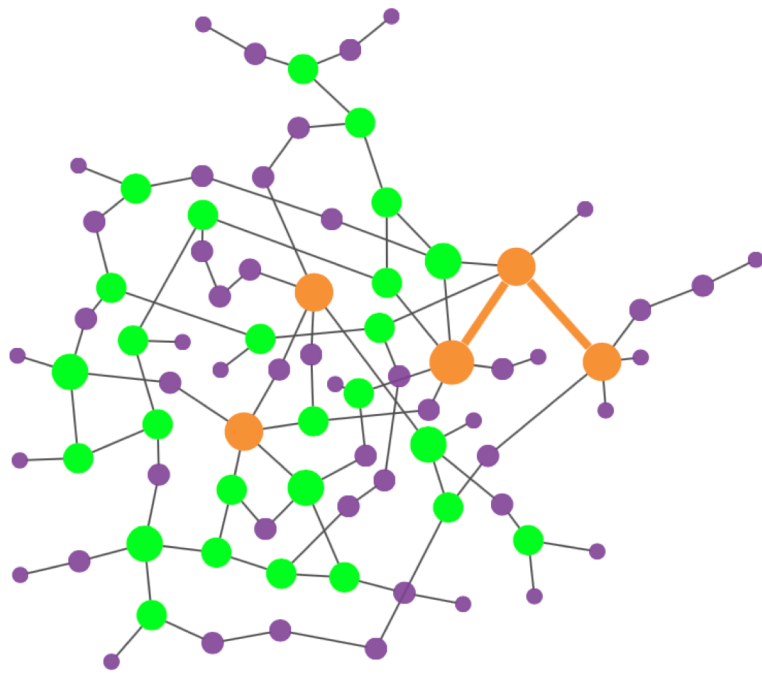
i.e., we expect social networks to be assortative

# Neutral networks

The **degree correlation matrix**  $E_{k_1, k_2}$  is visually centred around the average degree

In the neutral case we expect  $E_{k_1, k_2} = q_{k_1} q_{k_2}$ , i.e., independence

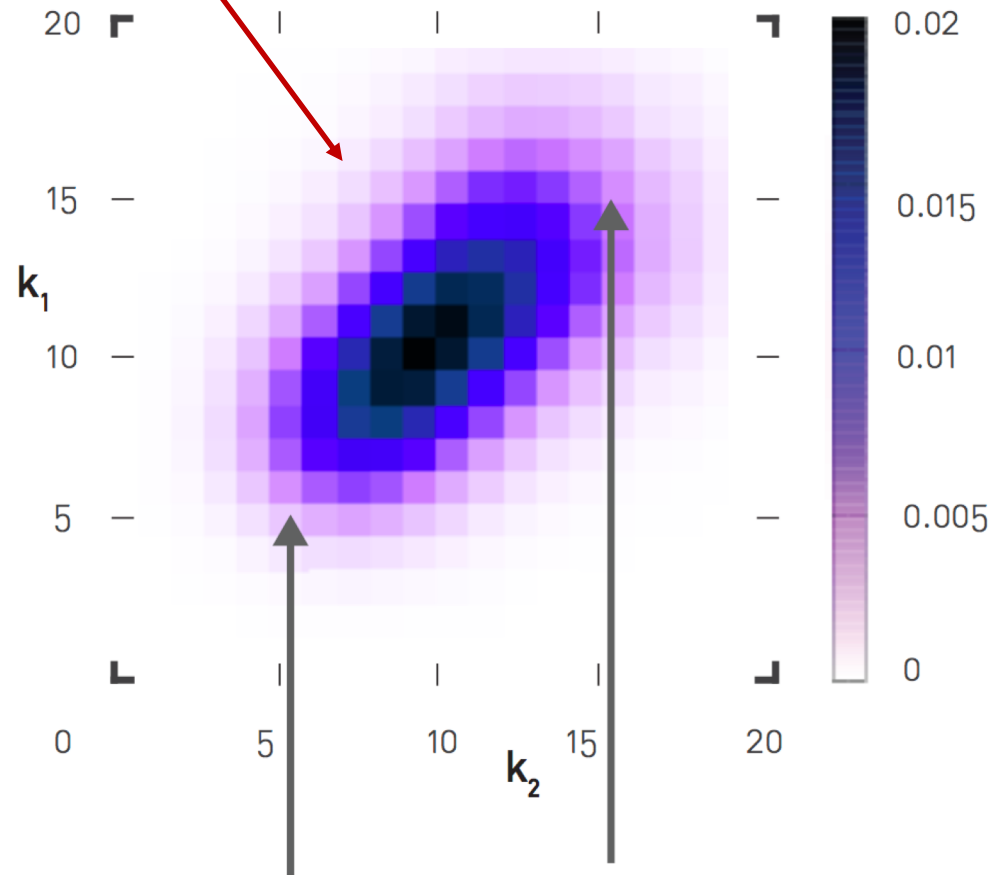
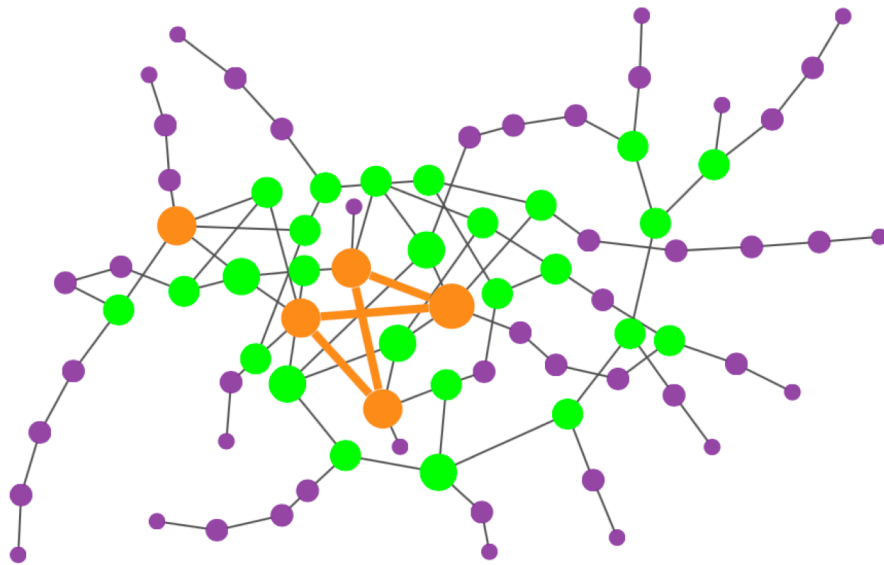
NEUTRAL



# Assortative networks

The degree correlation matrix  $E_{k_1, k_2}$  is turning to the right

ASSORTATIVE

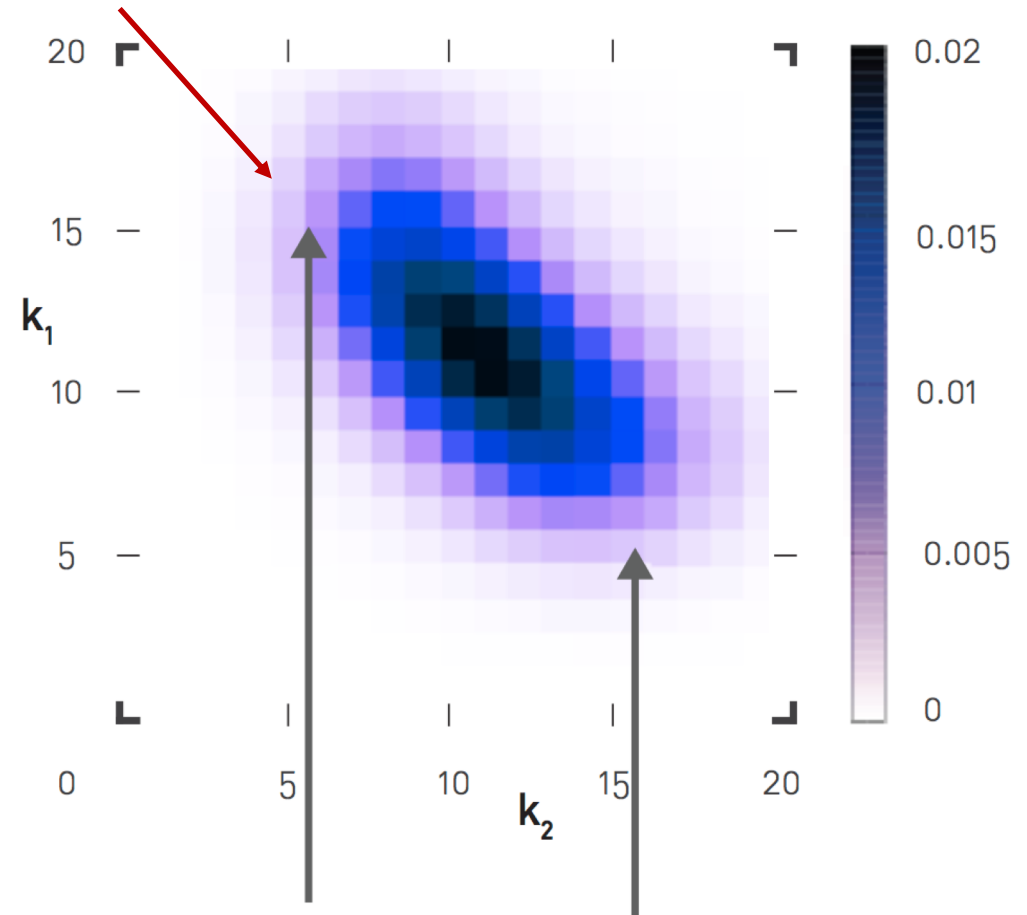
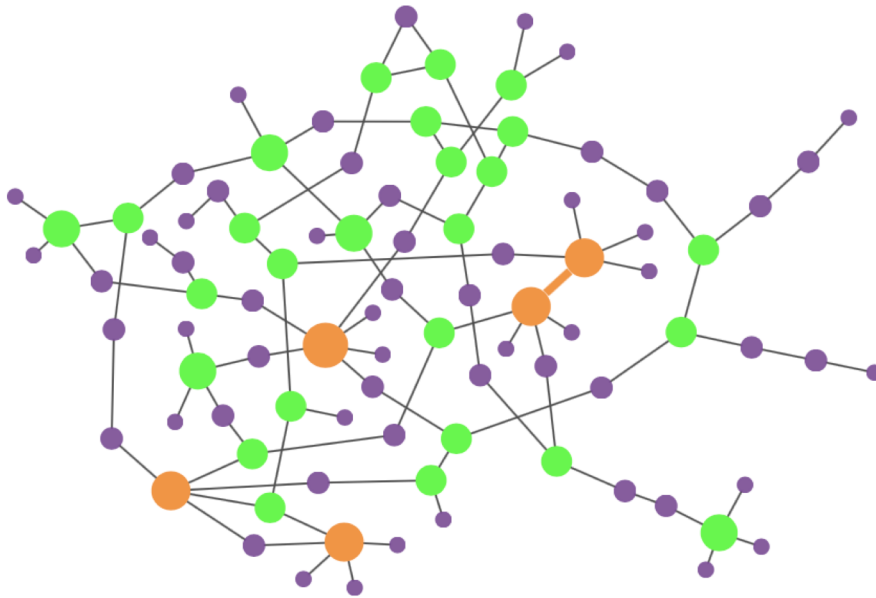




# Disassortative networks

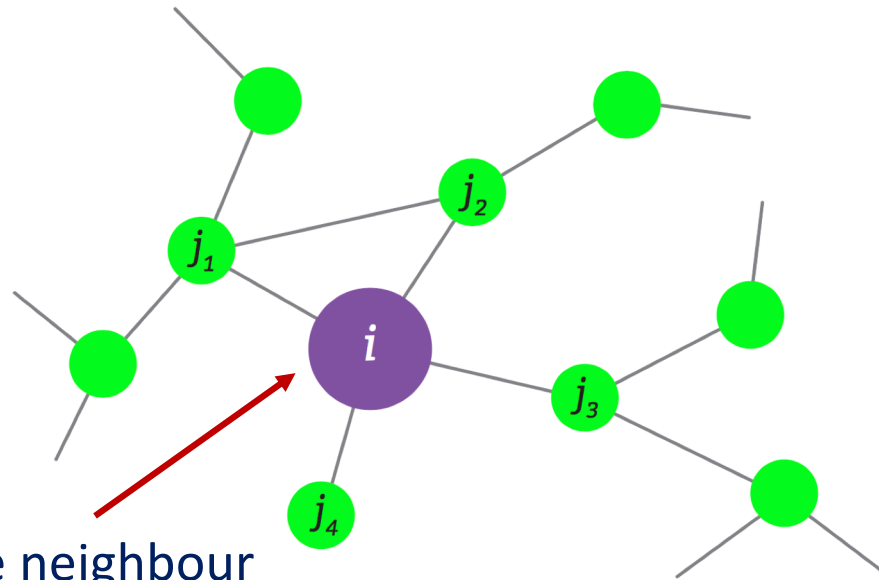
The degree correlation matrix  $E_{k_1, k_2}$  is turning to the left

DISASSORTATIVE



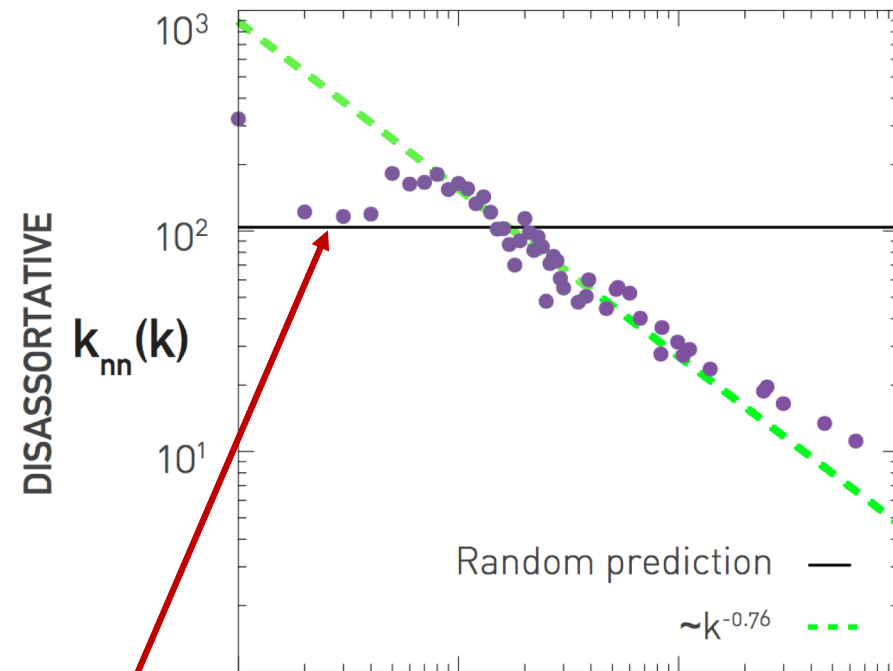
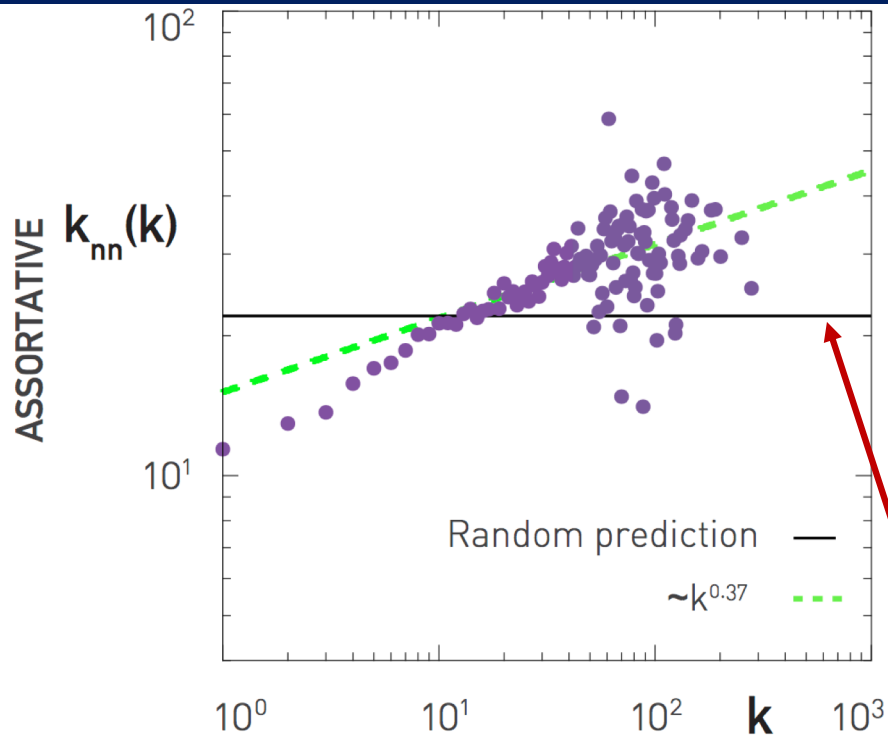
# Nearest neighbour degree

- **Idea** : inspect the degrees of the **neighbouring** nodes (easier than matrices)



average neighbour  
degree of node  $i$  is  
 $\frac{1}{4} (4 + 3 + 1 + 3) = 2.75$

# Examples



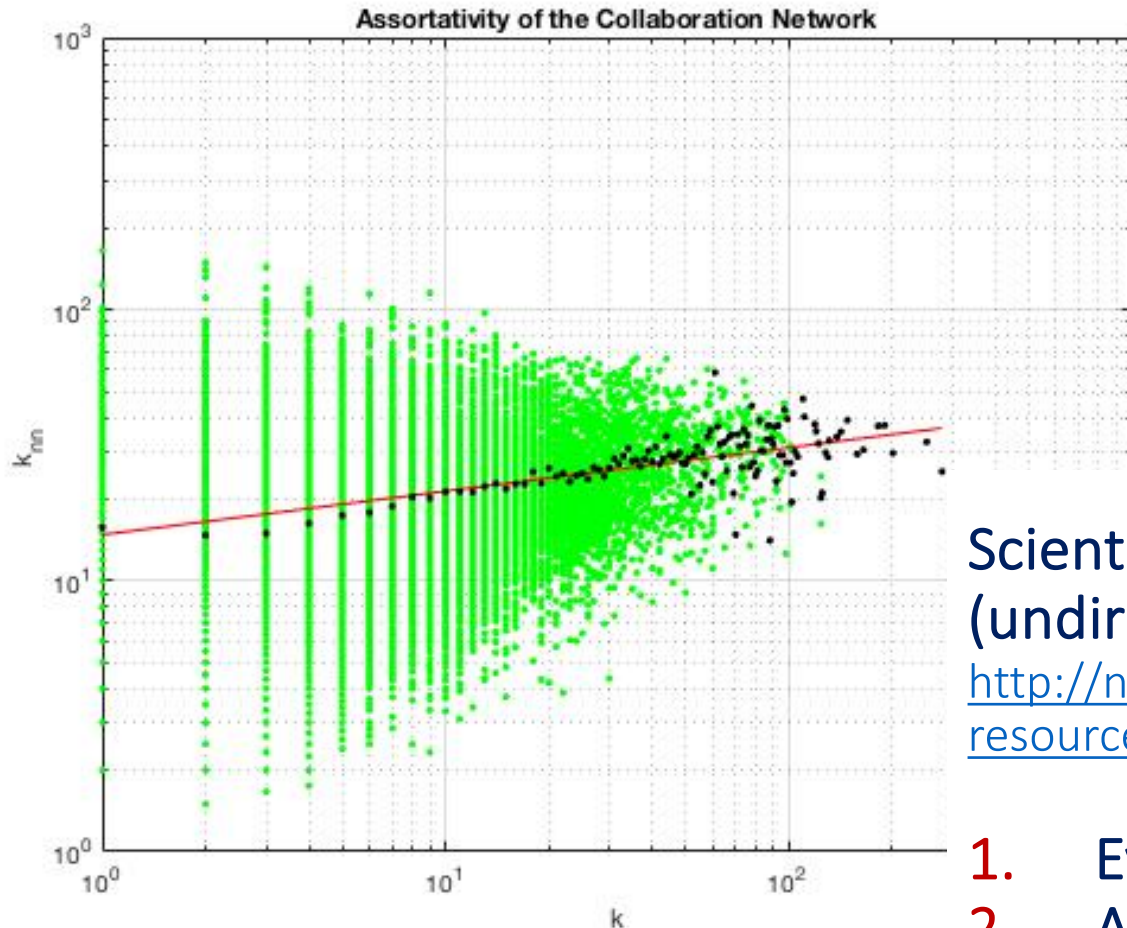
constant = independent of the degree (i.e., random = neutral)

$$\ln(k_{nn}) = \mu \ln(k_i) \quad \rightarrow$$

$\mu > 0 =$  assortative

$\mu < 0 =$  disassortative

# Scientific collaboration network

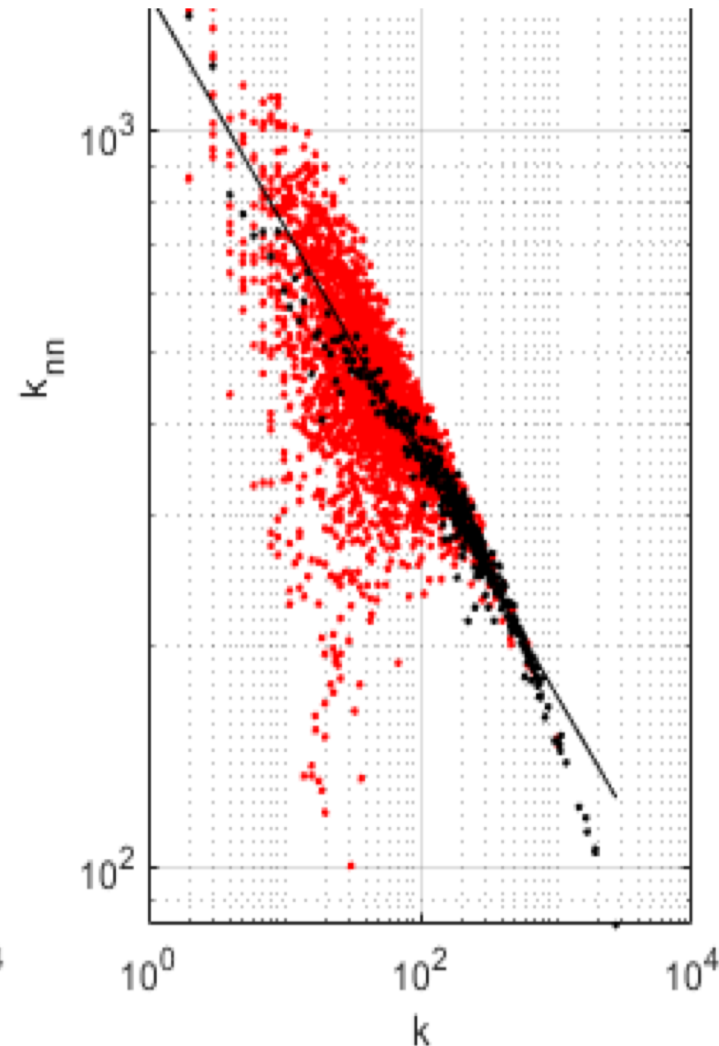
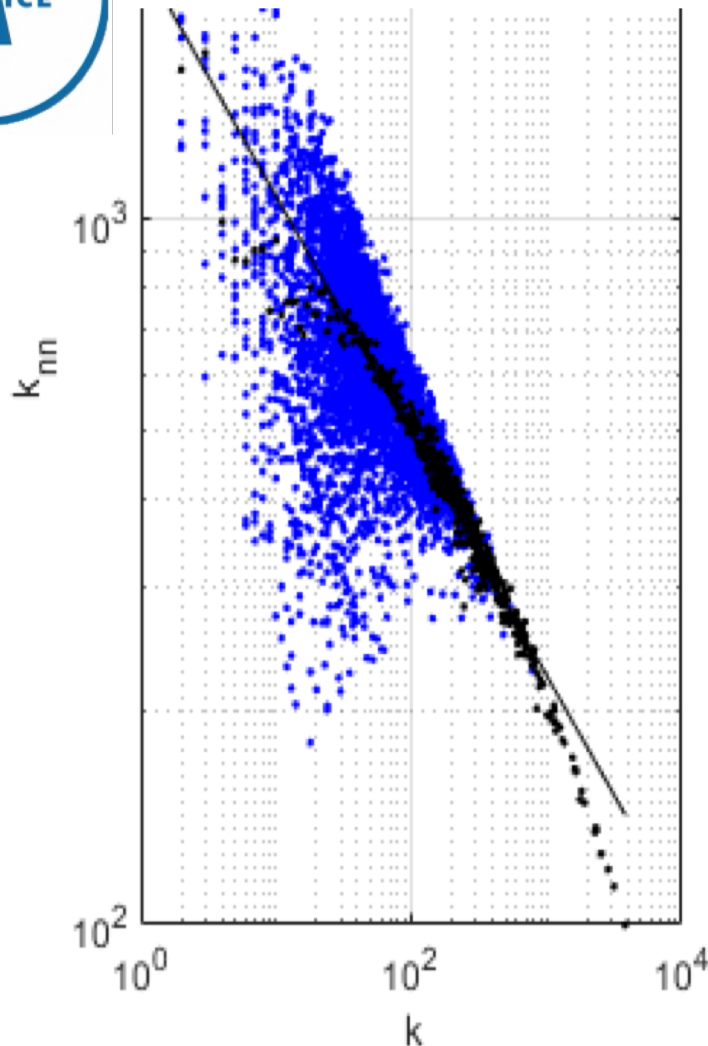


Scientific collaboration network  
(undirected, assortative)

<http://networksciencebook.com/translations/en/resources/data.html>

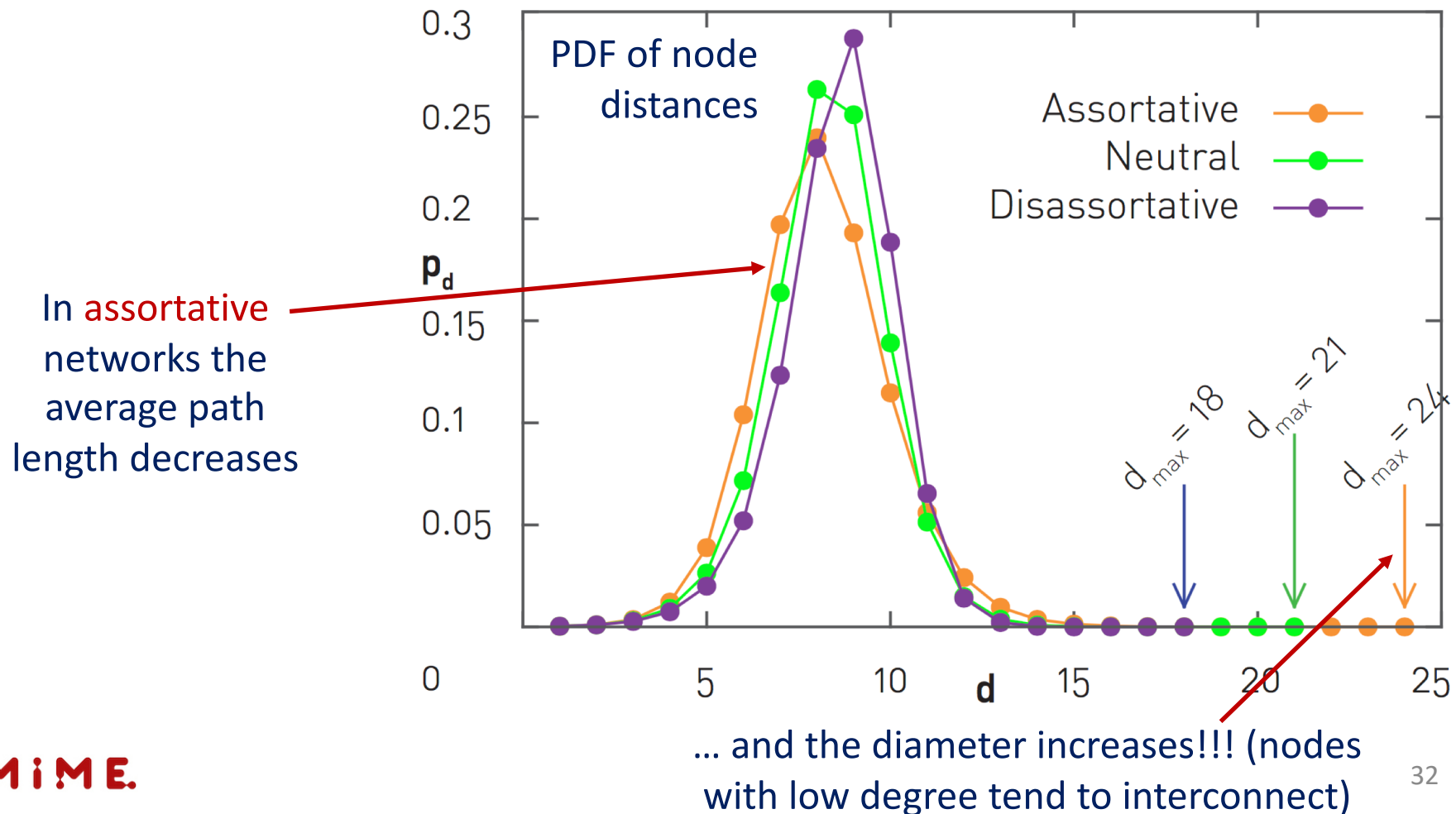
1. Evaluate average neigh. deg.  $k_{nn}$
2. Average w.r.t.  $k$
3. Extract the assortativity value  $\mu=0.16$

# Hashtag network disassortativity



# Implications of assortativity

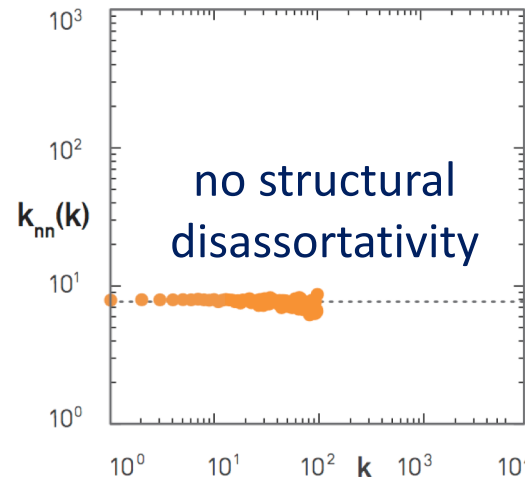
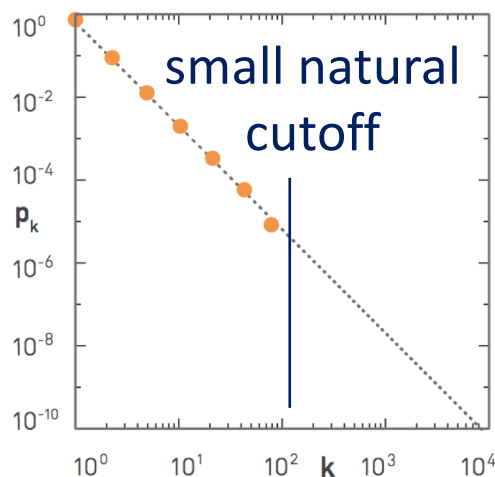
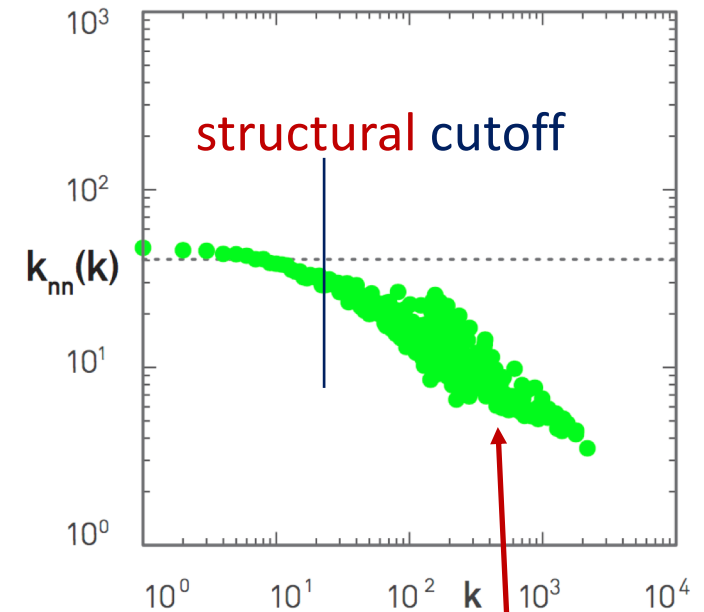
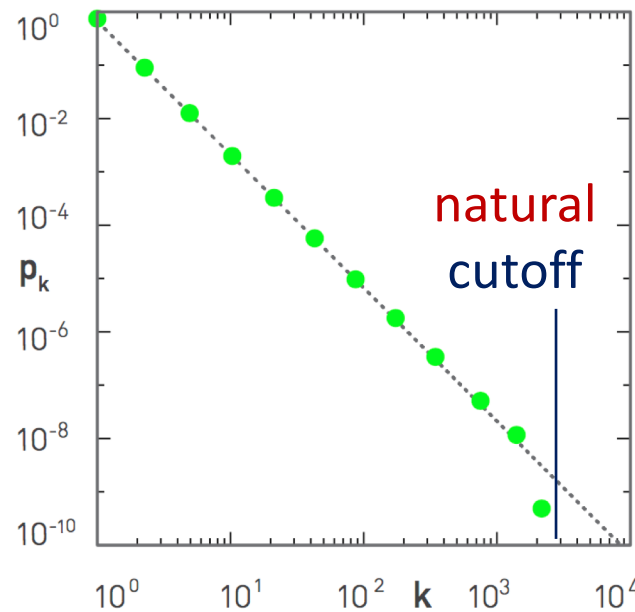
(dis)assortativity influences the path length and the network diameter



# Structural Disassortativity

# Rationale for (dis)assortativity

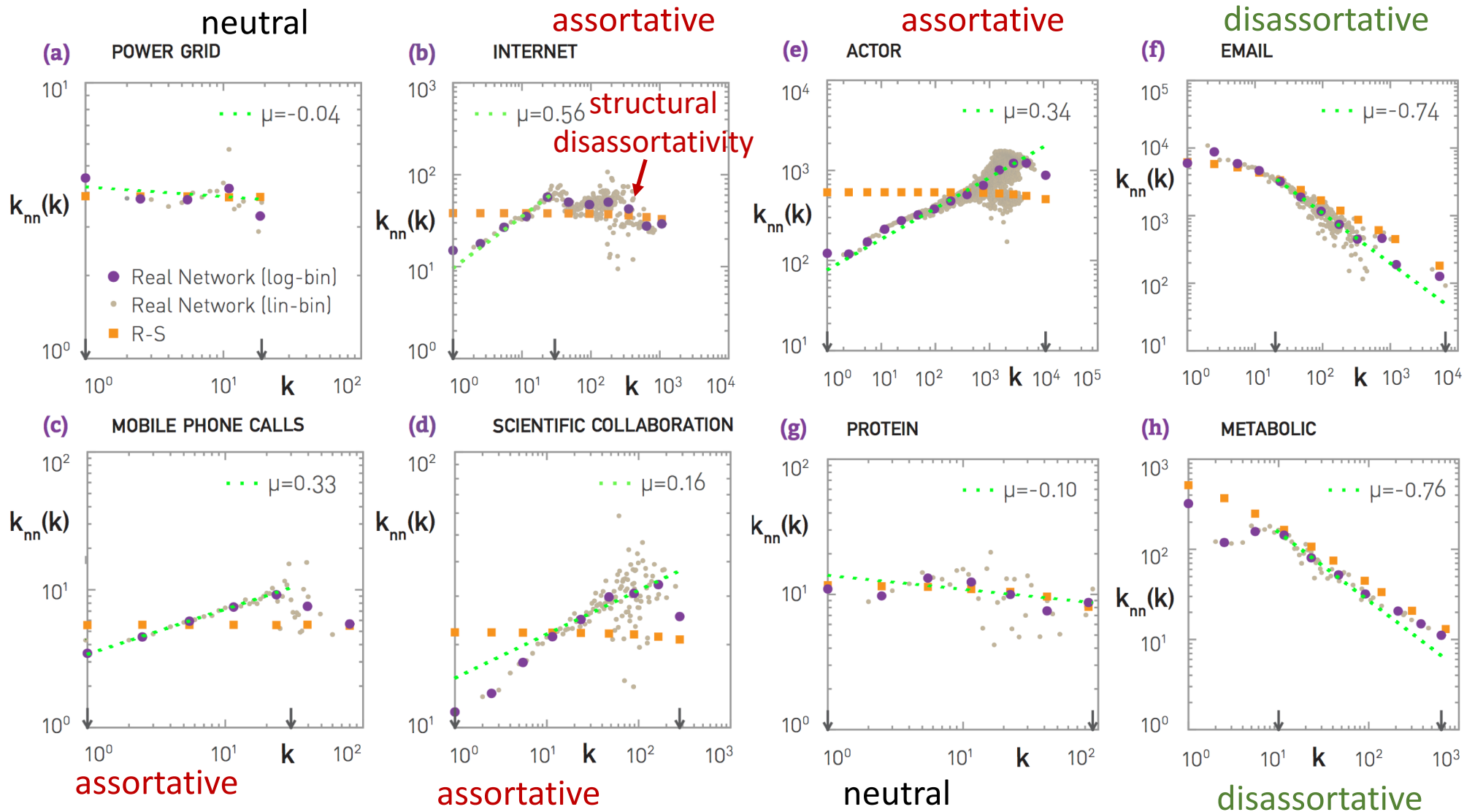
(dis)Assortativity can be linked to **structural** network properties



**structural disassortativity**  
large degrees cannot be supported by a neutral network



# Real networks



# Randomization curve

Real networks may look as disassortative because

- ❑ they really involve **disassortative** effects
- ❑ they **do not** but just have it as structural

Check with the yellow R-S curve (**null model/unbiased**):

- ❑ it is a **degree preserving** randomization
- ❑ at each randomization step we check that we do not have more than one link between any node pairs
- ❑ obtained for 100 independent trials
- ❑ If  $k_{nn}$  does not change → **disassortativity** is due to a **structural** reason (i.e., on the degree distribution)
- ❑ if something changes → deeper reasons

# Questions ?



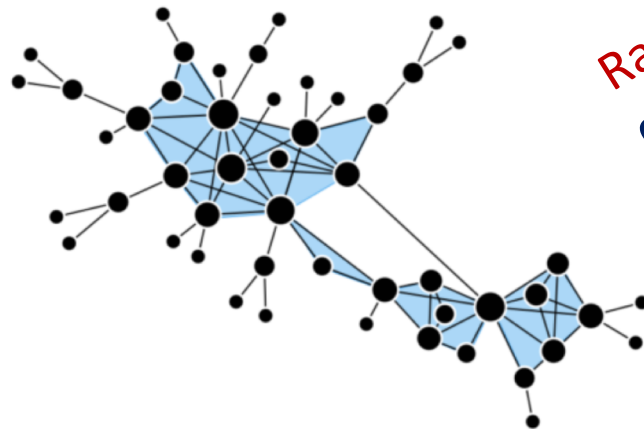
# Clustering coefficient

# What is the Clustering coefficient?



## Local clustering coefficient [\[ edit \]](#)

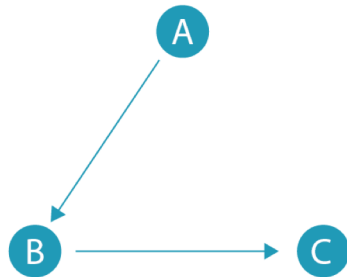
The **local clustering coefficient** of a **vertex** (node) in a **graph** quantifies how close its **neighbours** are to being a **clique** (complete graph). **Duncan J. Watts** and **Steven Strogatz** introduced the measure in 1998 to determine whether a graph is a **small-world network**.



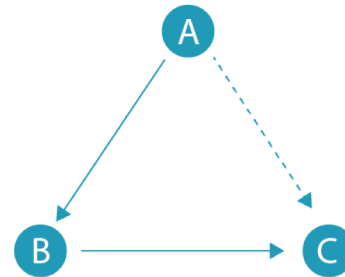
**Rationale:** how strongly connected is the network locally / general indication of the graph's tendency to be organized into clusters

# Triadic closure

Forbidden triad



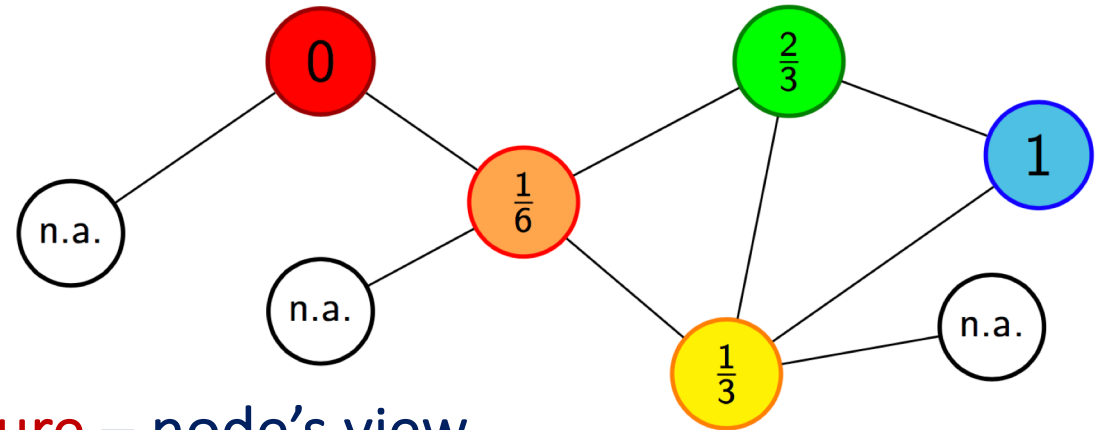
Triadic closure  
(A and C are likely to be friends)



## Triadic closure

- ❑ A and C are likely to have the opportunity to meet because they have a common friend B
- ❑ The fact that A and C is friends with B gives them the basis of **trusting** each other
- ❑ B may have the **incentive** to bring A and C together, as it may be hard for B to maintain disjoint relationships

# Clustering coefficient and triadic closure



A measure for **triadic closure** – node's view

- ❑ **Clustering coefficient**  $C_i$
- ❑ Counts the **fraction** of pairs of neighbours which form a triadic closure with node  $i$

$$C_i = \frac{1}{|\mathcal{N}_i|(|\mathcal{N}_i| - 1)} \sum_{\substack{(j,k) \in \mathcal{N}_i^2 \\ j \neq k}} t_{C_{i,j,k}}$$

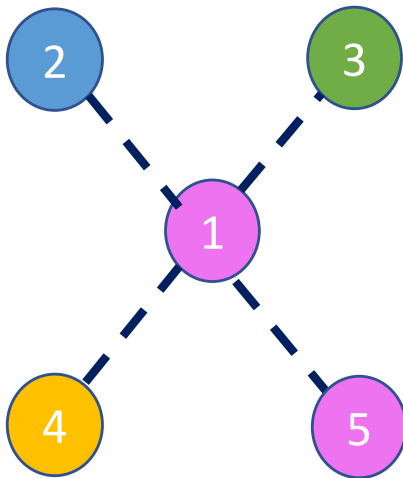
where  $t_{C_{ijk}} = 1$  if the triplet  $(i,j,k)$  forms a triadic closure, and zero otherwise



# Examples

not connected  
neighbourhood

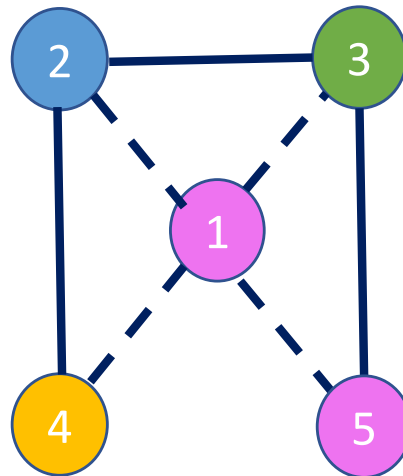
$$C_1 = 0$$



$$\langle C \rangle = 0$$

weakly connected  
neighbourhood

$$C_1 = \frac{1}{2} = \frac{3}{(4 \times 3/2)}$$

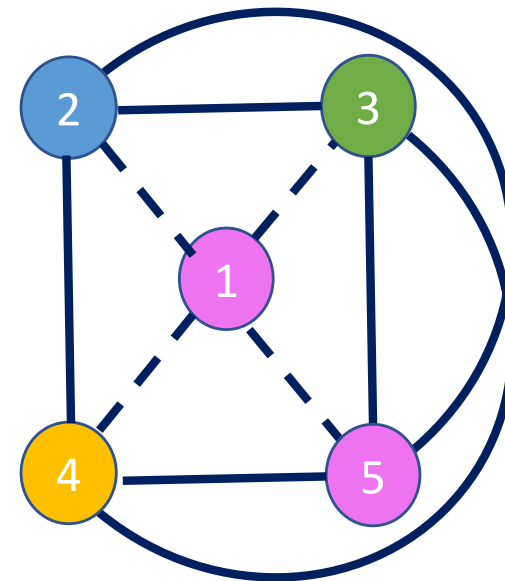


$$C_2 = C_3 = \frac{2}{3}, C_4 = C_5 = 1$$

$$\langle C \rangle = 0.766$$

strongly connected  
neighbourhood

$$C_1 = 1 = \frac{6}{(4 \times 3/2)}$$

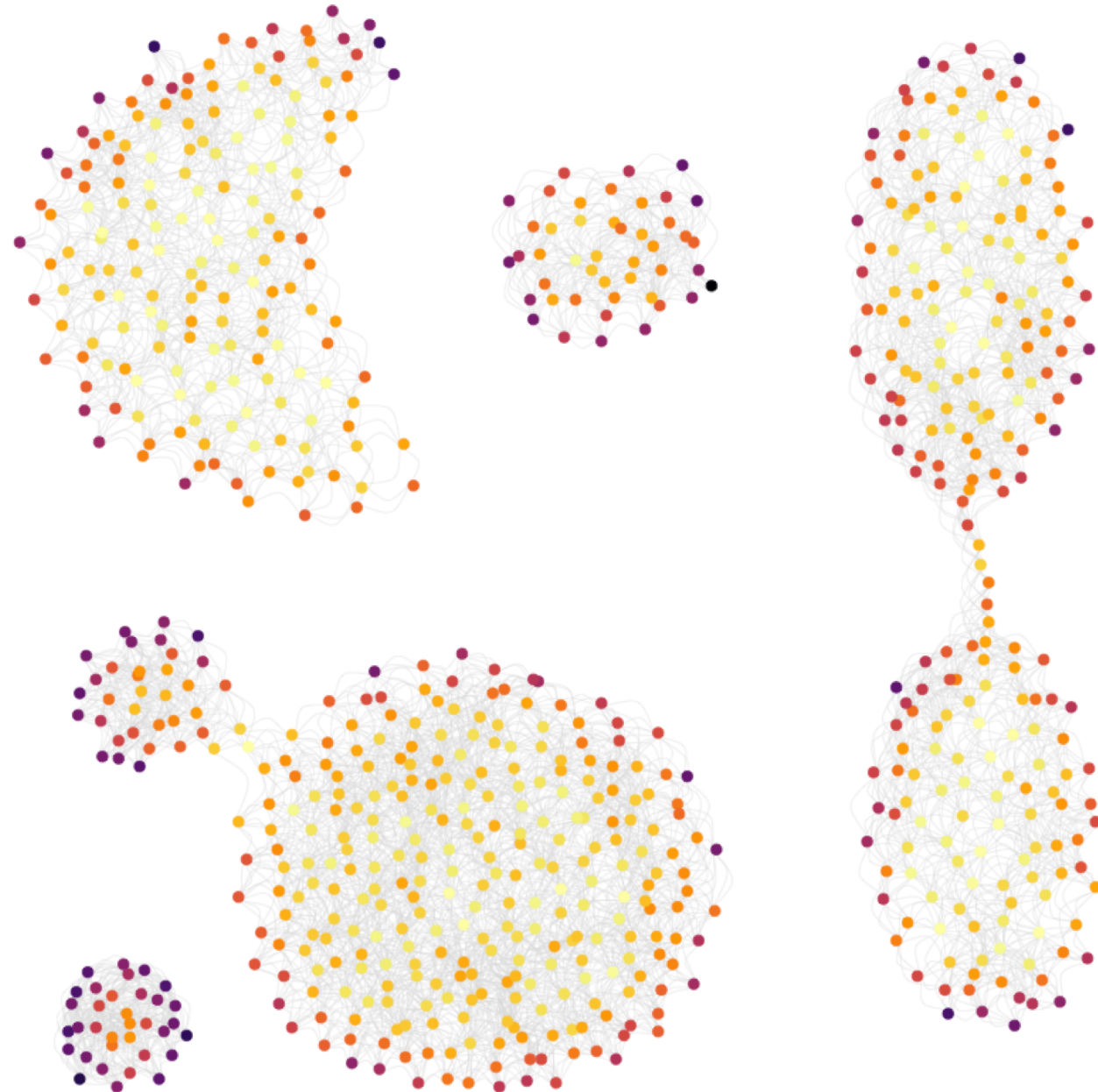


$$\langle C \rangle = 1$$



# Visual example 1

MIME.



# Visual example 2



But clustering coefficient is generally hard to see and visual interpretation is considered unreliable