# Towards data-informed network models (social physics revisited)

Fariba Karimi

*GESIS - Leibniz Institute for the Social Sciences, Cologne*

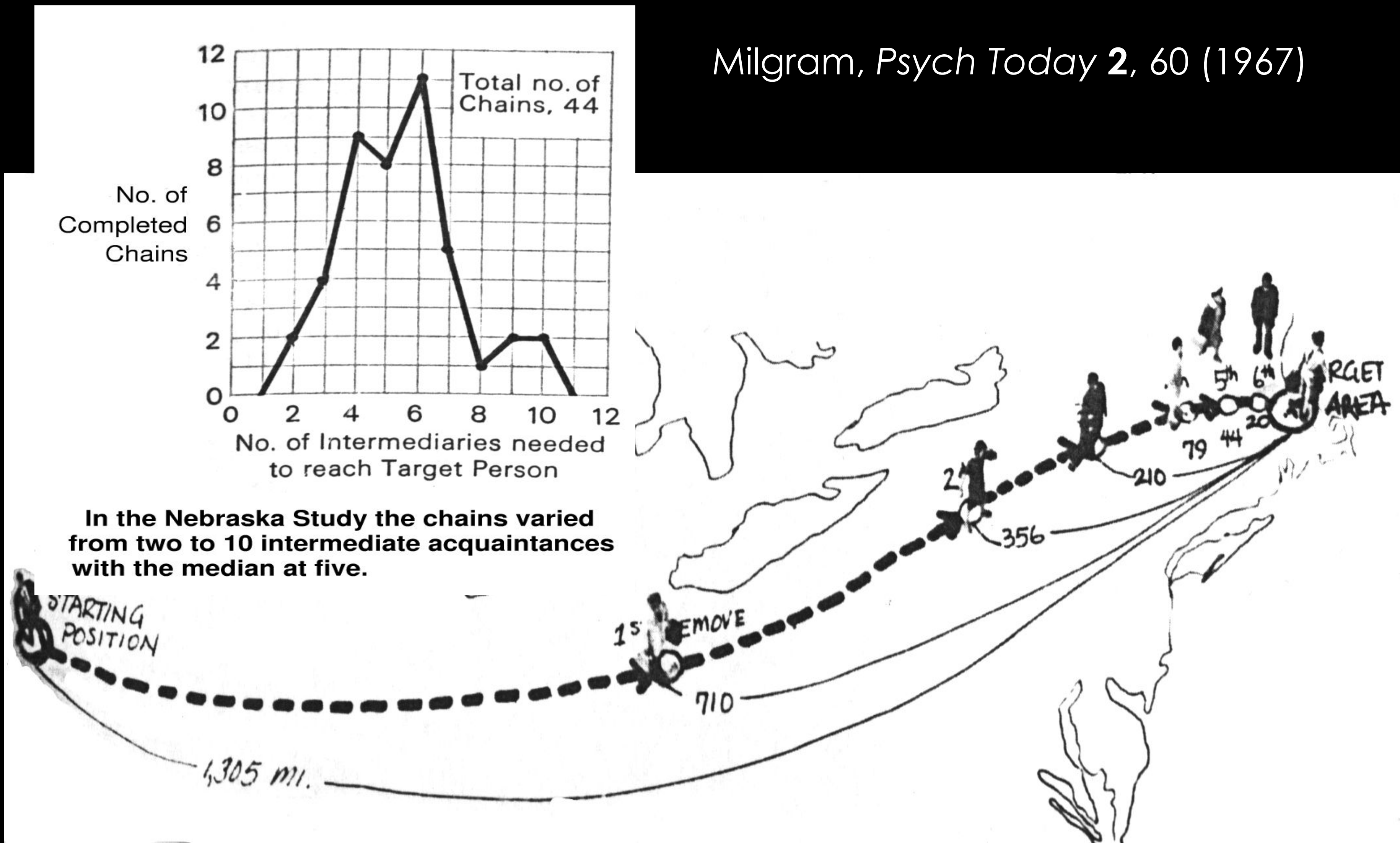
Department of Computational Social Science

Why network science?

Why SNA is so interdisciplinary?

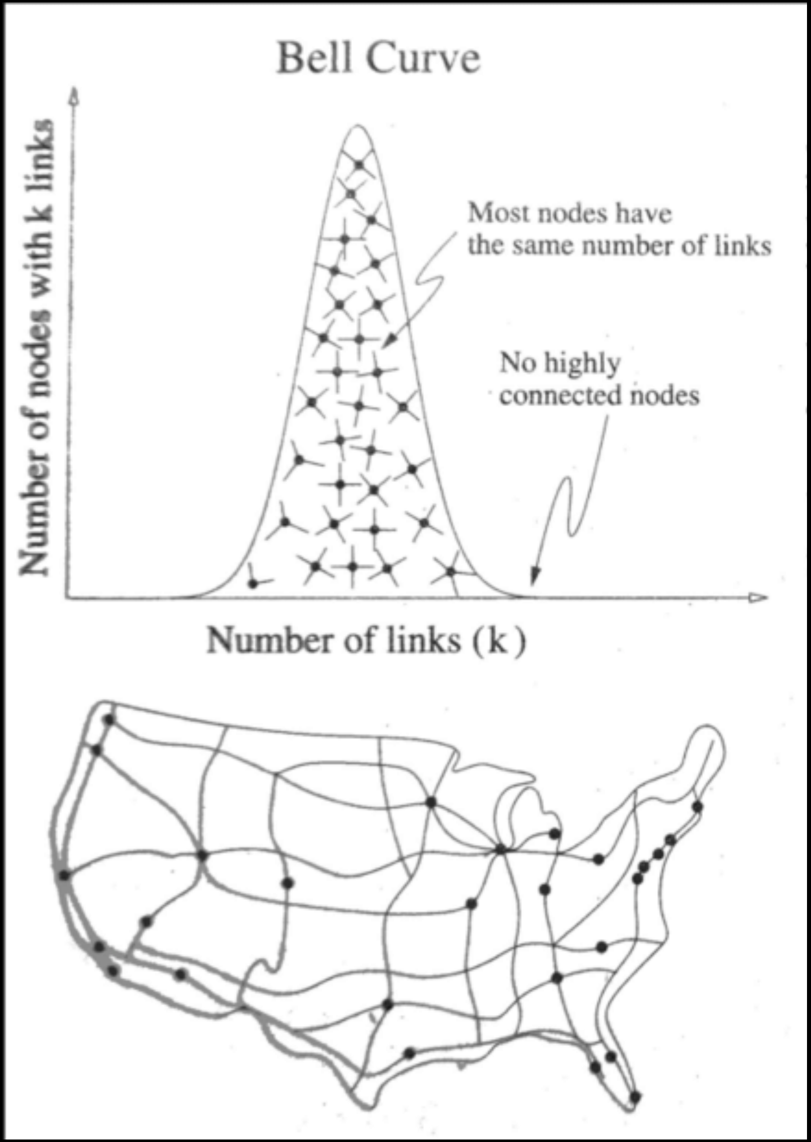
# Milgram Experiment (six degree of separation)

Milgram, *Psych Today* **2**, 60 (1967)




**In the Nebraska Study the chains varied from two to 10 intermediate acquaintances with the median at five.**

# Classical view to networks




Classical view to social network assumed that connections follow a normal distribution.

In this view, people in the network on average have a certain number of connections.

Researchers used random graph models as models of social networks.

Random networks have small-world properties.

# In reality ...

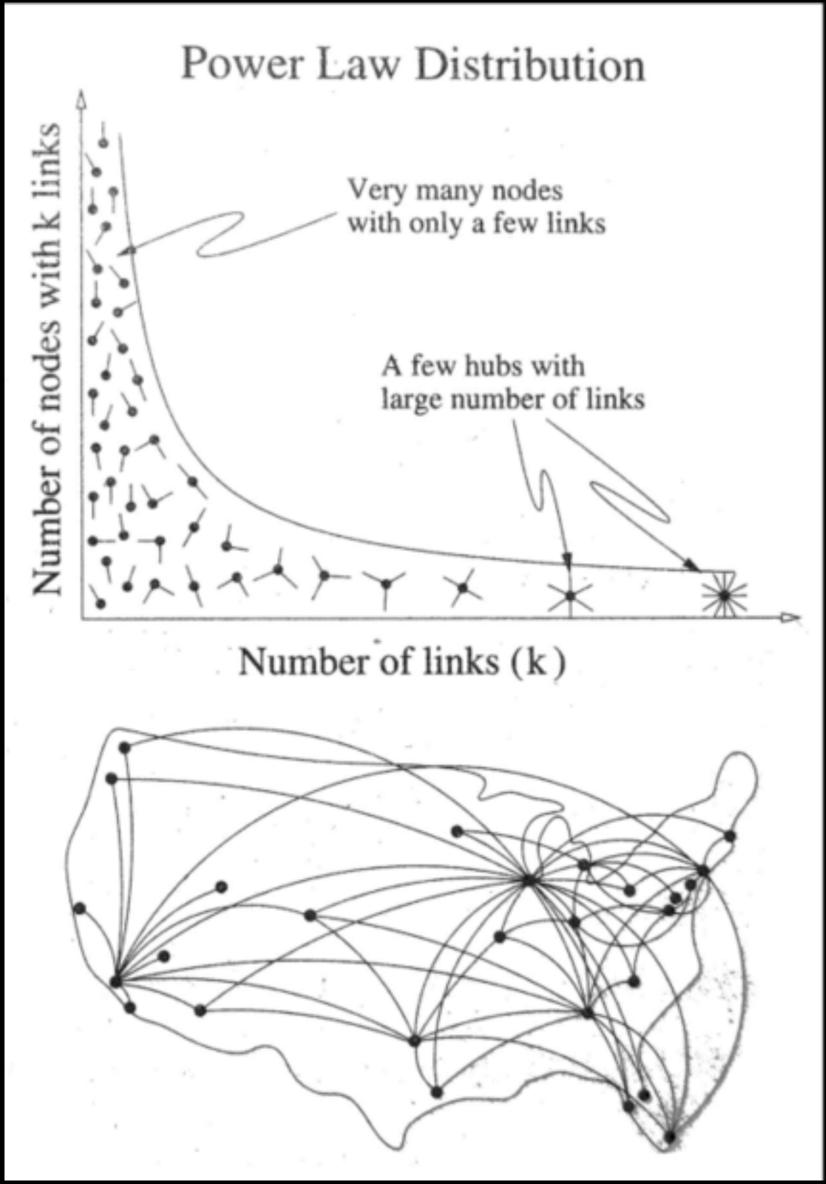
In reality, many large-scale social and technical systems follow a different kind of distribution.

Many social and technical networks follow a power-law degree distribution.

Power-law networks are more heterogeneous.

We can no longer talk about an "average man".

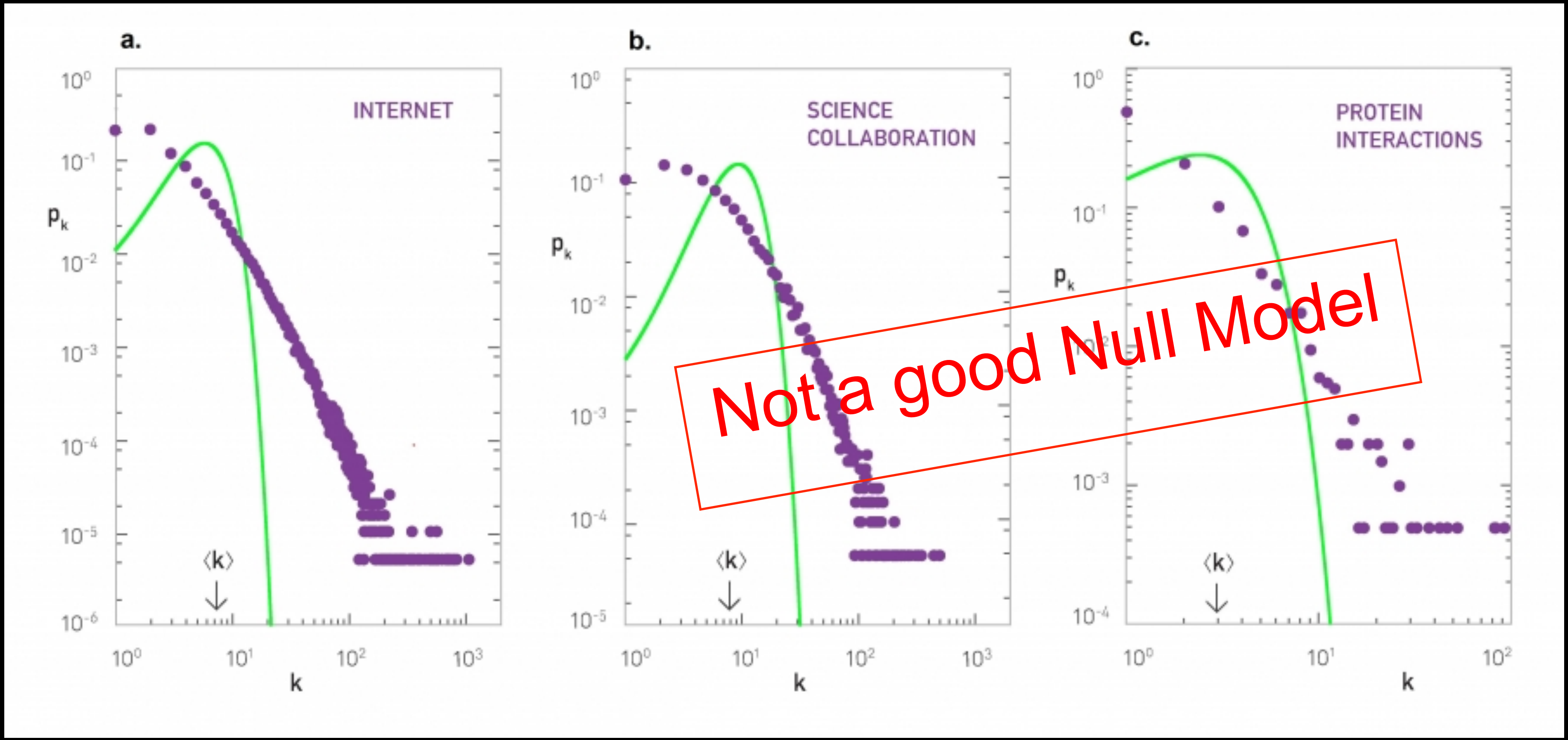
Average degree is not well-defined. We need to revisit the mathematical tools.



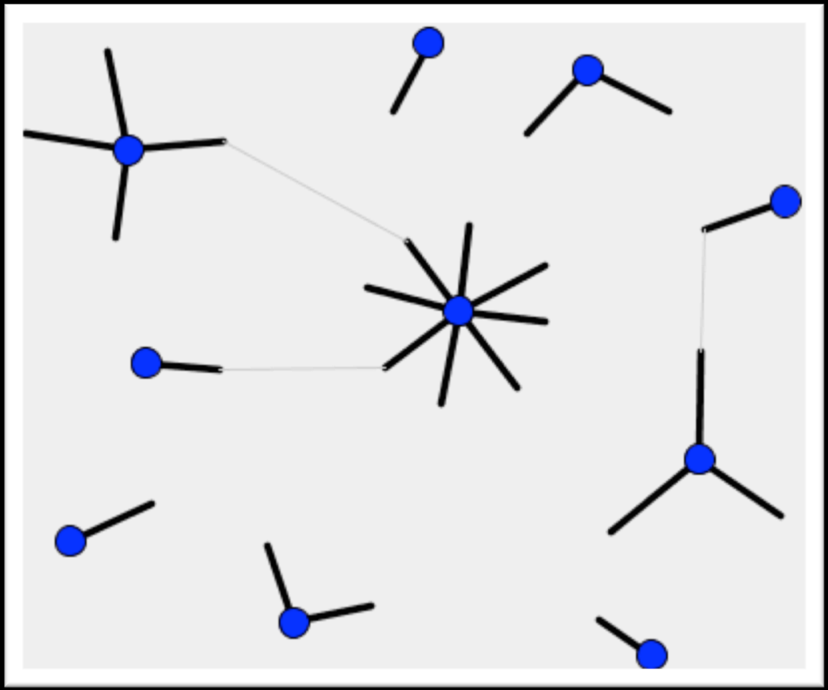
# Models of Networks- Why models?

- Models make us a better thinkers
- Null models help us to test the statistical significance of our network measure
- Models help to disentangle the causal relations
- Enable us to implement social theories and study them in the lab
- Models can be regarded as thought experiments, enabling us to evaluate various scenarios that otherwise would be impossible to test.

# Models of Networks
# Random models as a null model



# Configuration model - a better null model



Keep the degree of the nodes but reshuffle links.

Destroying meaningful interactions.

Null models help to examine how significant the network measures are.

# Probabilistic Models vs. Mechanistic Models

Examples of probabilistic models: ERGM, Configuration models, etc.

- Good null models for testing statistical significance of a network measure

Examples of Mechanistic models: Preferential attachment models, fitness
model, homophily models etc.

- Understand causality, micro to macro behaviour, analytically tractable

# Micro-level and Meso-level structure of Networks

Clustering and motifs: Social networks have more clusters than we would expect! what are the building blocks of a stable social networks?

Centrality: How central nodes are in accessing/spreading information? PageRank to rank important websites.

K-core and Core Periphery: rich club

Degree correlations: e.g. Do popular nodes connect to popular nodes?

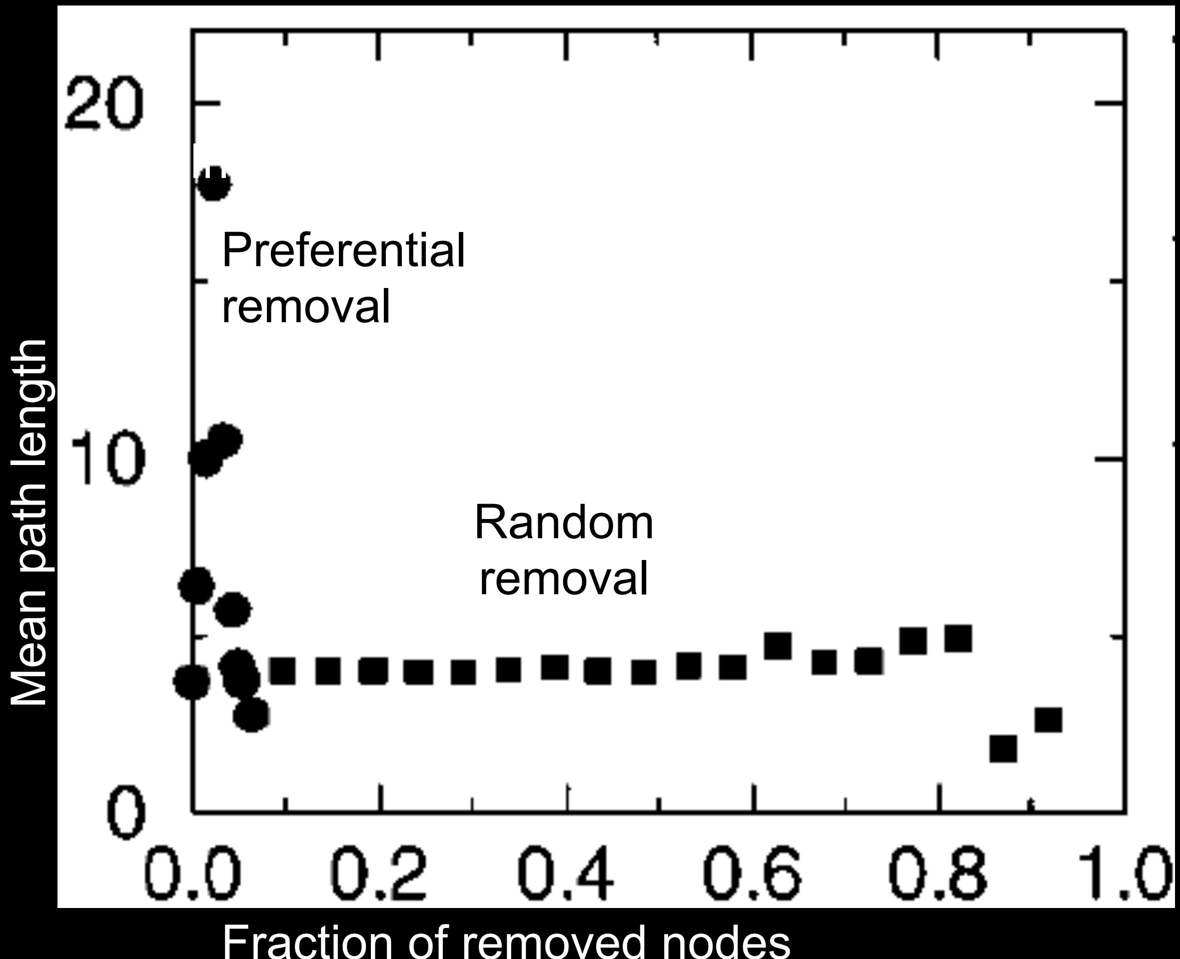
Homophily: people are more likely to interact with similar others.

# Dynamics on Networks

- The structure of networks impacts its resilience to attack, the capacity to spread ideas and information, and other dynamical processes

# Network resilience

## Scale-free networks are vulnerable against targeted attacks



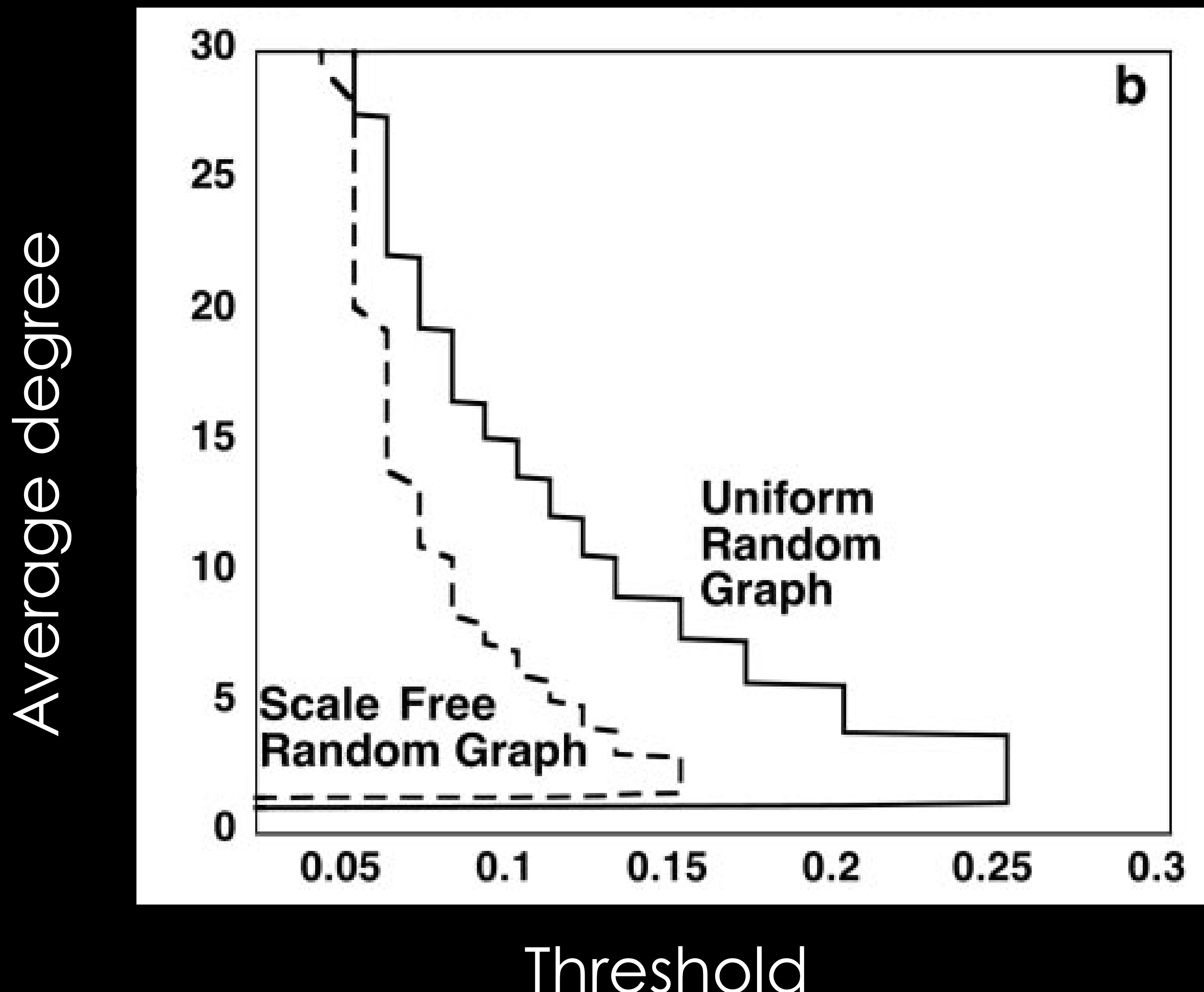
# Dynamics on Networks

- The structure of networks impacts its resilience to attack, the capacity to spread ideas and information, and other dynamical processes

# Case study:
# Diffusion models on Networks and temporal networks


$\Phi = 0.4$

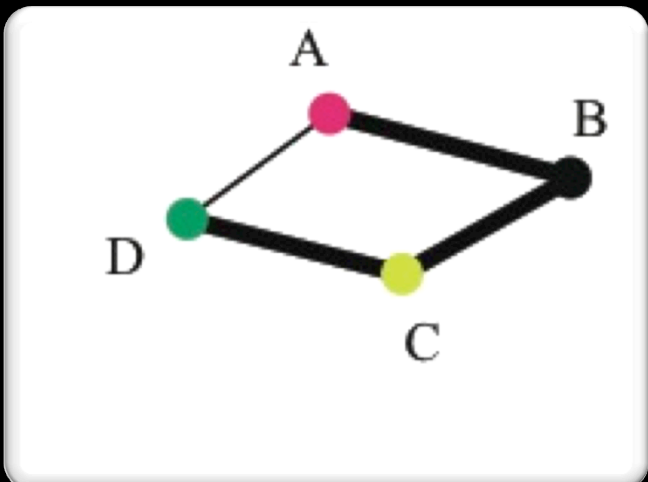
Granovetter, Threshold model of collective behaviour(1978)



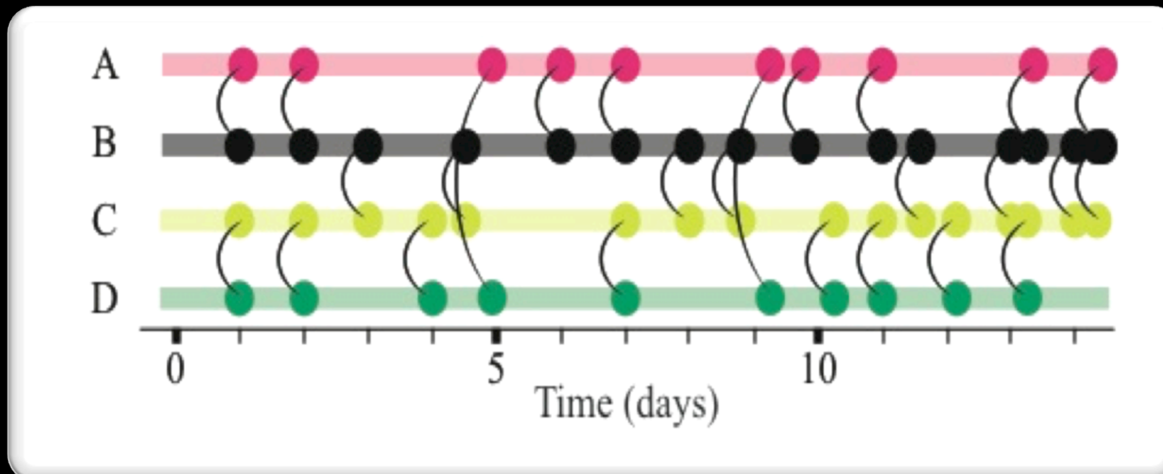

Watts, PNAS (2002)

- Structure of networks impacts dynamical processes.
- What about the timing of interaction?

# Temporal Networks




Static
Representation




Temporal
Representation

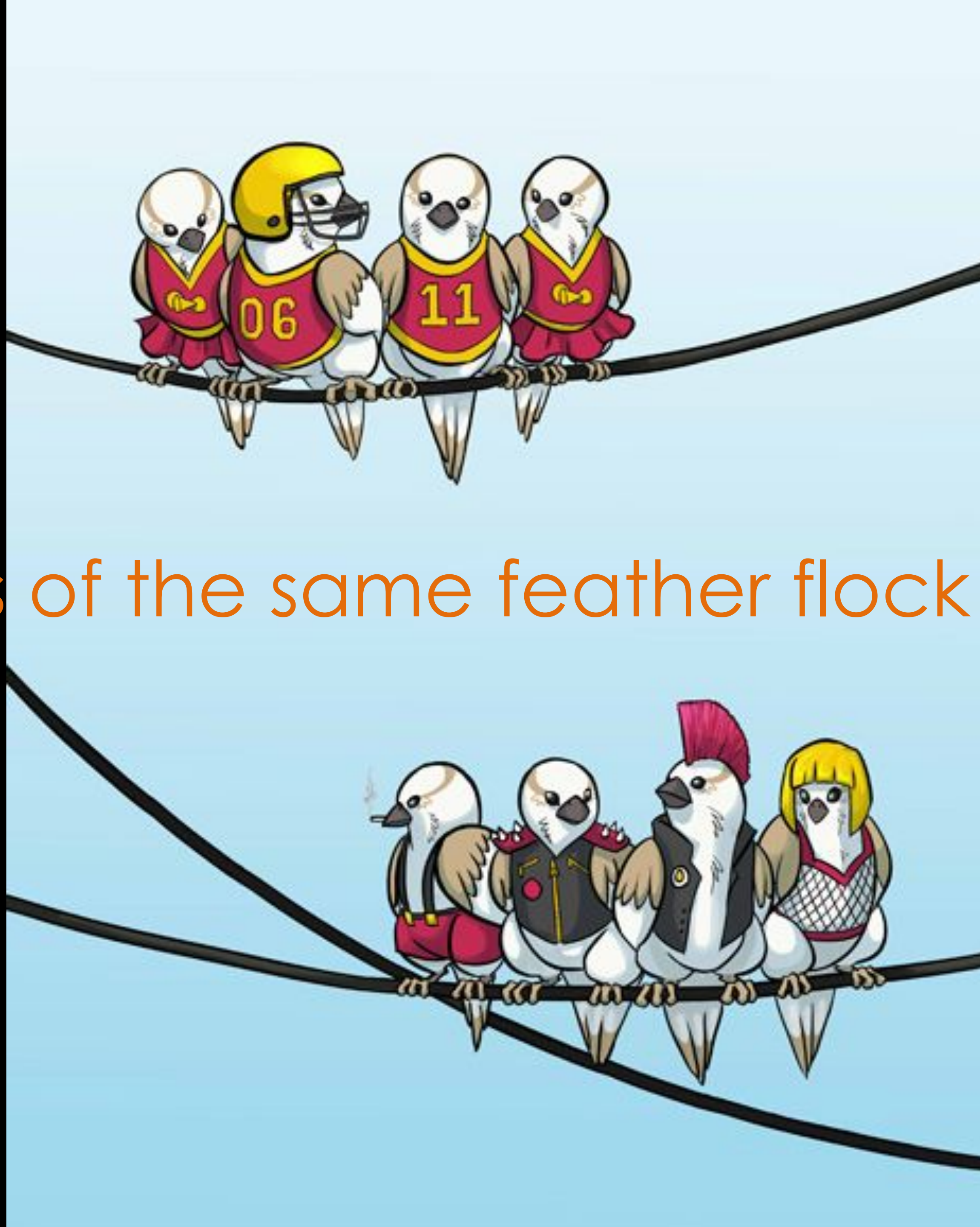
Holme & Saramäki, Temporal networks (2013)

- Structure of networks impacts dynamical processes.
- Timing of interaction impacts dynamical processes.

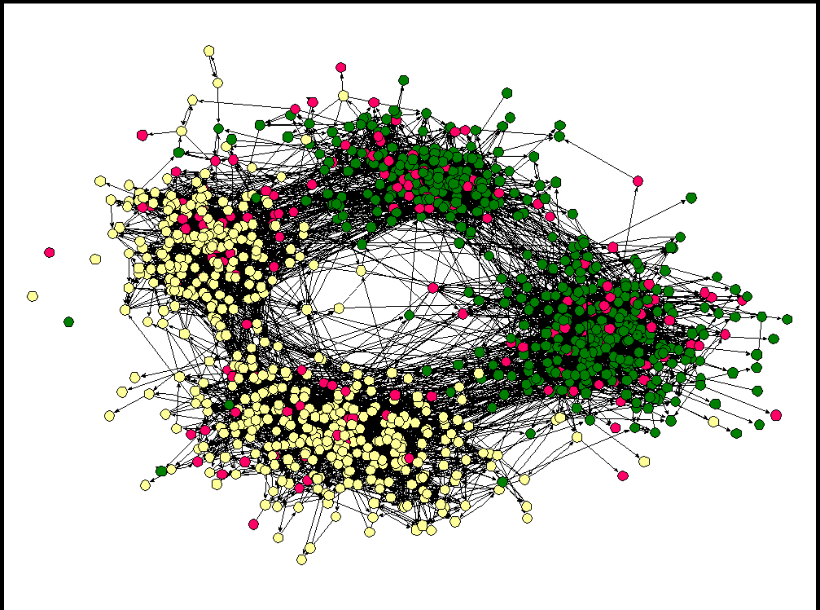
Karimi and Holme. Physica A (2013)

# Application of network analysis on Addressing societal challenges

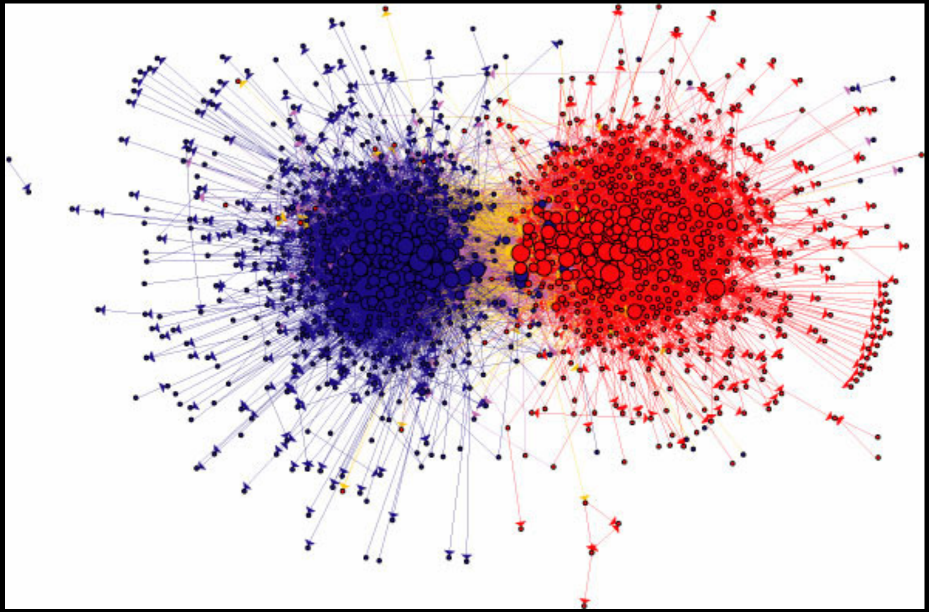
## Case study: Homophily



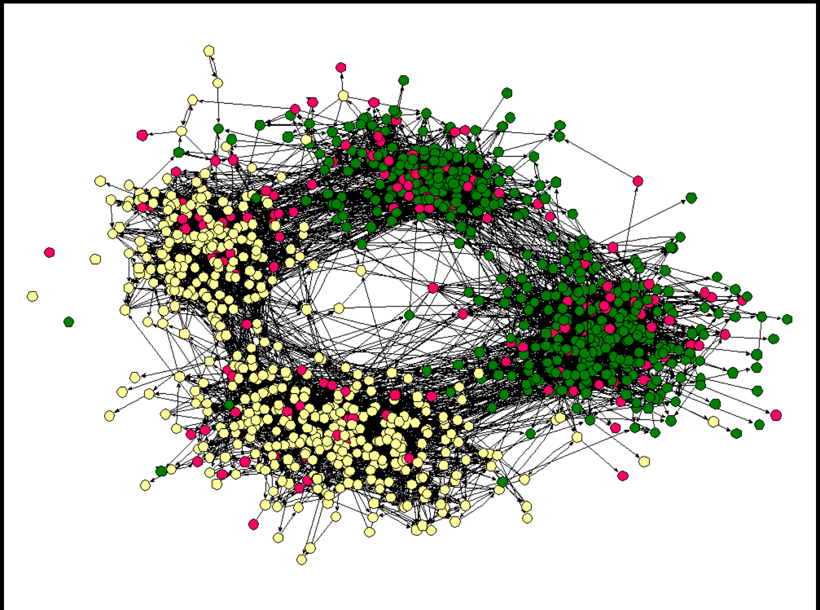

birds of the same feather flock together



Moody, AJS (2001)
Baerveldt et al (2004)



Political blog sphere,
Adamic & Glance (2004)



Moody, AJS (2001)
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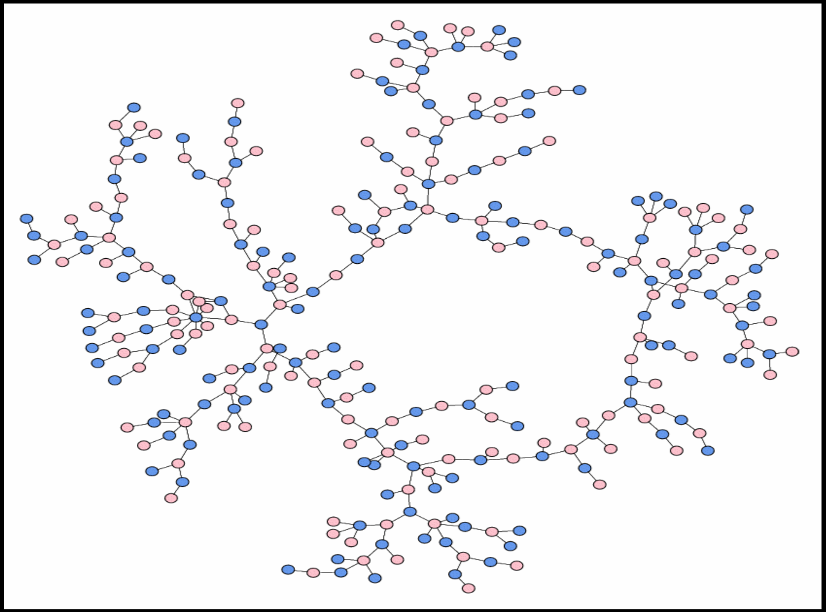
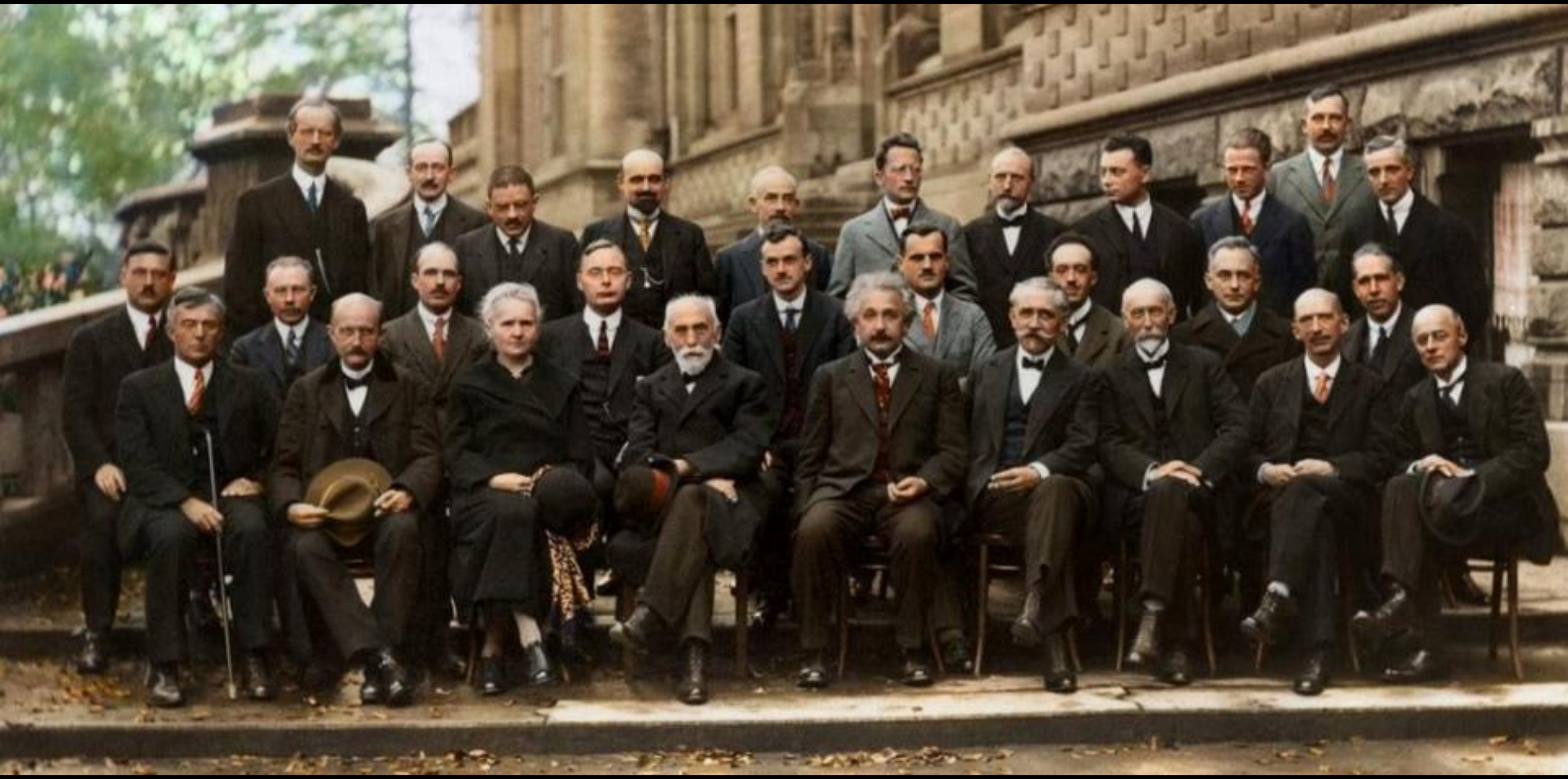
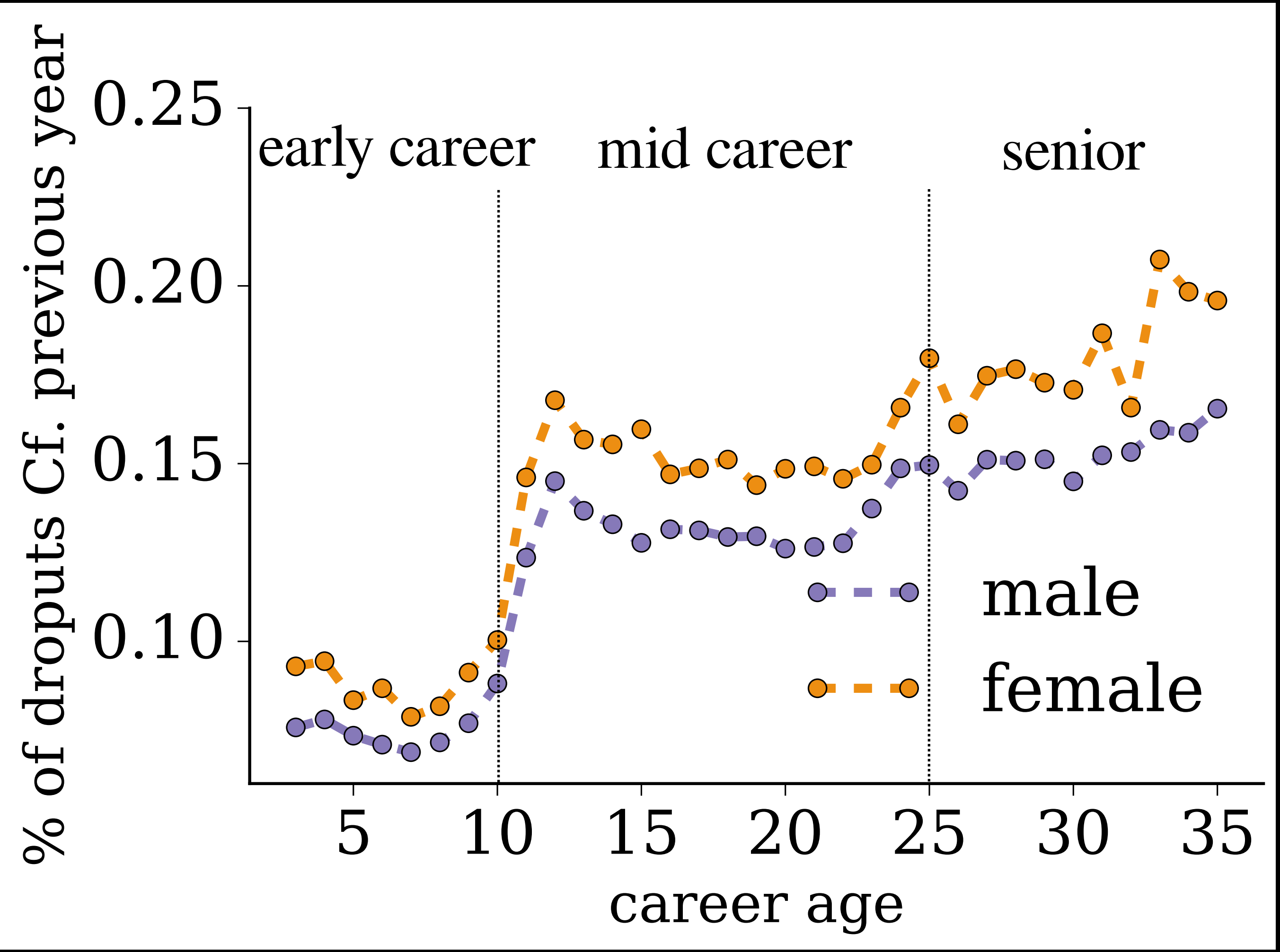


Sexual network at a high school
Bearman, Moody & Stovel (2004)

Homophily = attribute assortativity

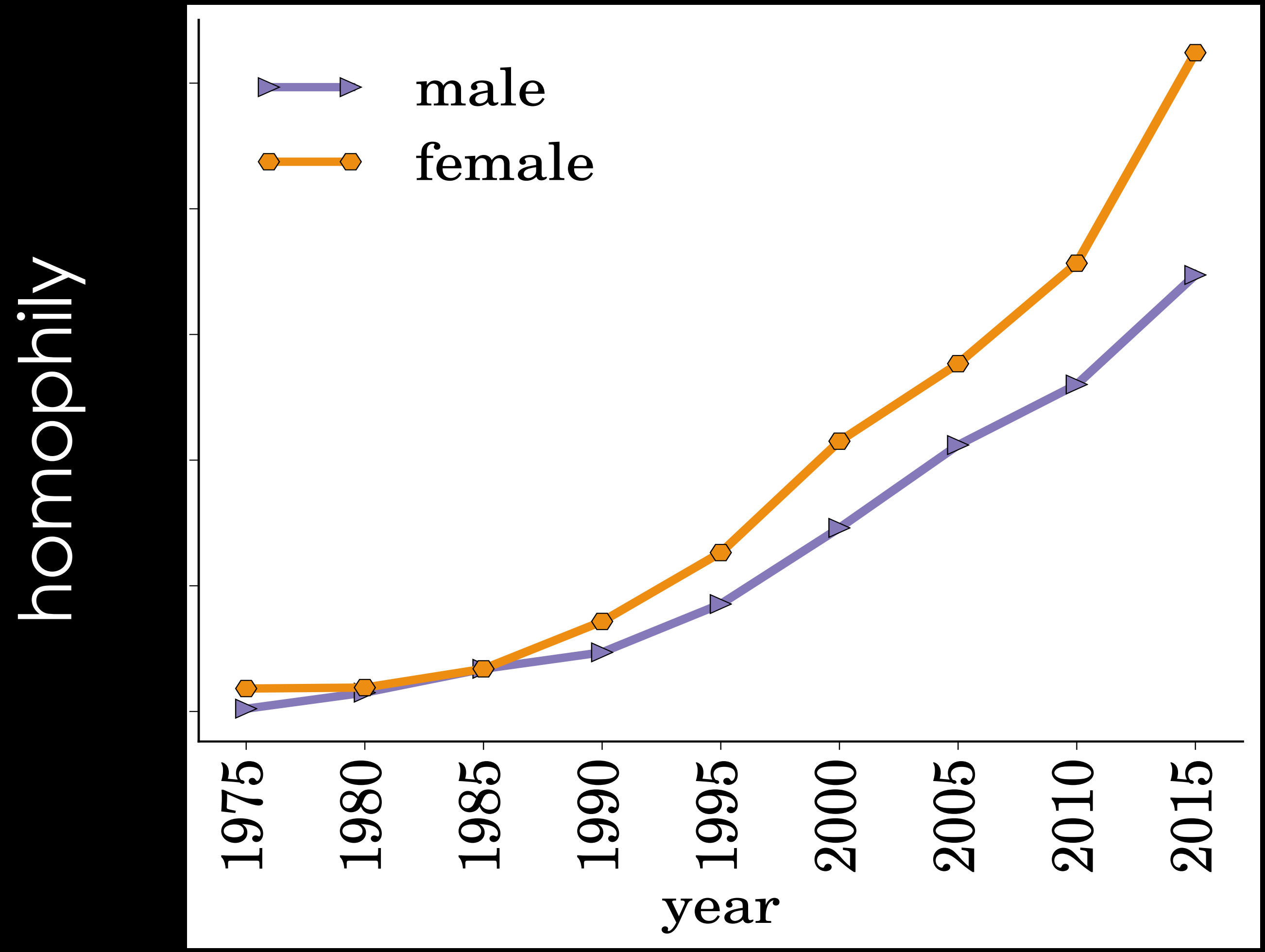


# Dropout vs. Career Age




Jadidi, Karimi, Lietz, & Wagner. Advances in Complex Systems (2017)

# Homophily in Co-authorhship Network




Jadidi, Karimi, Lietz, & Wagner. Advances in Complex Systems (2017)

In many networks we observe
homophilic / heterophilic
interactions and groups with
different size.

Why does it matter?

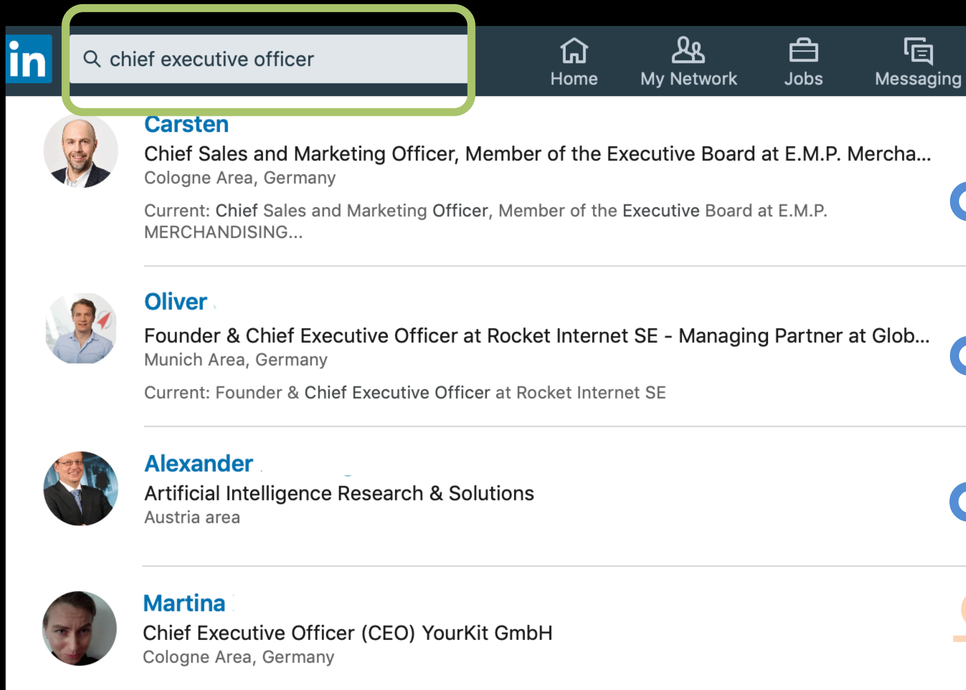
LinkedIn

ResearchGate

twitter

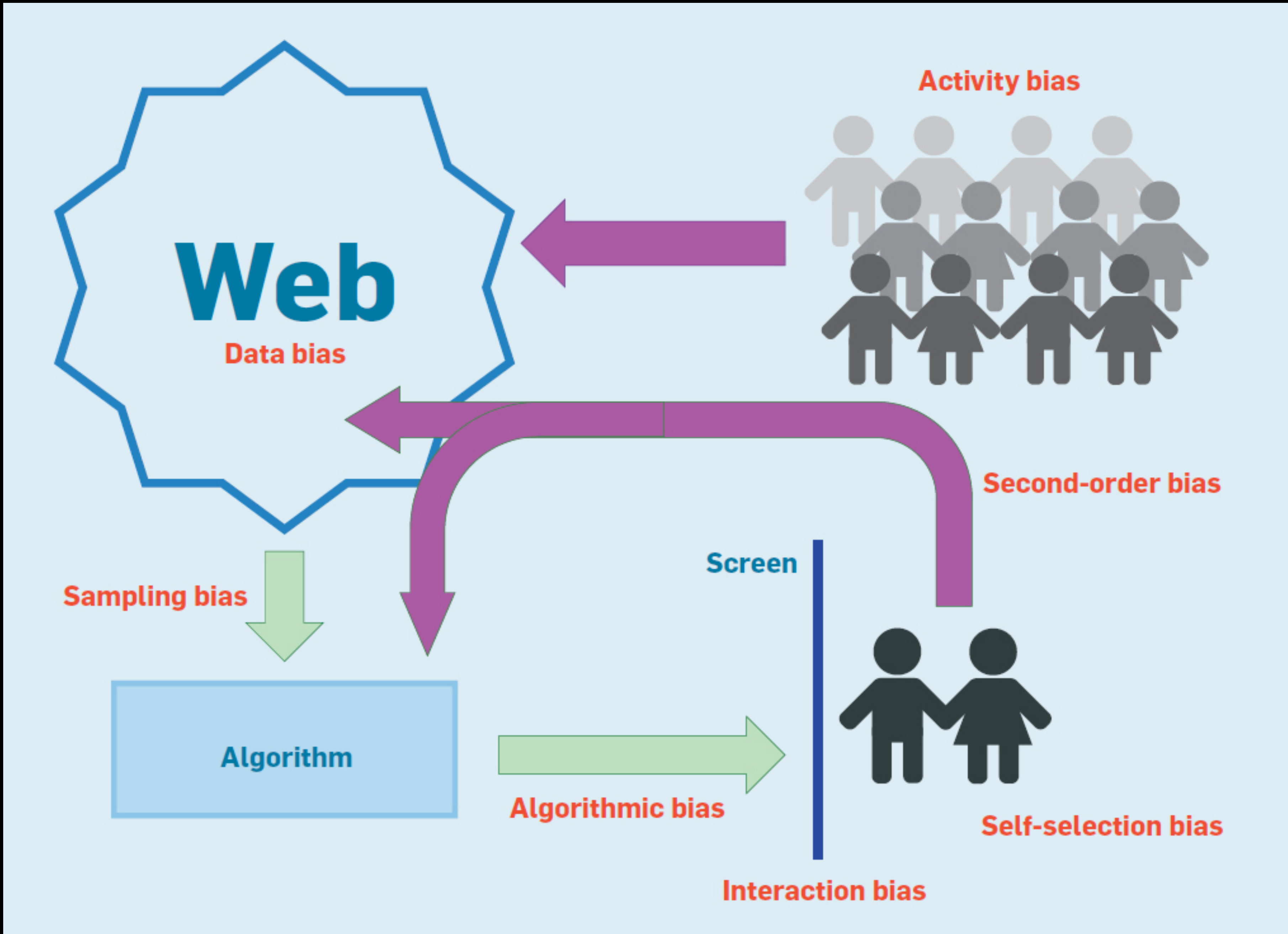
Google Scholar

# Example: Ranking of people in online social networks




| Rank | Gender |
|---|---|
| 1. | m |
| 2. | m |
| 3. | m |
| 4. | f |

¼ (25%) women in the top 4 results



Activity bias
Web
Data bias
Second-order bias
Screen
Sampling bias
Algorithm
Algorithmic bias
Self-selection bias
Interaction bias

https://www.washingtonpost.com/news/morning-mix/wp/2016/06/10/google-faulted-for-racial-bias-in-image-search-result

Morning Mix

# Google faulted for racial bias in image search results for black teenagers

By Ben Guarino June 10, 2016

(Google Images)

If you searched for "three white teenagers" on Google Images earlier this month, the result spat up shiny, happy people in droves — an R.E.M. song in JPG format. The images, mostly stock photos, displayed young Caucasian men and women laughing, holding sports equipment or caught whimsically mid-selfie.

If you searched for "three black teenagers," the algorithm offered

Artificial intelligence (AI)

# Discrimination by algorithm: scientists devise test to detect AI bias

Researchers devise test to determine whether machine learning algorithms are introducing gender or racial biases into decision-making

This article is 3 months old

770 183

Hannah Devlin, Science correspondent

@hannahdev

Monday 19 December 2016 07.30 GMT

The test is aimed at machine learning programs, which learn to make predictions about the future by crunching through vast quantities of existing data. Photograph: Alamy

There was the voice recognition software that struggled to understand women, the crime prediction algorithm that targeted black neighbourhoods and the online ad platform which was more likely to show men highly paid executive jobs.

Concerns have been growing about AI's so-called "white guy problem" and now scientists have devised a way to test whether an algorithm is introducing gender or racial biases into decision-making.

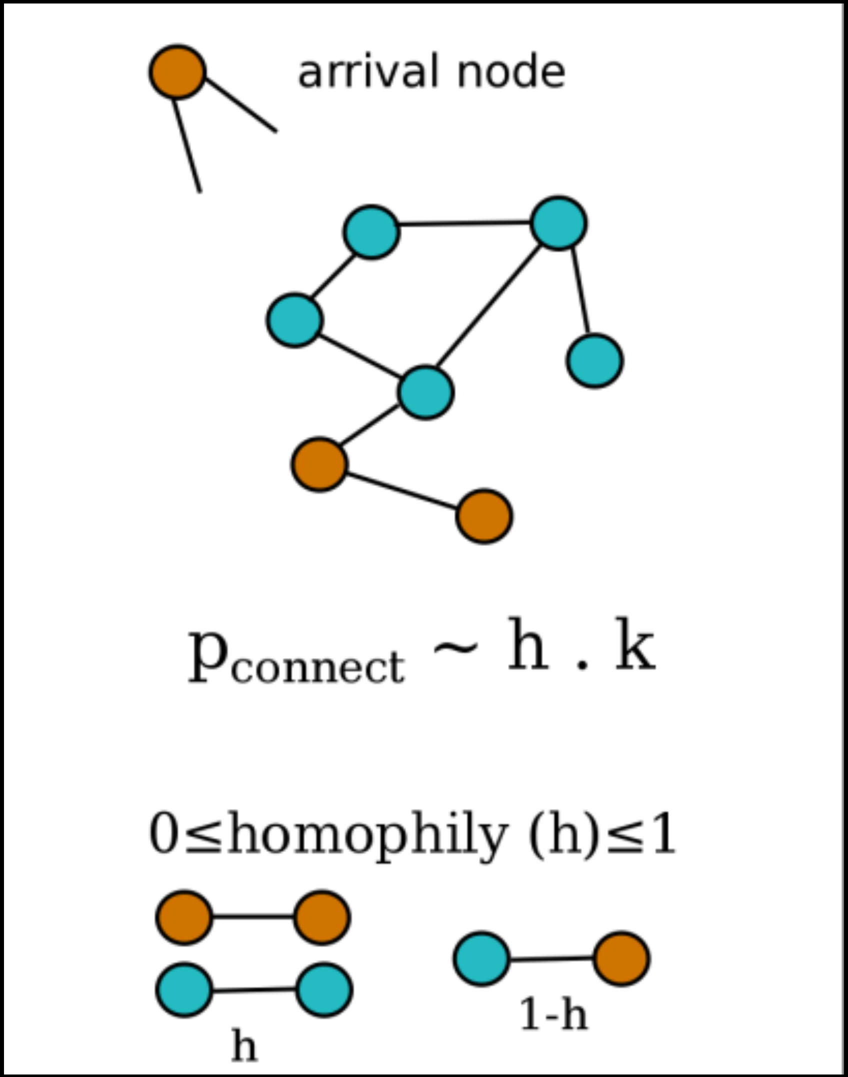
If minorities become less visible, this would create situations in which i) high-ranked minority members become less noticeable globally and therefore less influential in society, ii) minorities feel ignored or overlooked by the wider public, also known as the invisibility syndrome.

Franklin, Anderson J., and Nancy Boyd-Franklin. "Invisibility syndrome: a clinical model of the effects of racism on African-American males." American Journal of Orthopsychiatry (2000).

How does the inherent structure of social networks, (homophily and group size), impact ranking (visibility) of groups (minorities)?

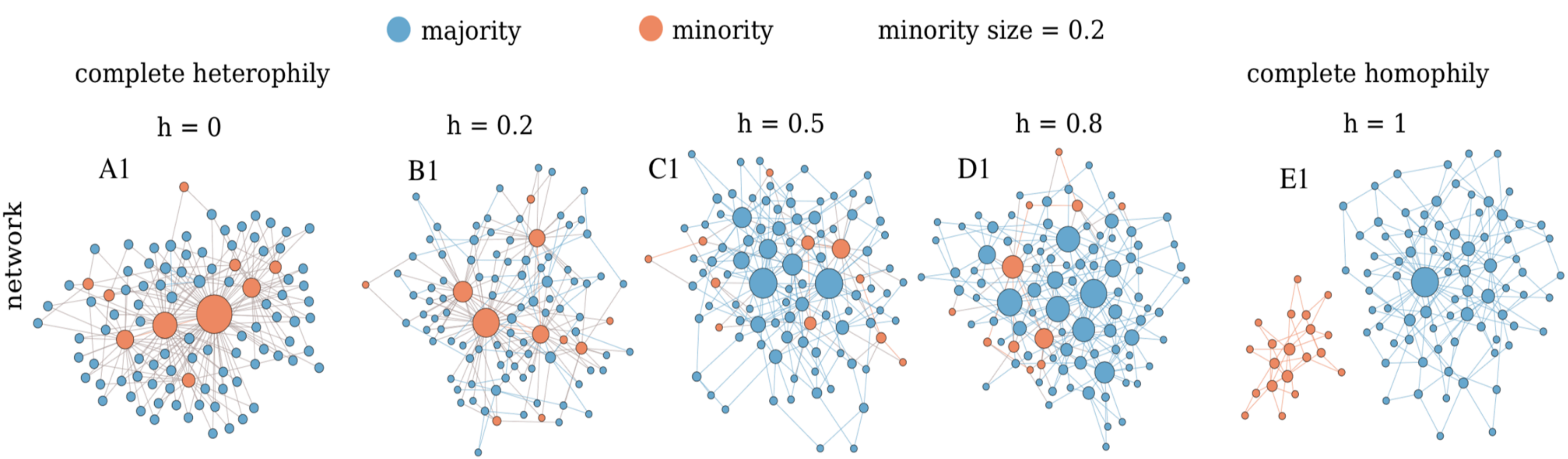
# Network Growth Model with tunable homophily and group size

- 2 group of nodes with unequal size
- Arrival node connects to existing nodes based on preferential attachment (k) and homophily (h)
- homophily can be asymmetric

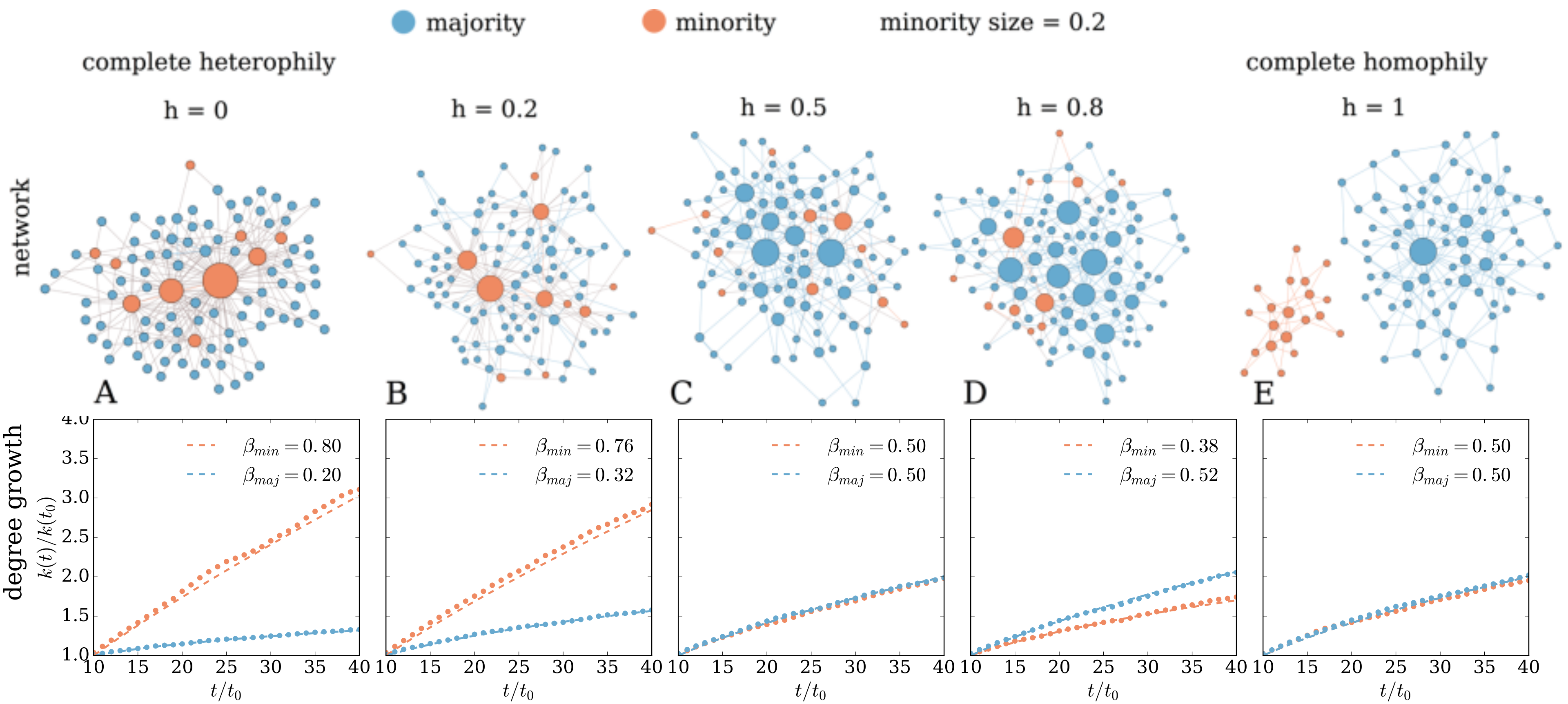



Karimi et al. Homophily influences ranking of minorities in social networks, Scientific Reports (2018)

# BA-Homophily network model



# BA-Homophily network model

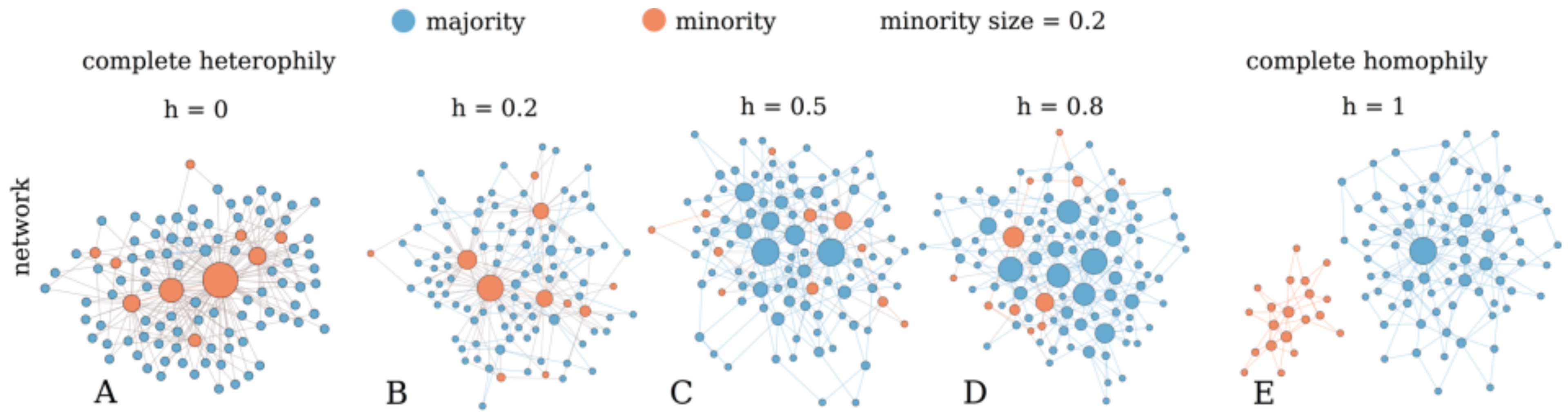



$$\left(\frac{f_a h_{aa}}{h_{aa}C + h_{ab}(2-C)} + \frac{f_b h_{ba}}{h_{ba}C + h_{bb}(2-C)}\right)$$

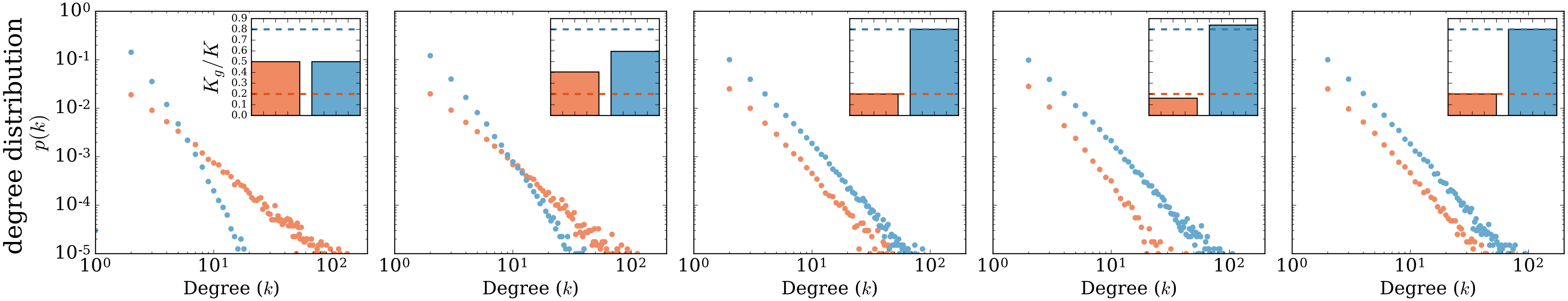
$$k_a \propto t^{\beta a}$$

$$\begin{aligned}
&(h_{aa} - h_{ab})(h_{ba} - h_{bb})C^3 \\
&+((2h_{bb} - (1-f)h_{ba})(h_{aa} - h_{ab}) + (2h_{ab} - f(2h_{aa} - h_{ab}))(h_{ba} - h_{bb}))C^2 \\
&+(2h_{bb}(2h_{ab} - f(2h_{aa} - h_{ab})) - 2fh_{ab}(h_{ba} - h_{bb}) - 2(1-f)h_{ba}h_{ab})C \\
&-4fh_{ab}h_{bb} = 0
\end{aligned}$$

# BA-Homophily network model

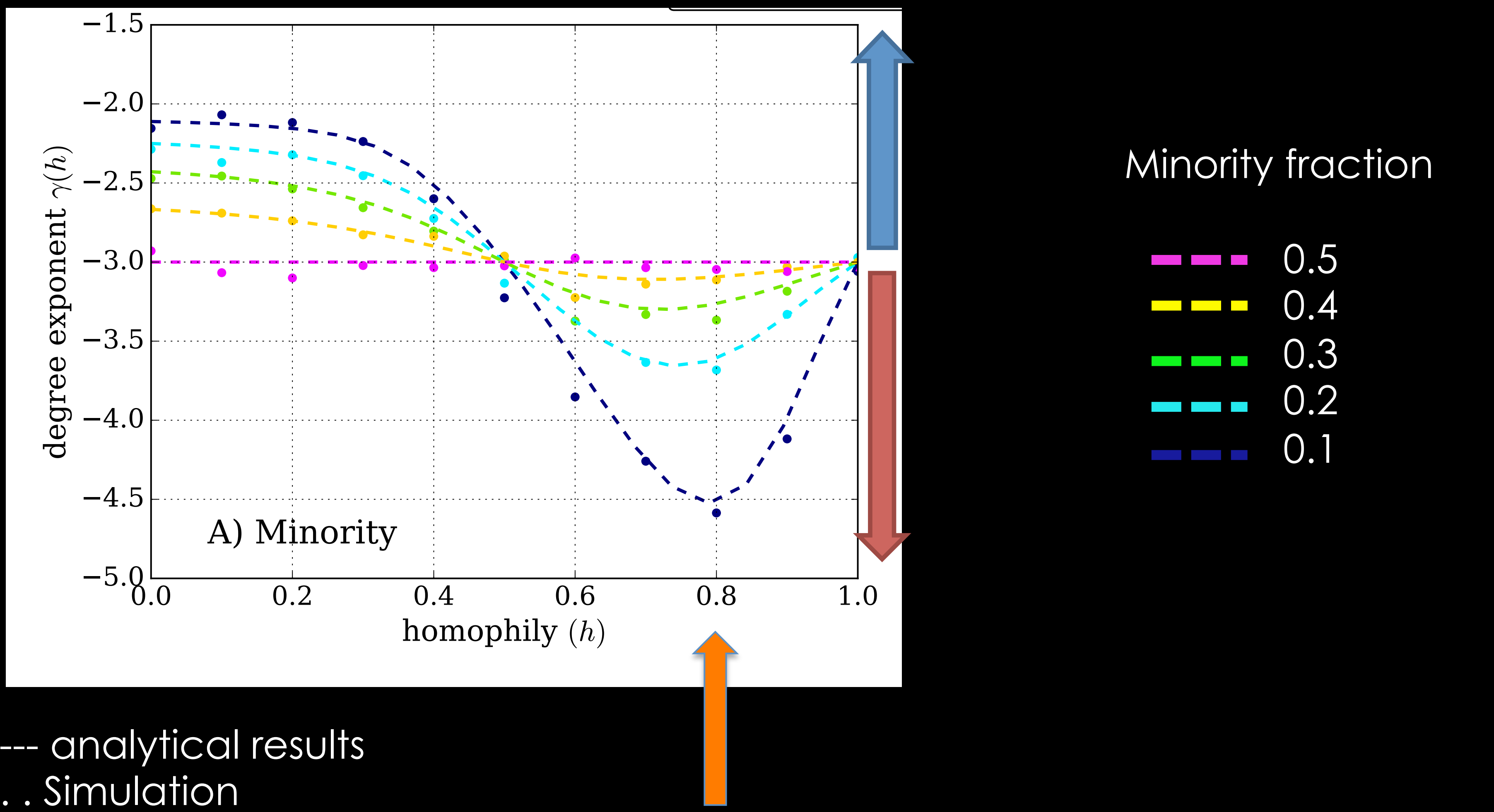



Degree distribution



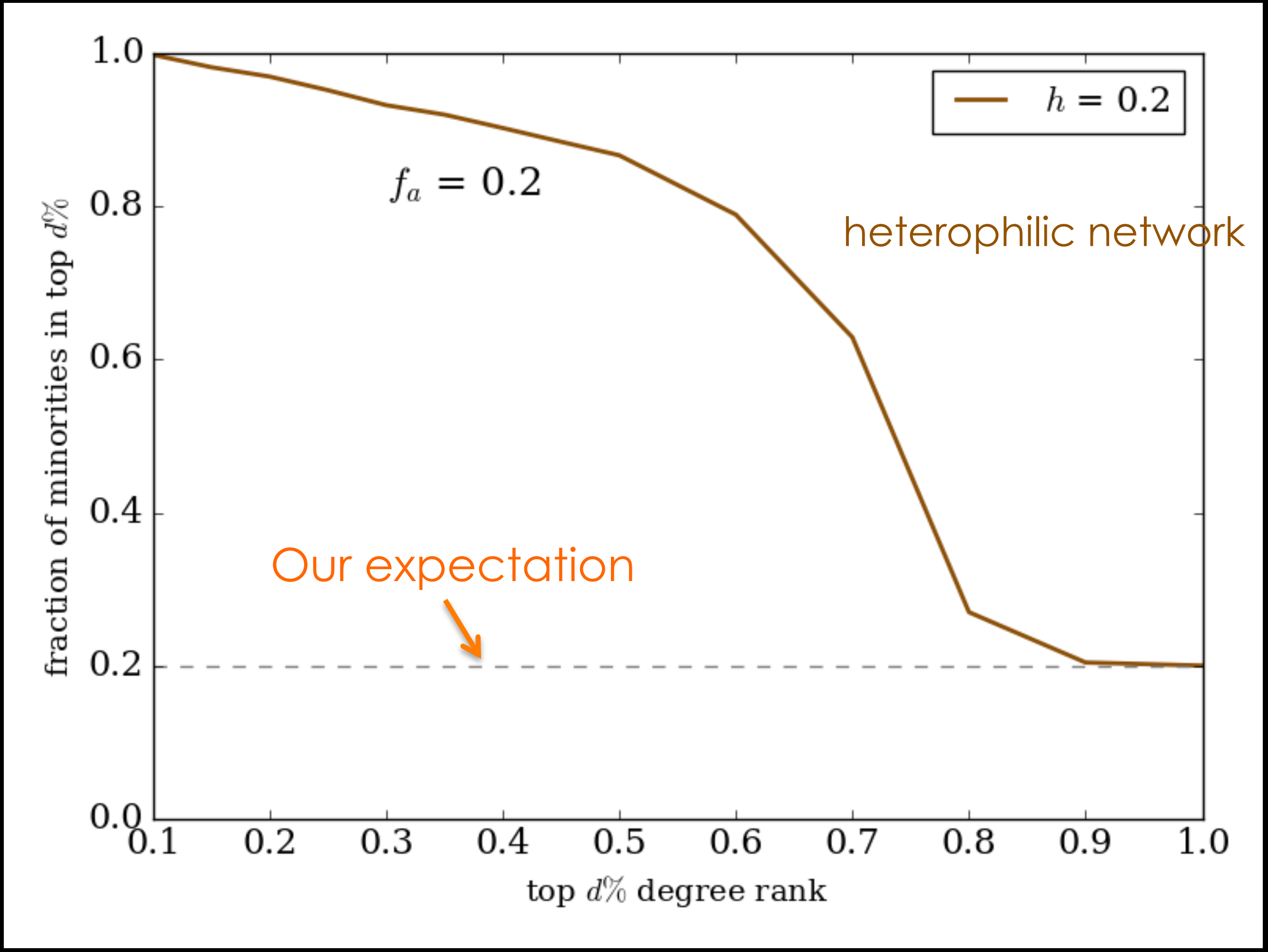

Minorities are in the
weakest position

# Exponent of the degree distribution depends on group size and homophily

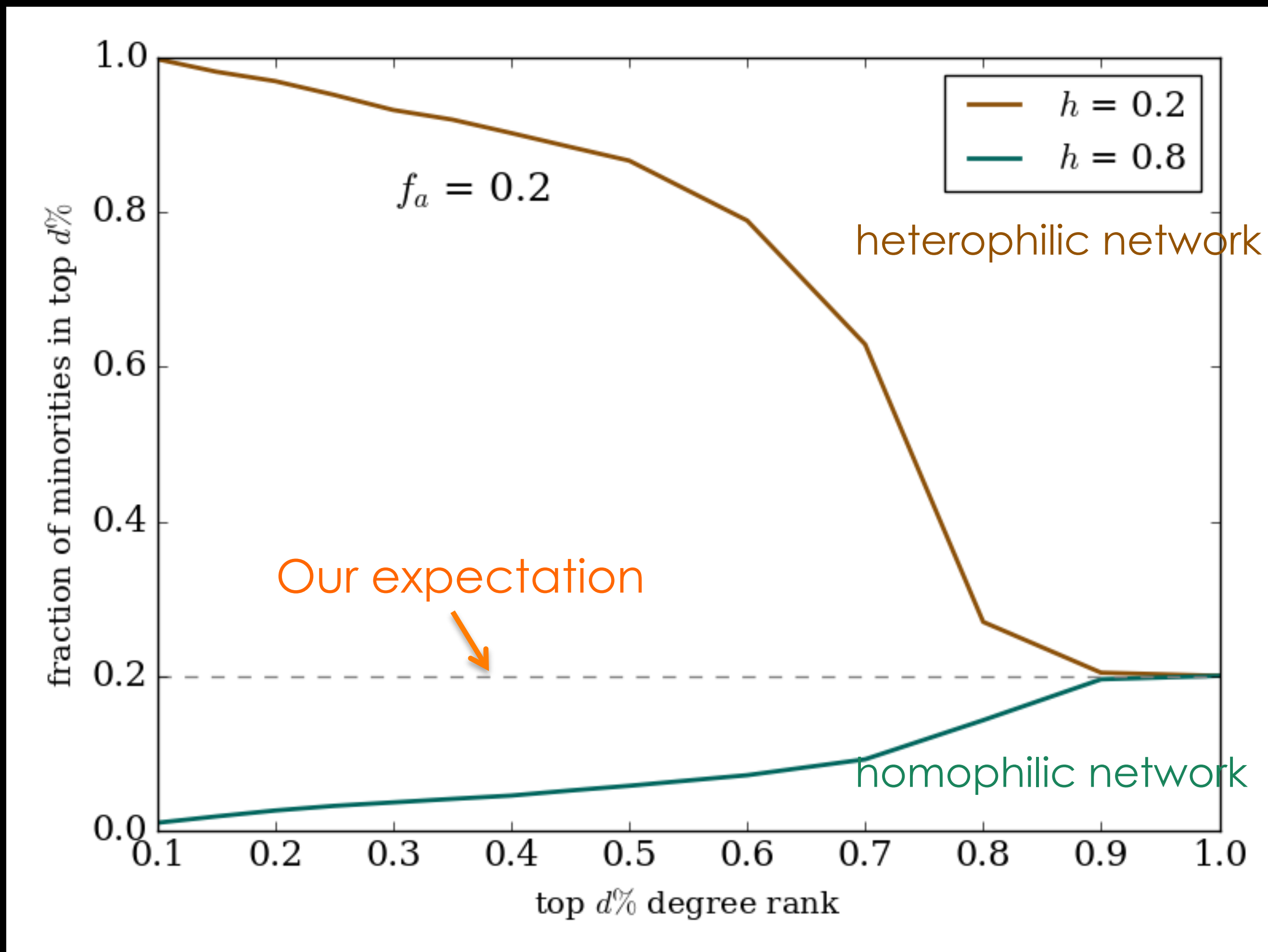



--- analytical results
. . Simulation

# Minority rank in top d%



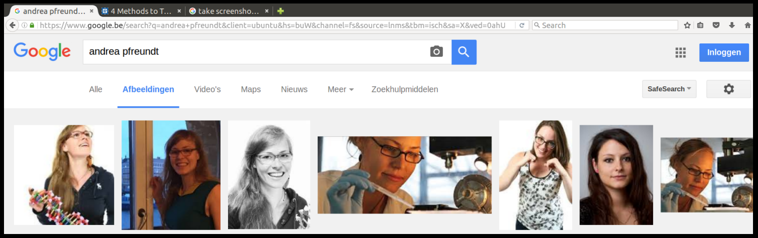
# Minority rank in top d%



# Ranking of minorities in Empirical Networks

# Ranking of minorities in empirical social networks

1. Online prostitution dataset. Rocha et al., PNAS
2. Online dating network. Holme. PRE
3. Co-authorship network among computer scientists.




*Karimi et al. WWW Conf. (2016)*

4. Citation network. APS

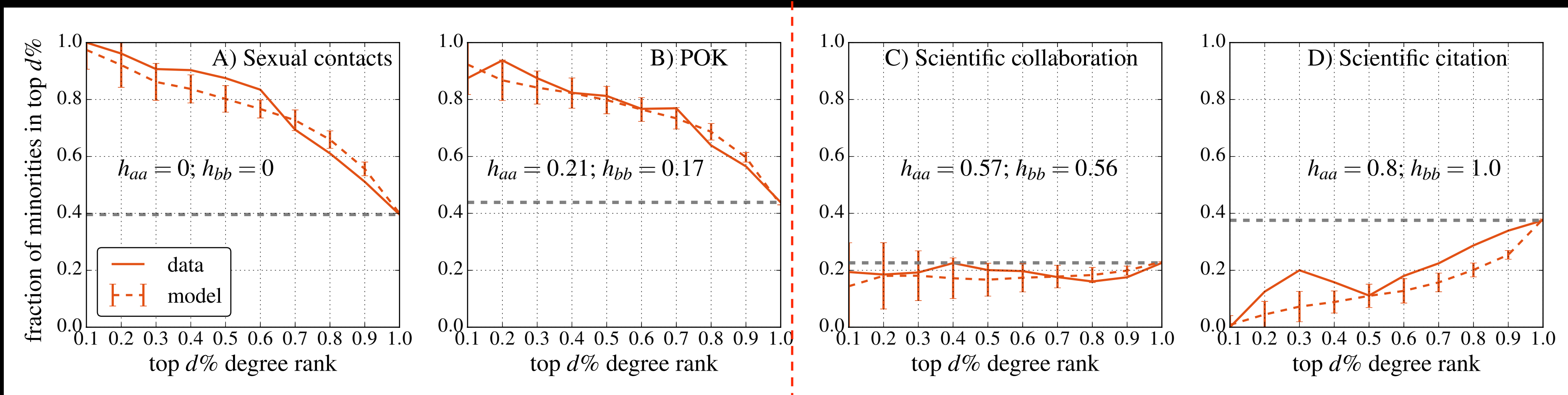
# Ranking of minorities in empirical social networks

Heterophilic networks

minority advantage

Homophilic networks

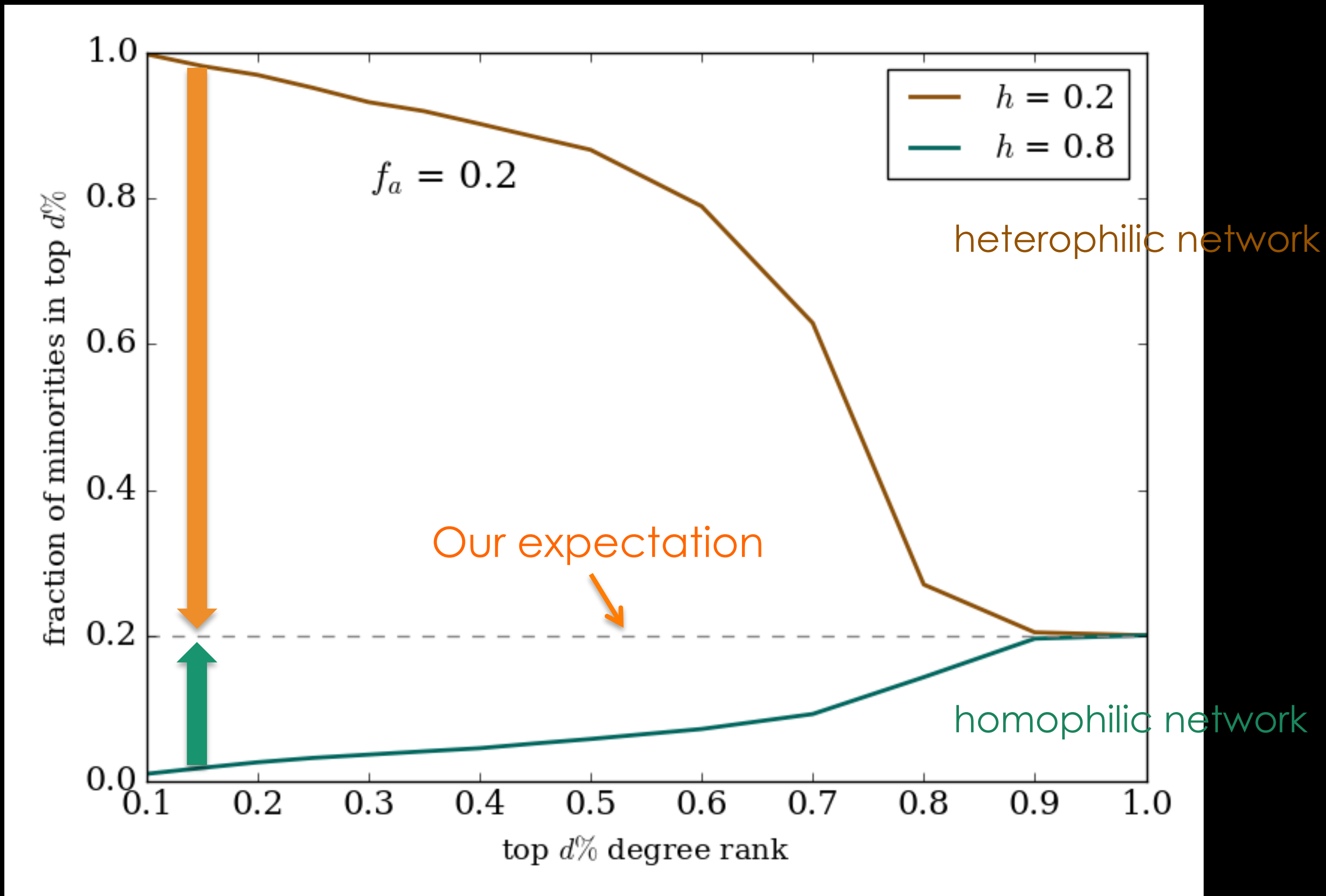
minority disadvantage




| Online prostitution | Online dating | Co-author network Comp. Science | Scientific citation Academic literature |
|---|---|---|---|
| Minority: Sex workers | Minority: Women | Minority: Women | Minority: Scientific subfield |

# Correcting for ranking biases?

# Correcting for Ranking Biases



# Practical implications

- Sampling networks with attributes.

  Wagner, Singer, Karimi, Pfeffer & Strohmaier. WWW 2017

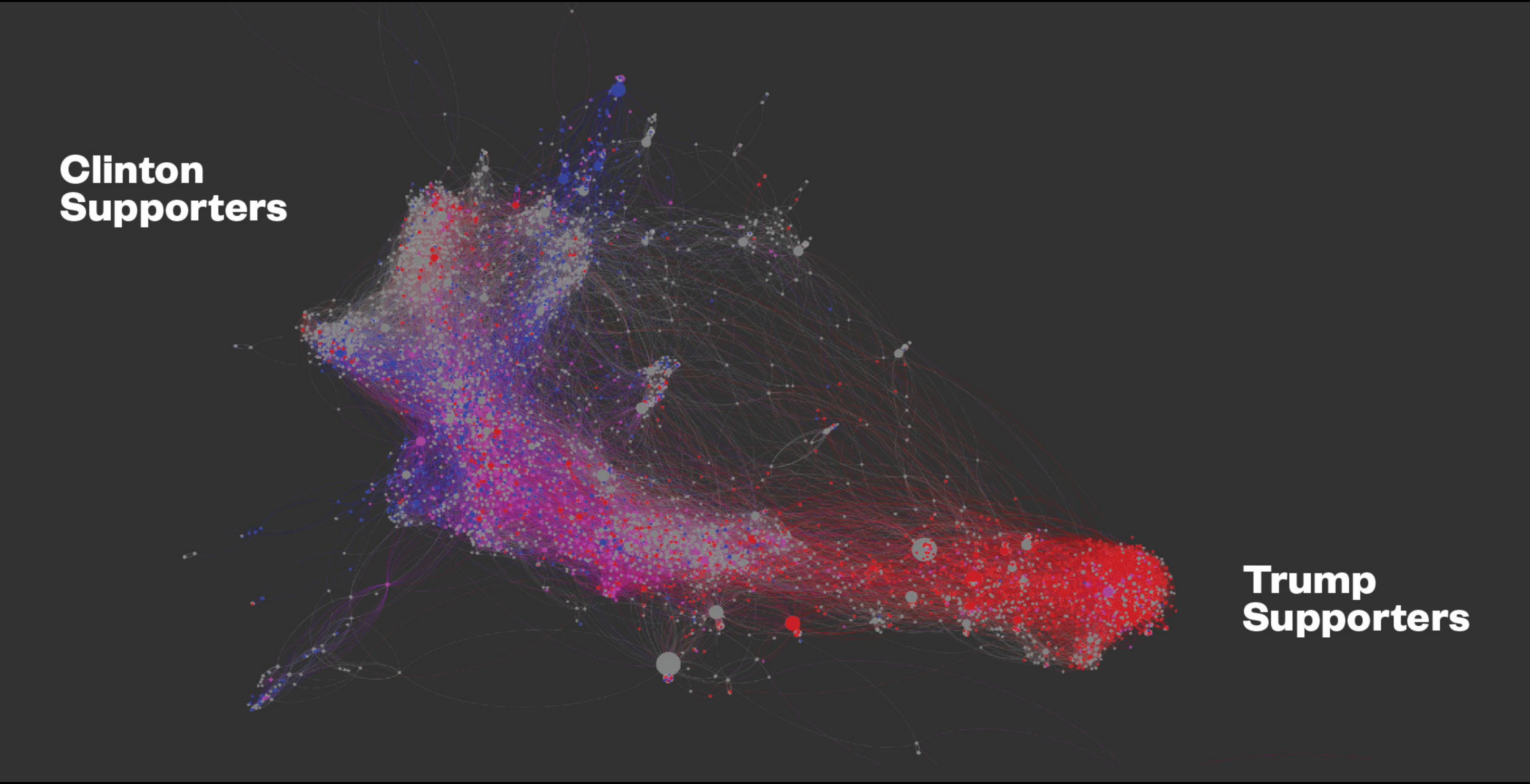
- Emergence of perception biases in social networks.

  Karimi*, Lee*, Wagner, Hang, Strohmaier & Galesic. (forthcoming in Nature Human Behavior) * equal contribution

- Clashing norms: How does homophily impact norm adoption among minorities and majorities (results of a group project)

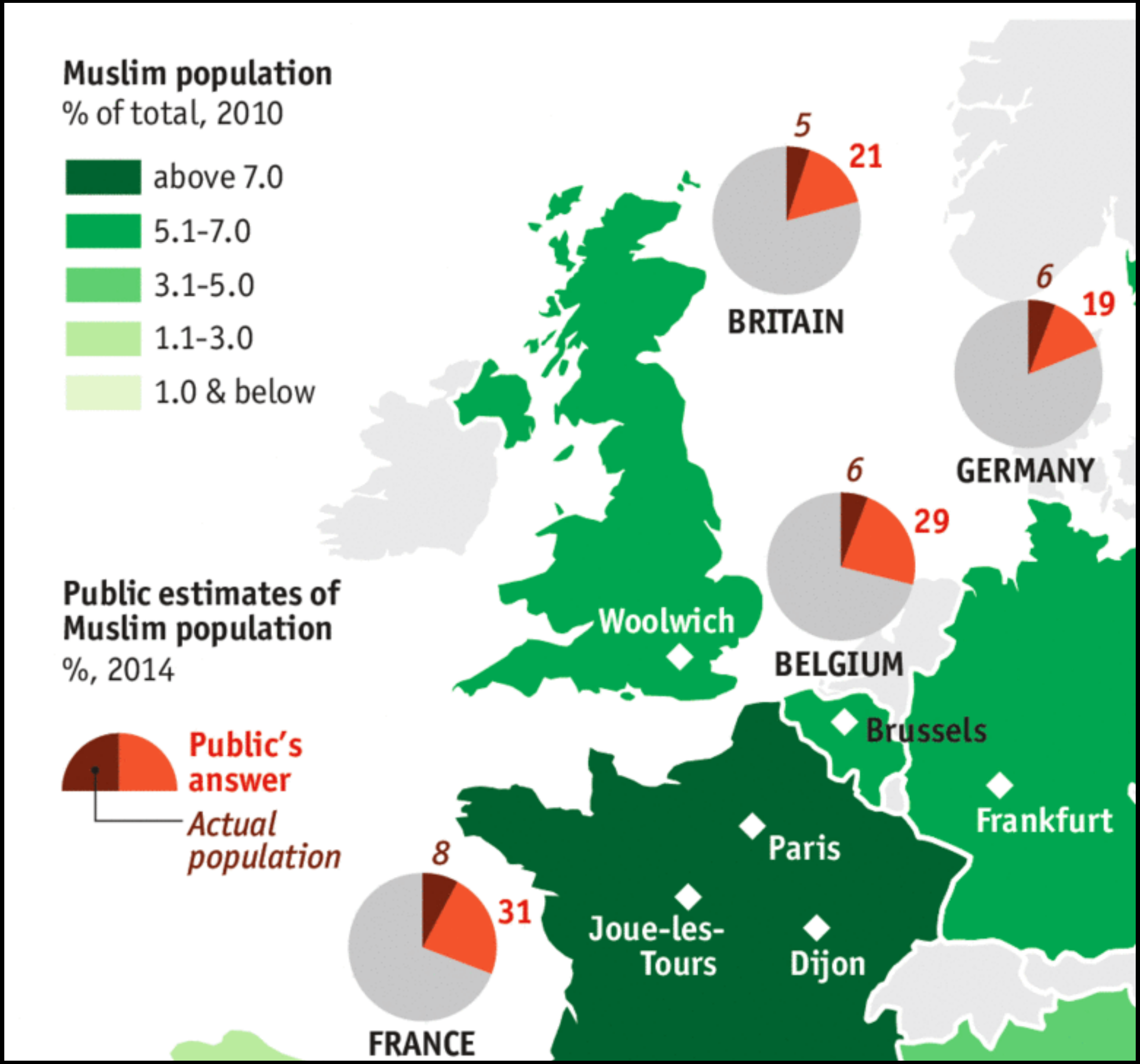
  Kohne, Gallagher, Kirgil, Paolillo, Padmos & Karimi (forthcoming in Computational conflict research)

# Perception bias – False Consensus (filter bubble)

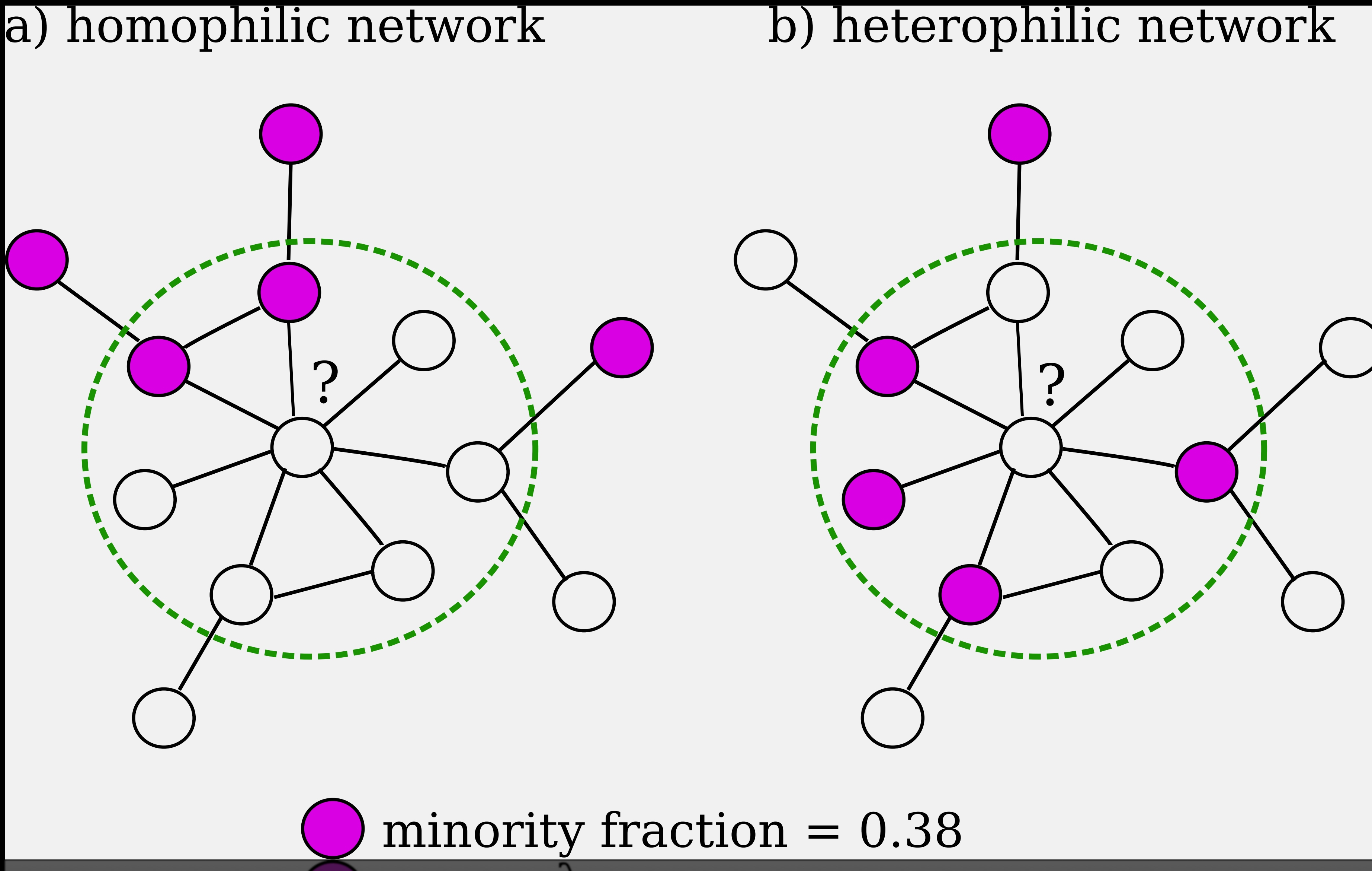



The electome, MIT Media Lab

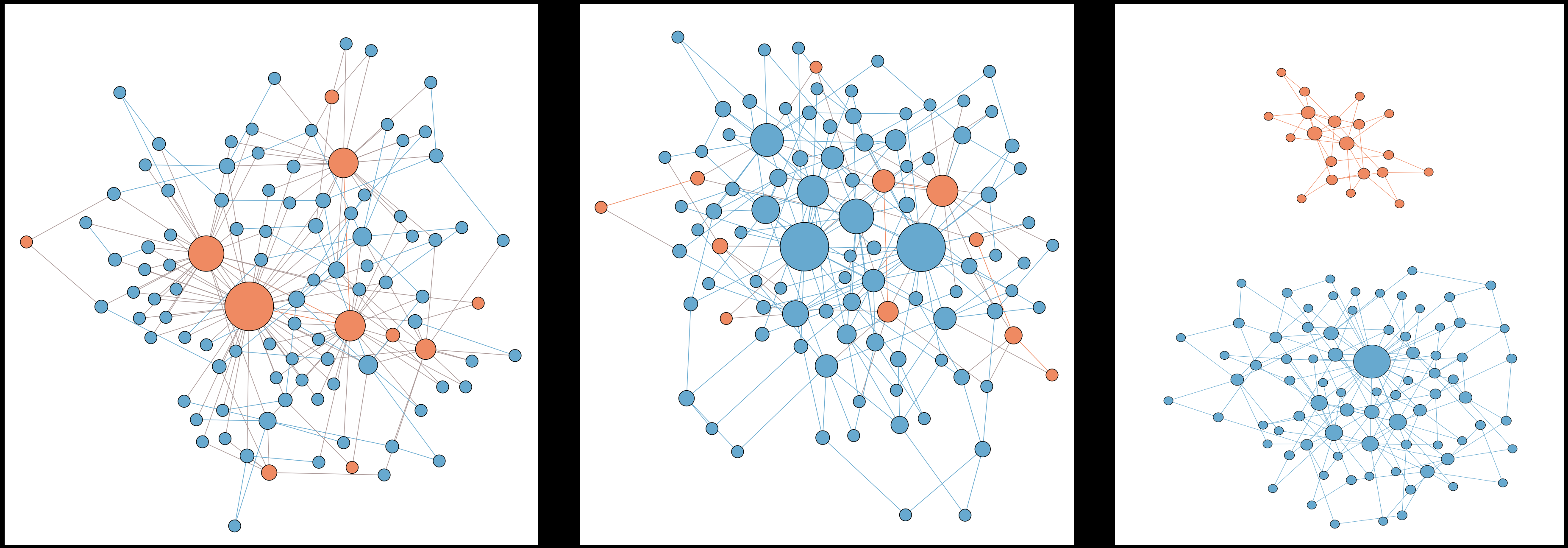
# Perception bias – False Uniqueness (majority illusion)




economist.com


a) homophilic network
b) heterophilic network
?
?
minority fraction = 0.38

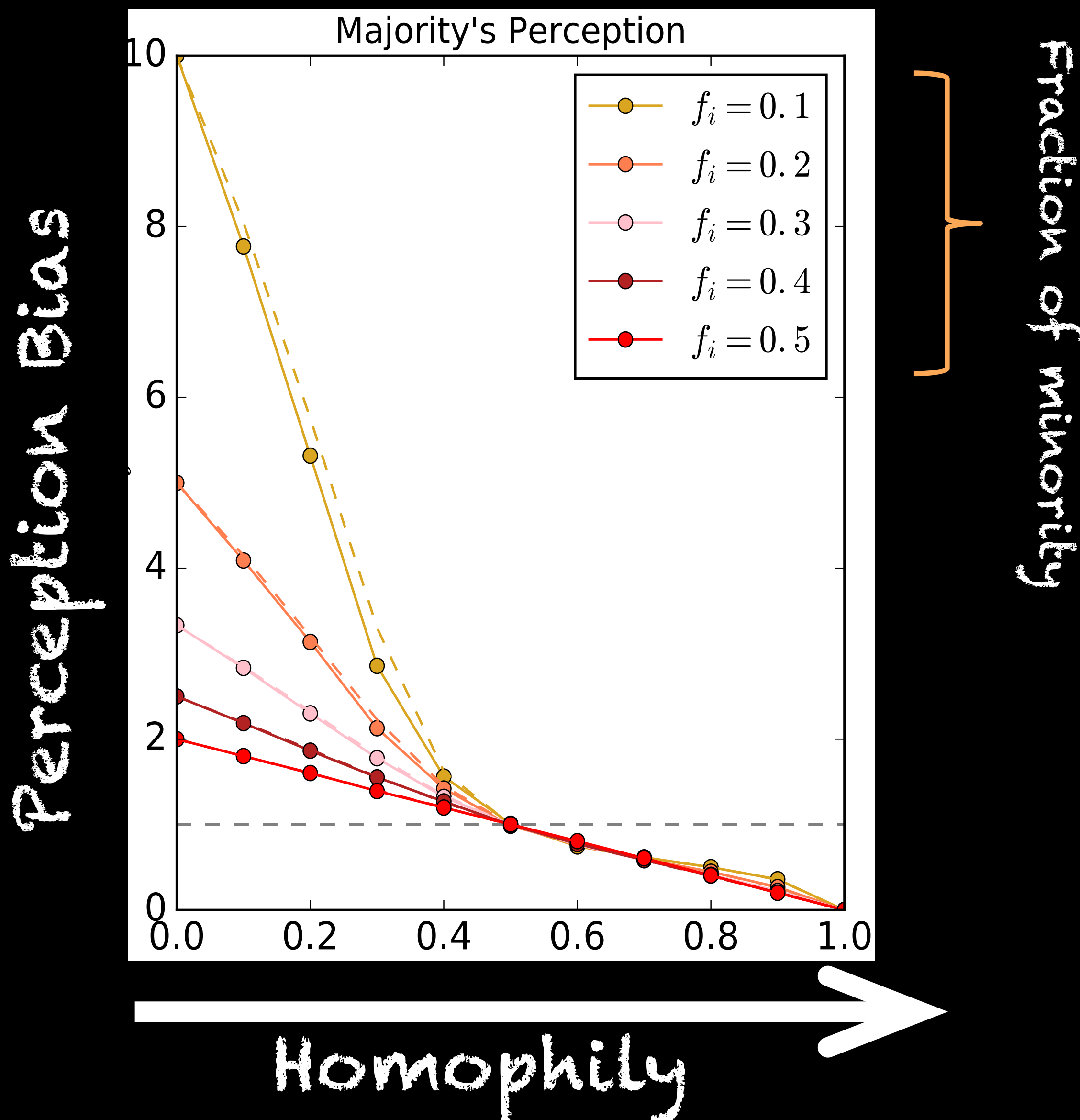
# Network model with tunable homophily and group size



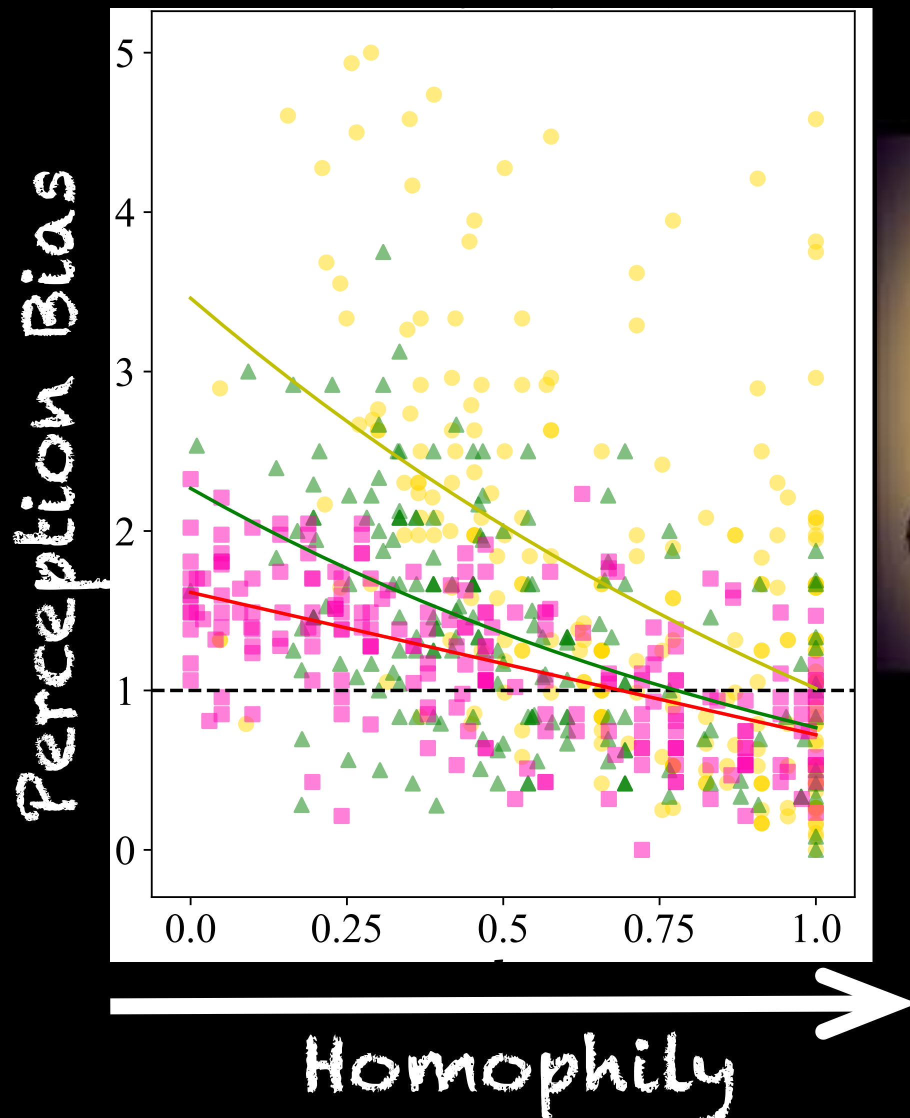
Homophily

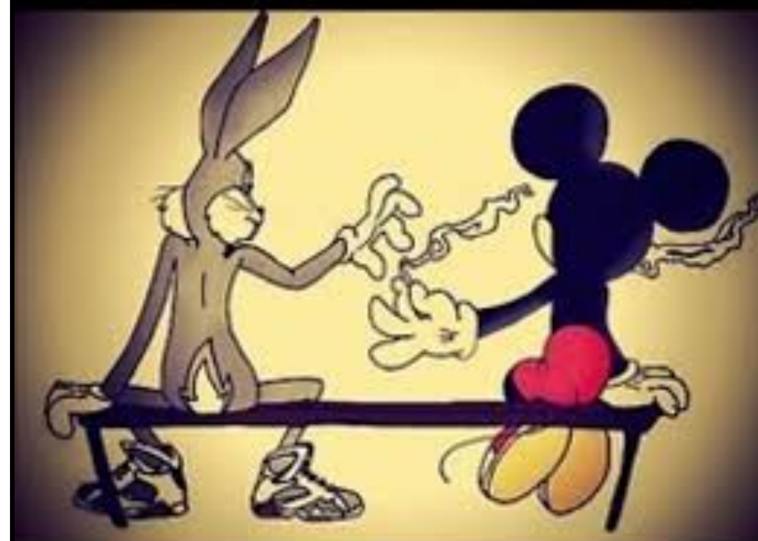
Karimi et al Sci Rep 2018

# Network model with tunable homophily and group size

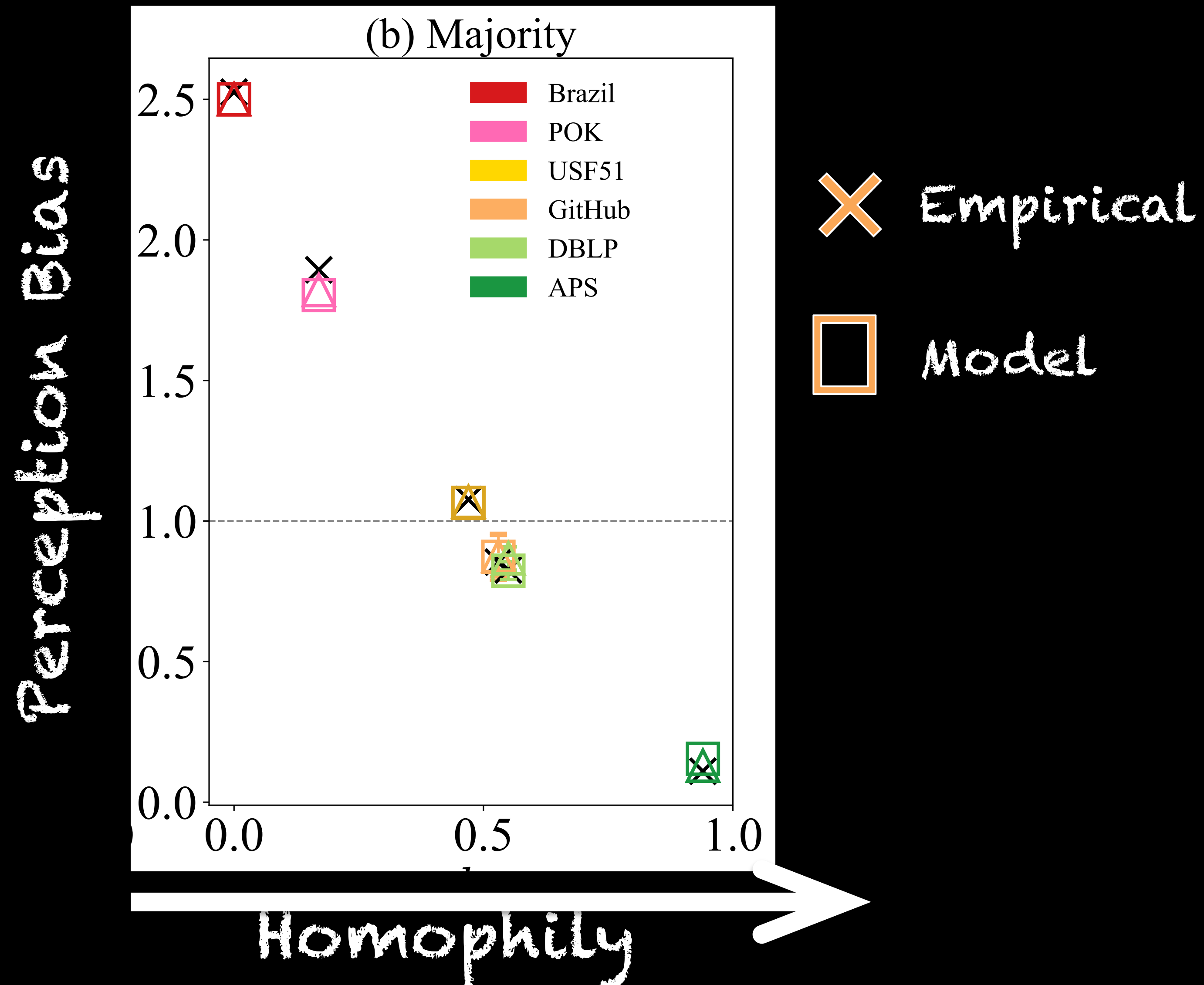


# Survey: Perception of non-smokers about smokers

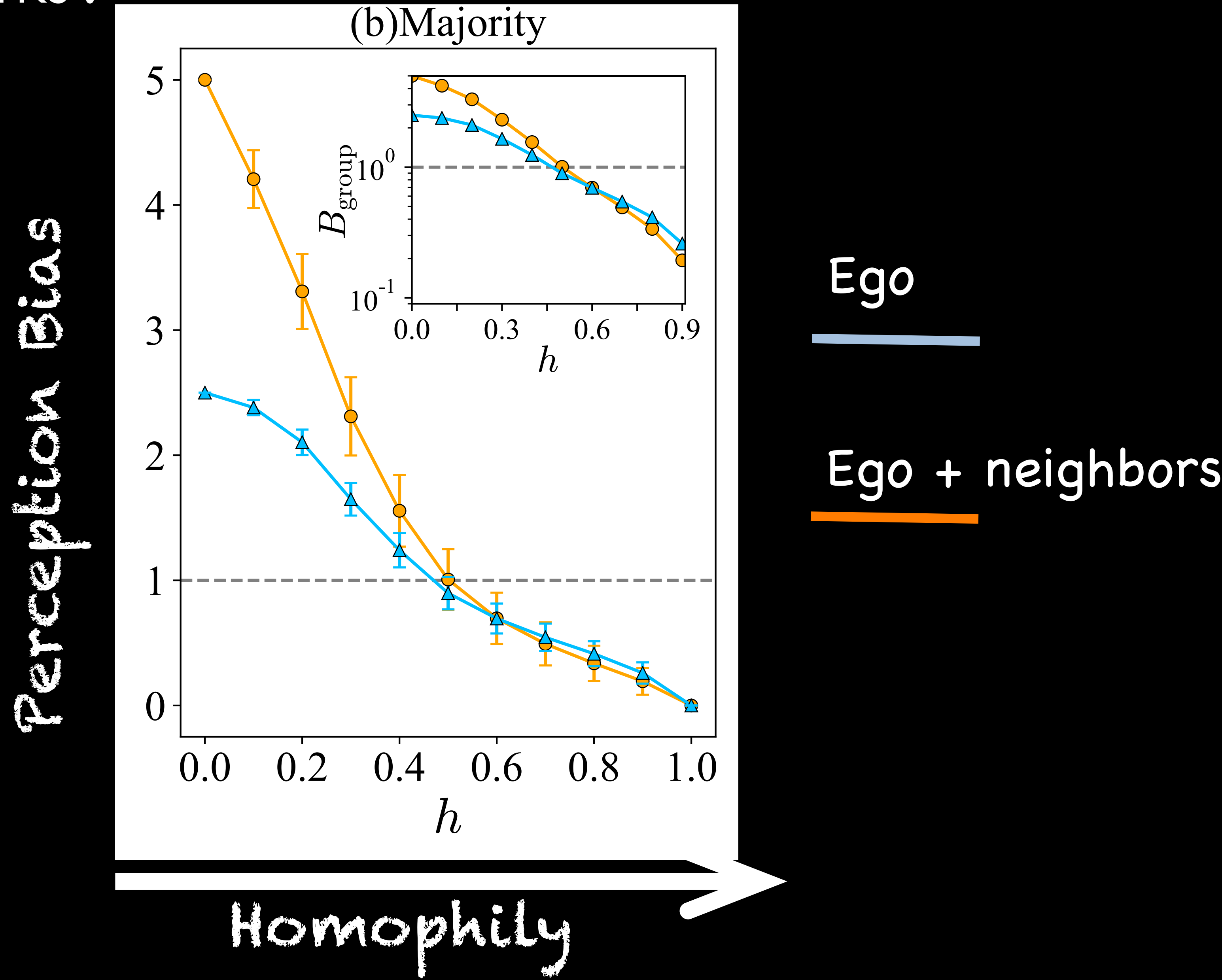


# Perception bias in large empirical networks



# Can we mitigate perception biases in social networks?



# Final Remarks

- Structure of networks and timing of interactions have a crucial impact on dynamical processes.

- Homophily impacts visibility and ranking of minorities.

- Social perception biases can be explained partly from the structure of social networks.

- Data-informed network models combined with surveys and digital trace data will enable us to understand, identify, and tackle societal problems.

# Thank You!

Selected References:

- Homophily influences ranking of minorities in social networks, *Scientific Reports* (2018)
- Homophily explains perception biases in social networks, *Nature Human Behaviour* (forthcoming)
- Threshold model of cascades in temporal networks, *Physica A* (2013)

## Collaborators:

Markus Strohmaier

Claudia Wagner

Eun Lee

Mathieu Genois

Mirta Galesic

Lisette Noboa

Mohsen Jadidi

Florian Lemmerich

Kristina Lerman

Julian Kohne