

Inequality II.

Networks and Algorithms

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<https://github.com/lisette-espin/TeachingMaterials>



Tanzania

www.poverty-inequality.com

What is inequality?

≠

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...in general?

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of wealth or opportunities”

AMERICAN (Cambridge dictionary)

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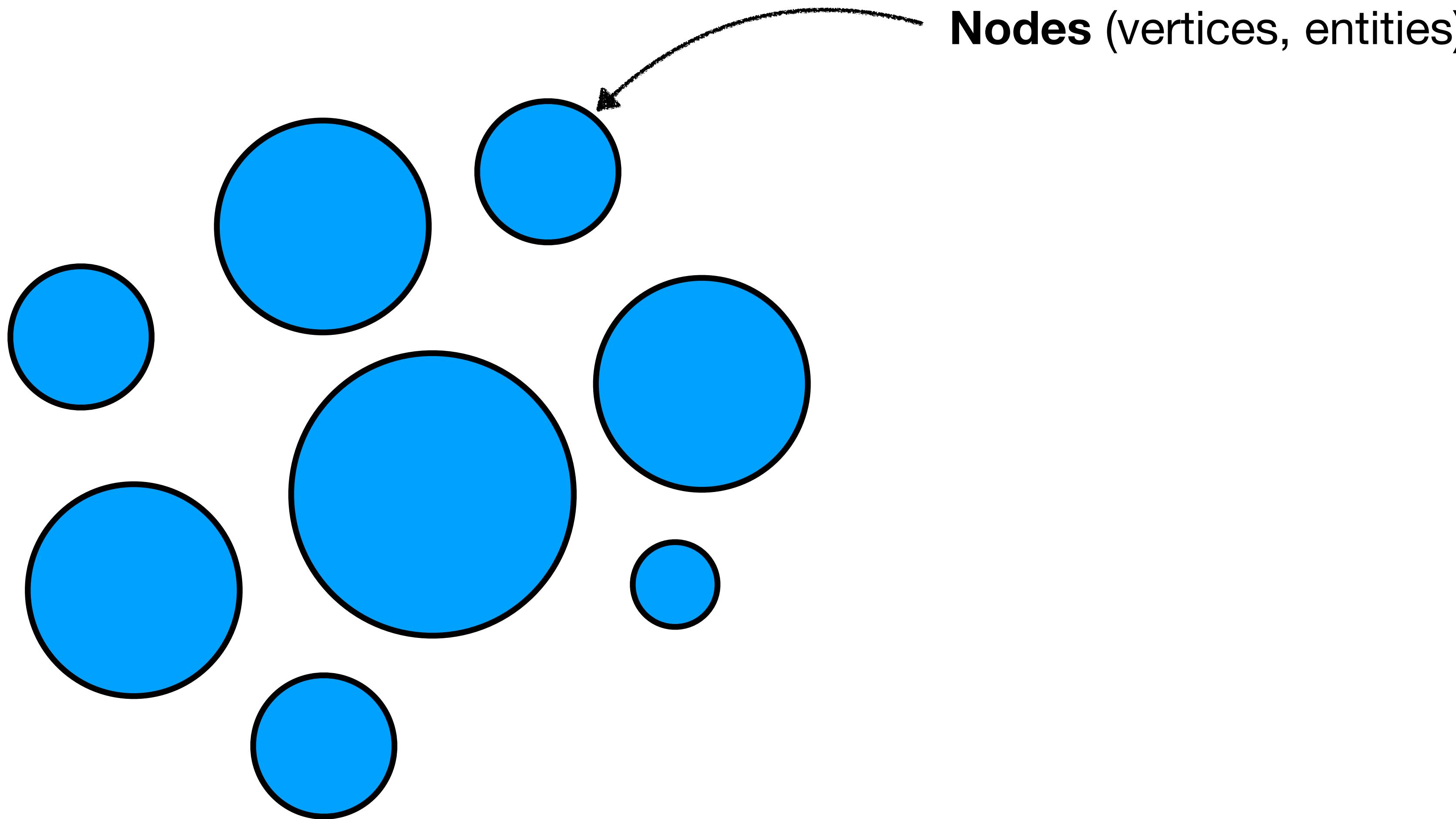
Inequality is also known as:
imbalance, disproportion,
dissimilarity, difference, bias.

What is inequality (bias)...

...in (social) networks?

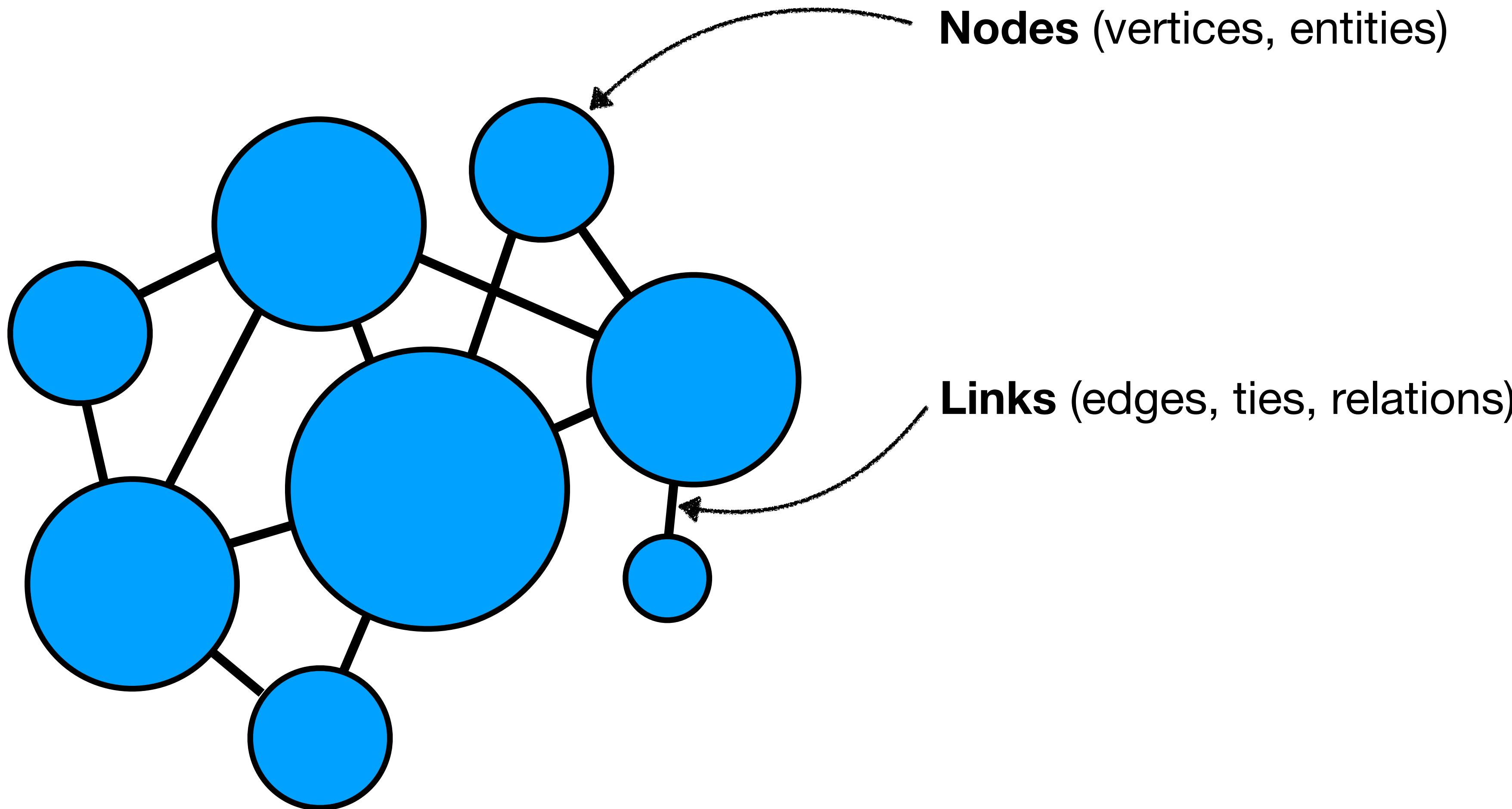
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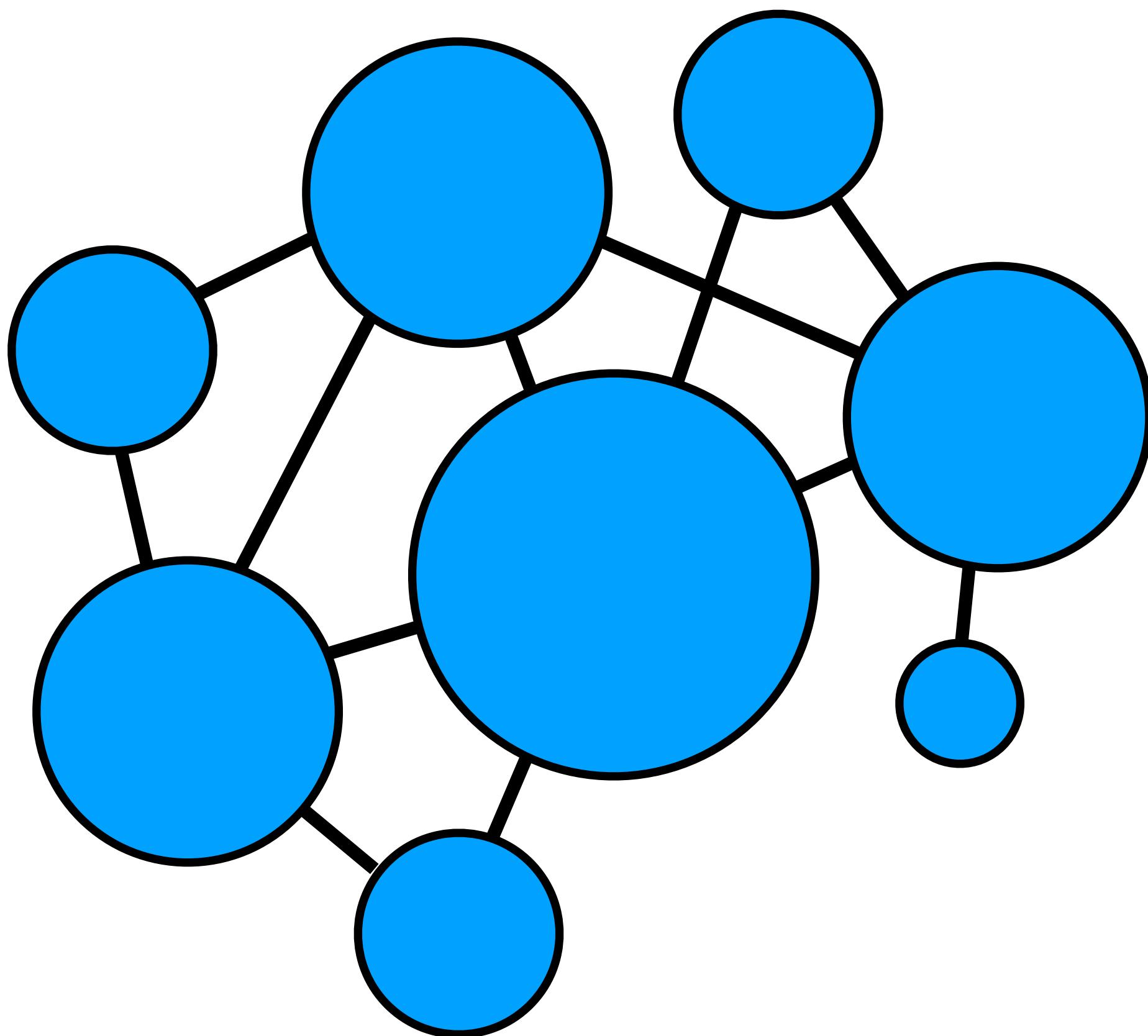
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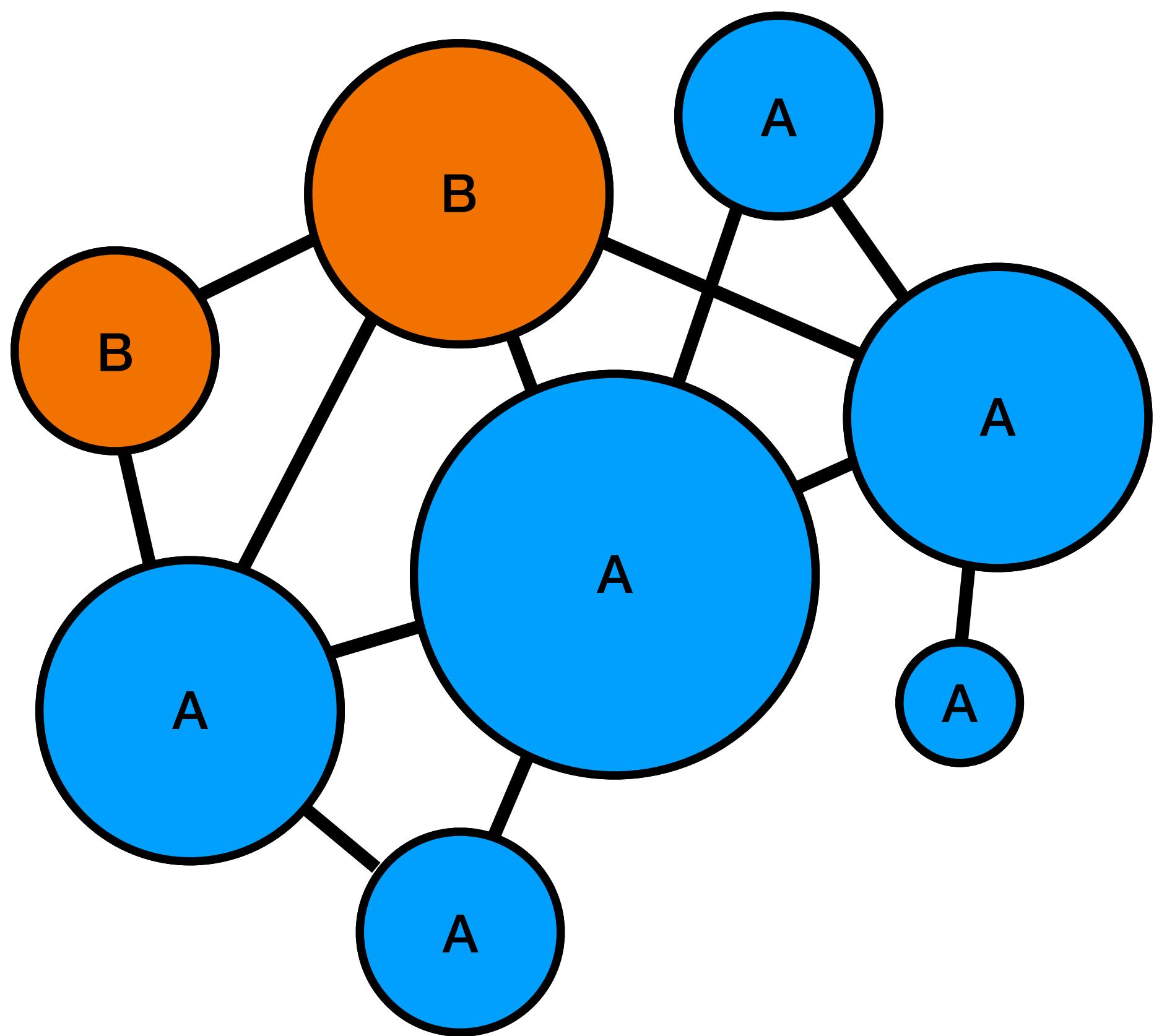


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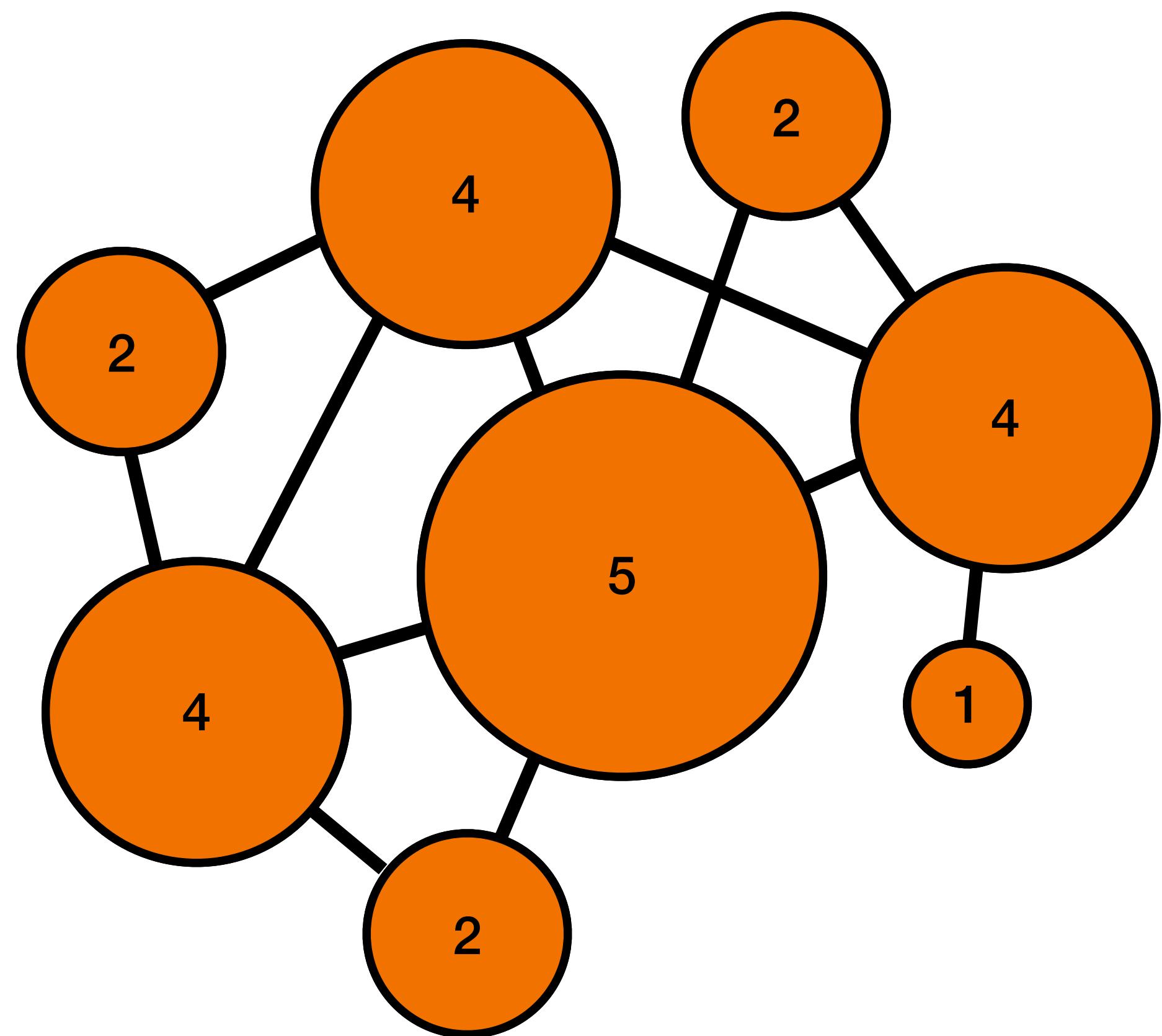
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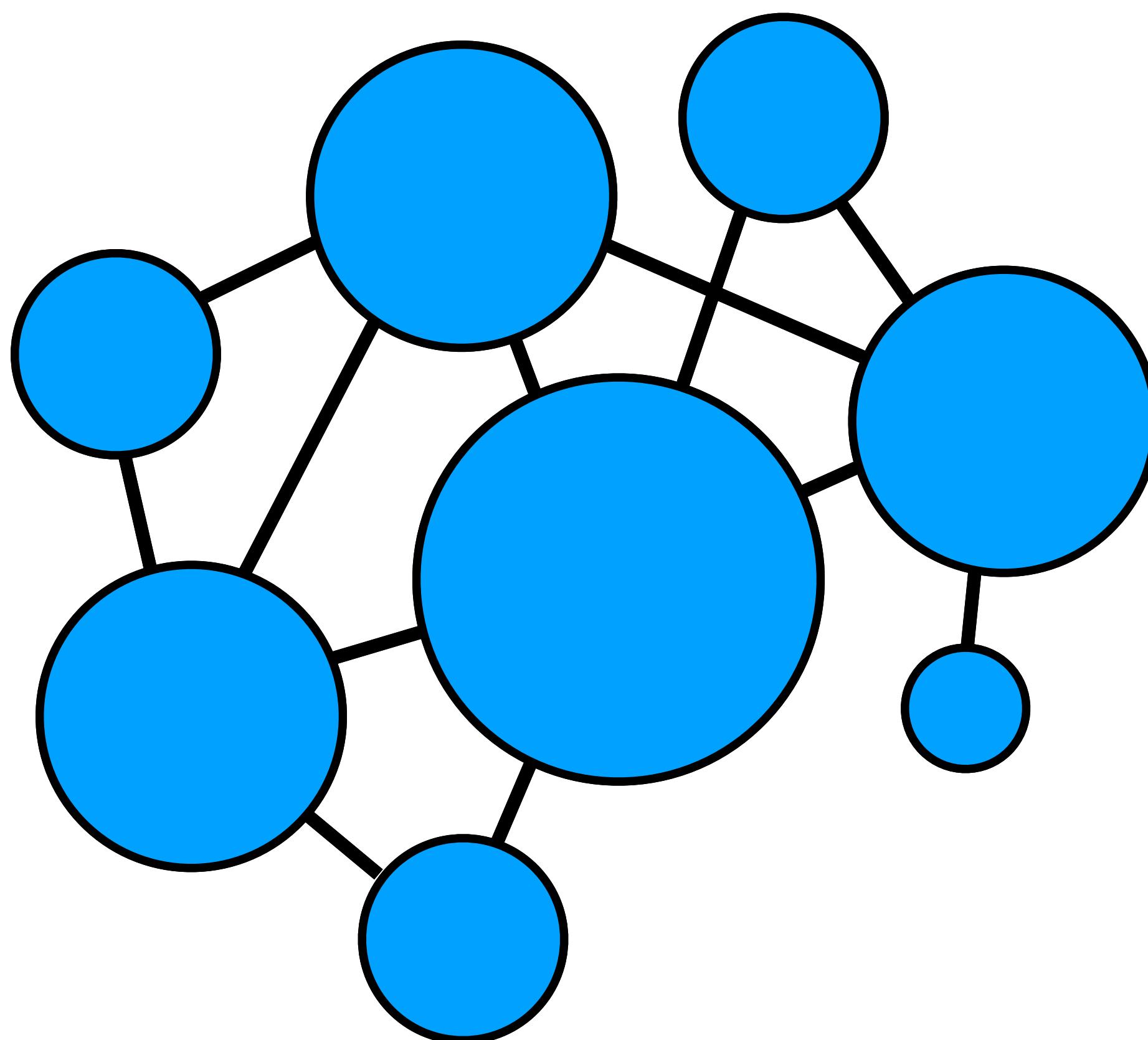


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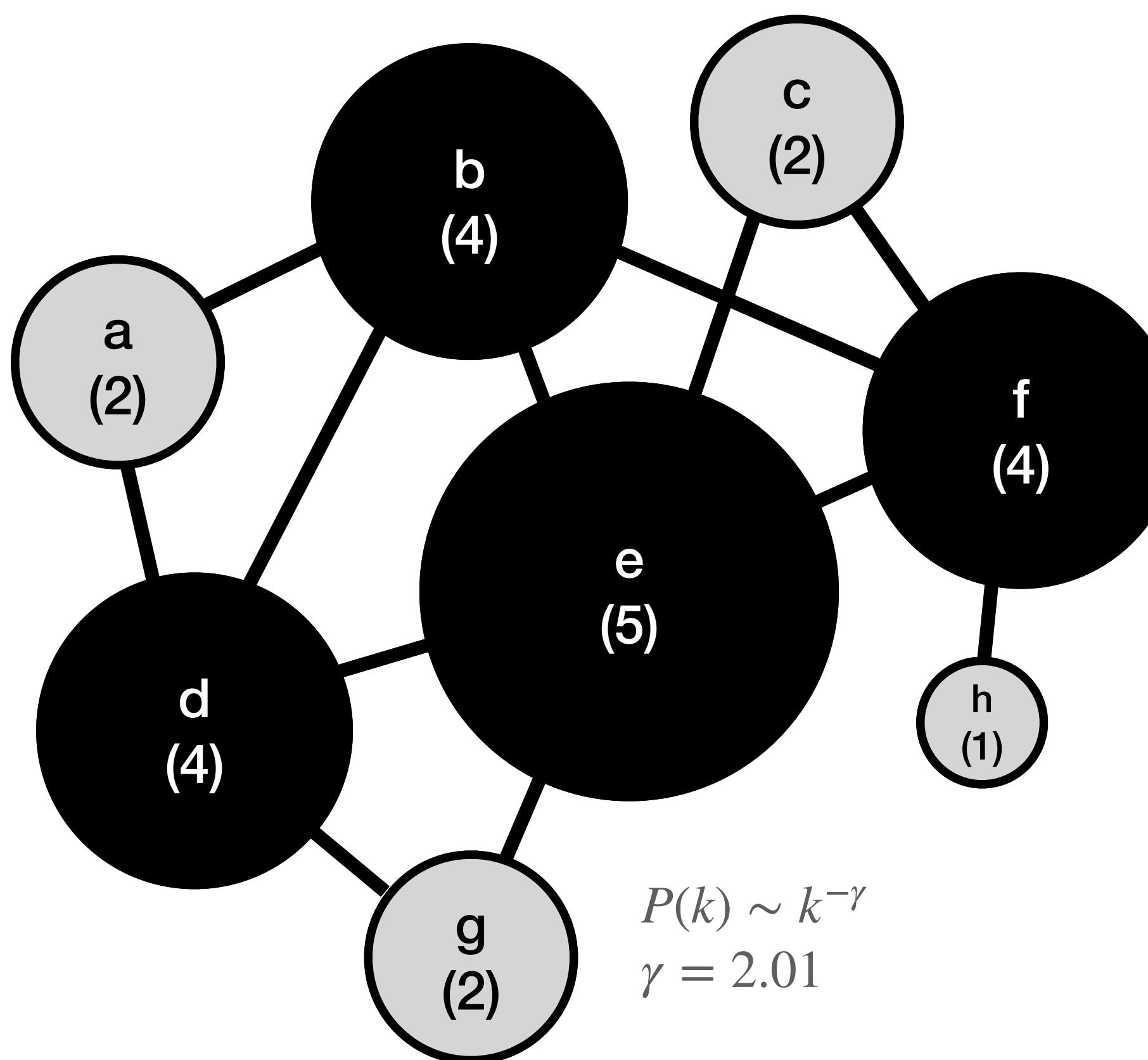
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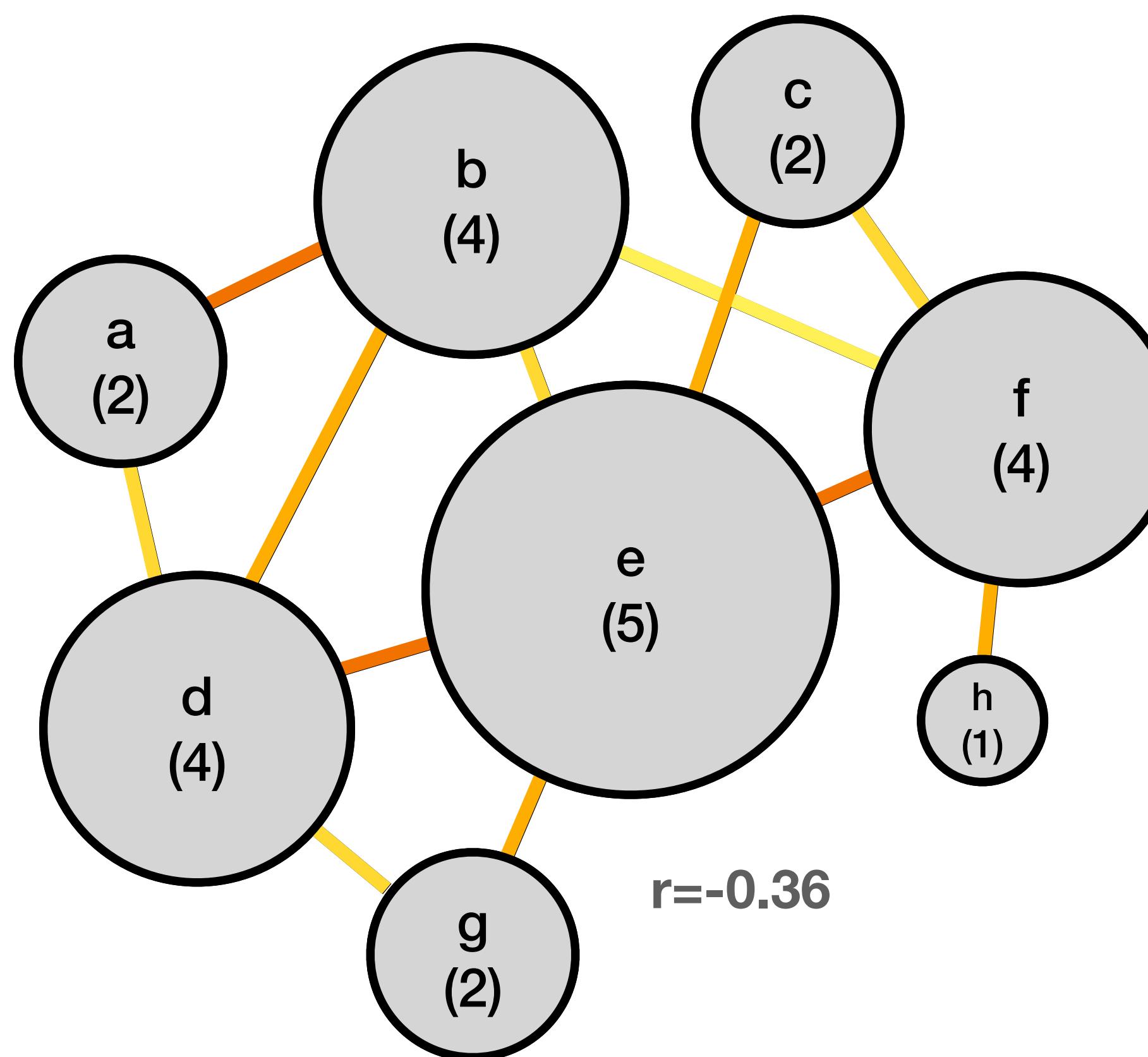
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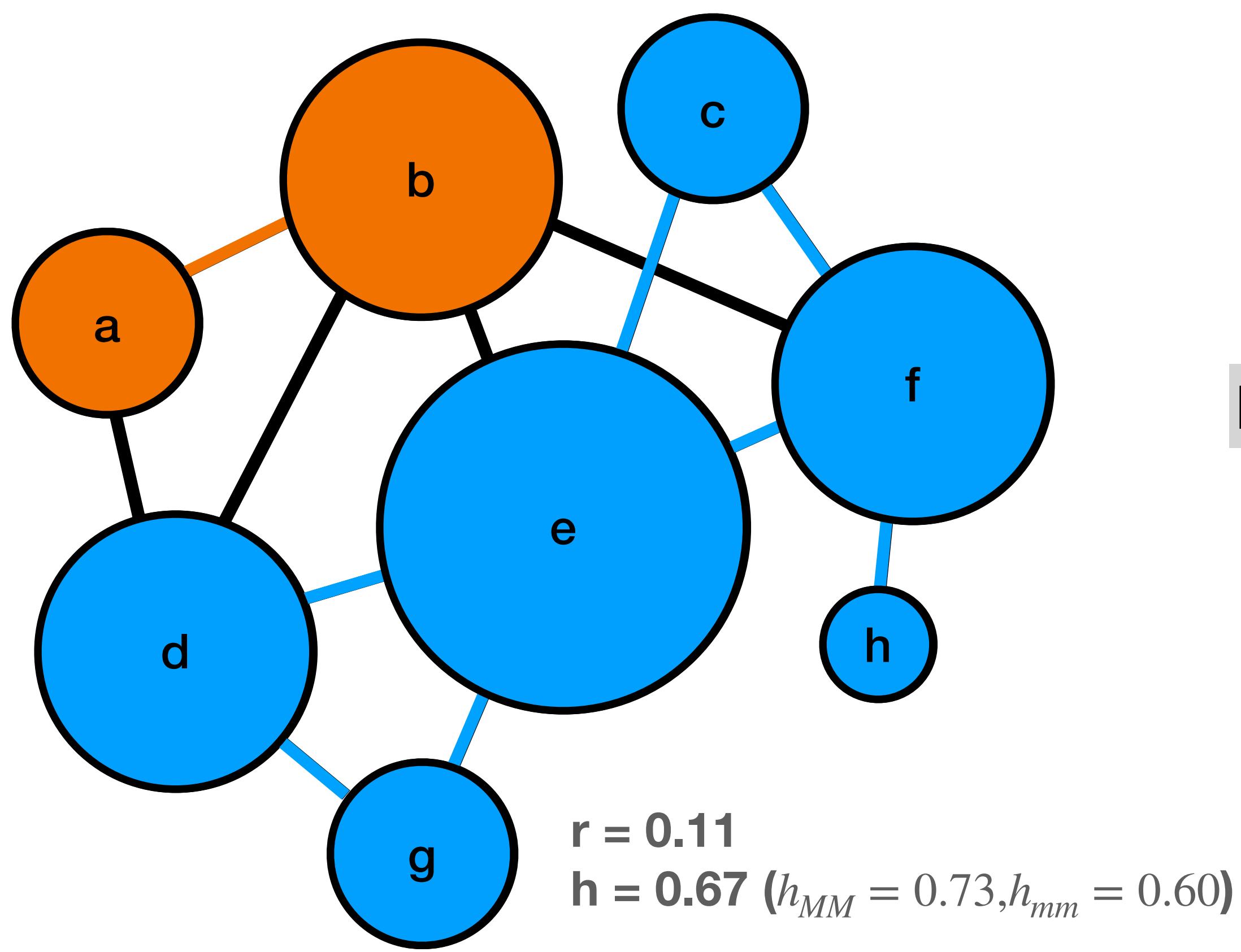
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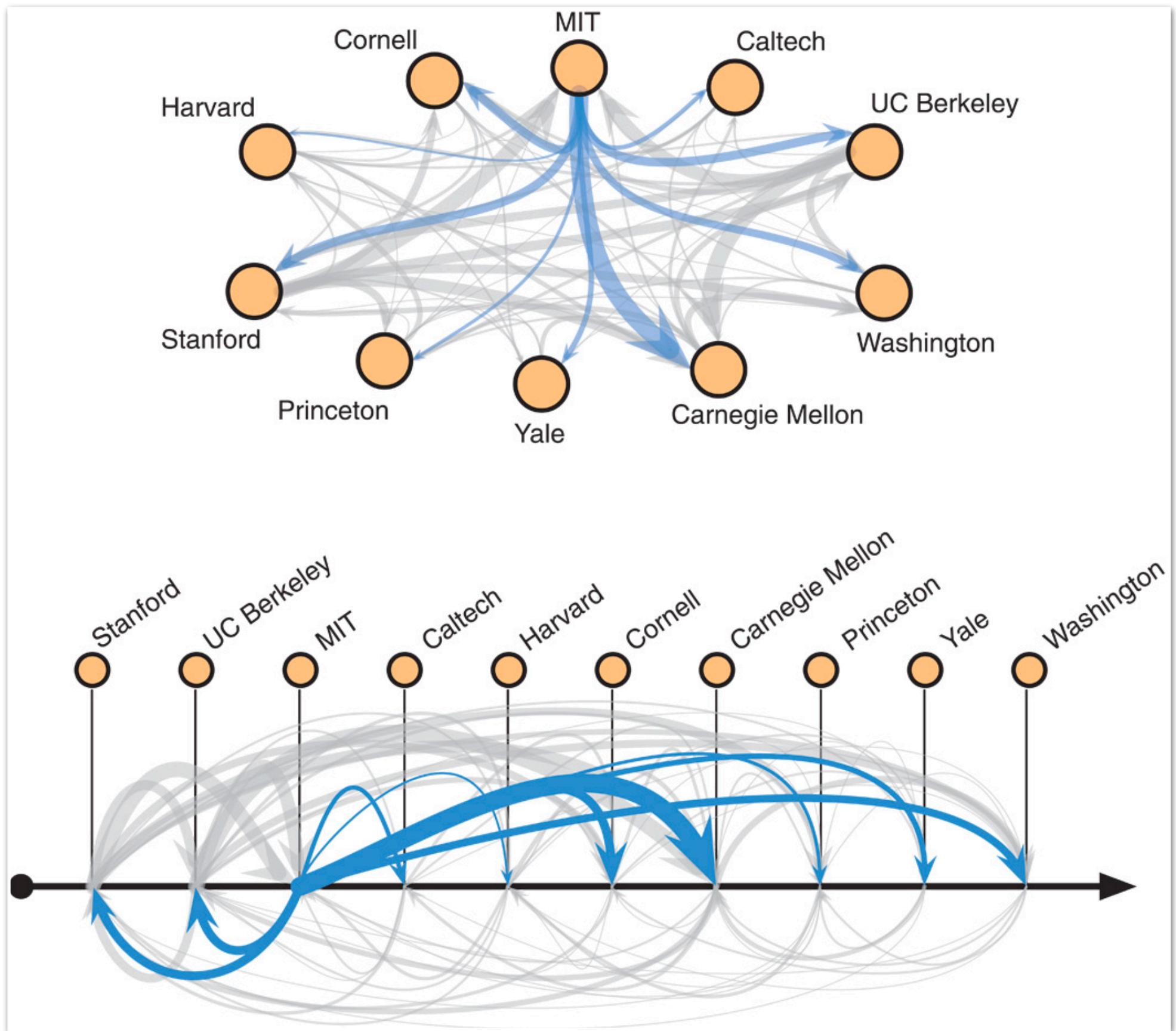
+/- attribute assortativity (Newman 2003)
High/low homophily with PA (Karimi et al. 2018)

Inequalities (biases) in networks

Examples

Inequalities (biases) in networks

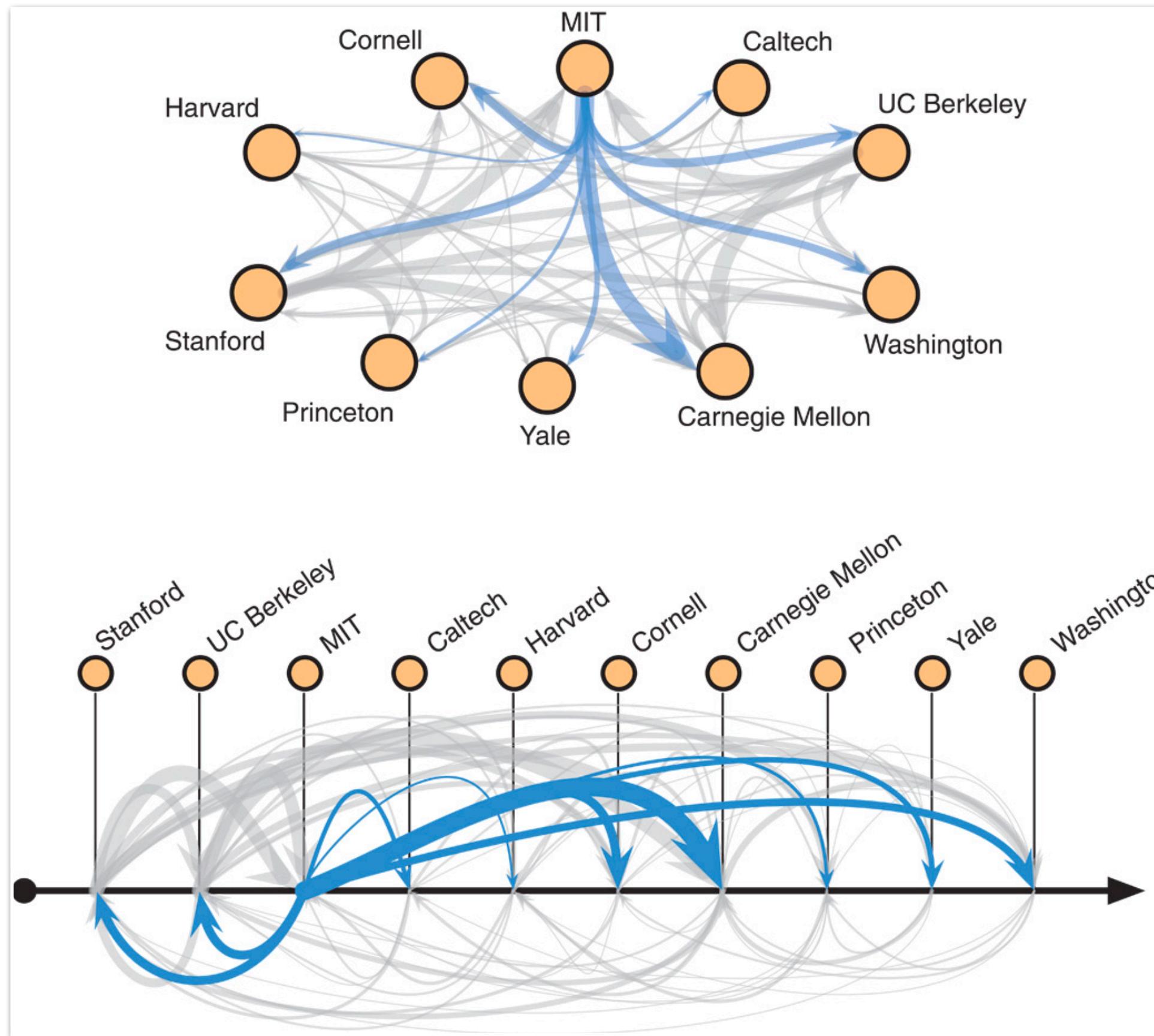
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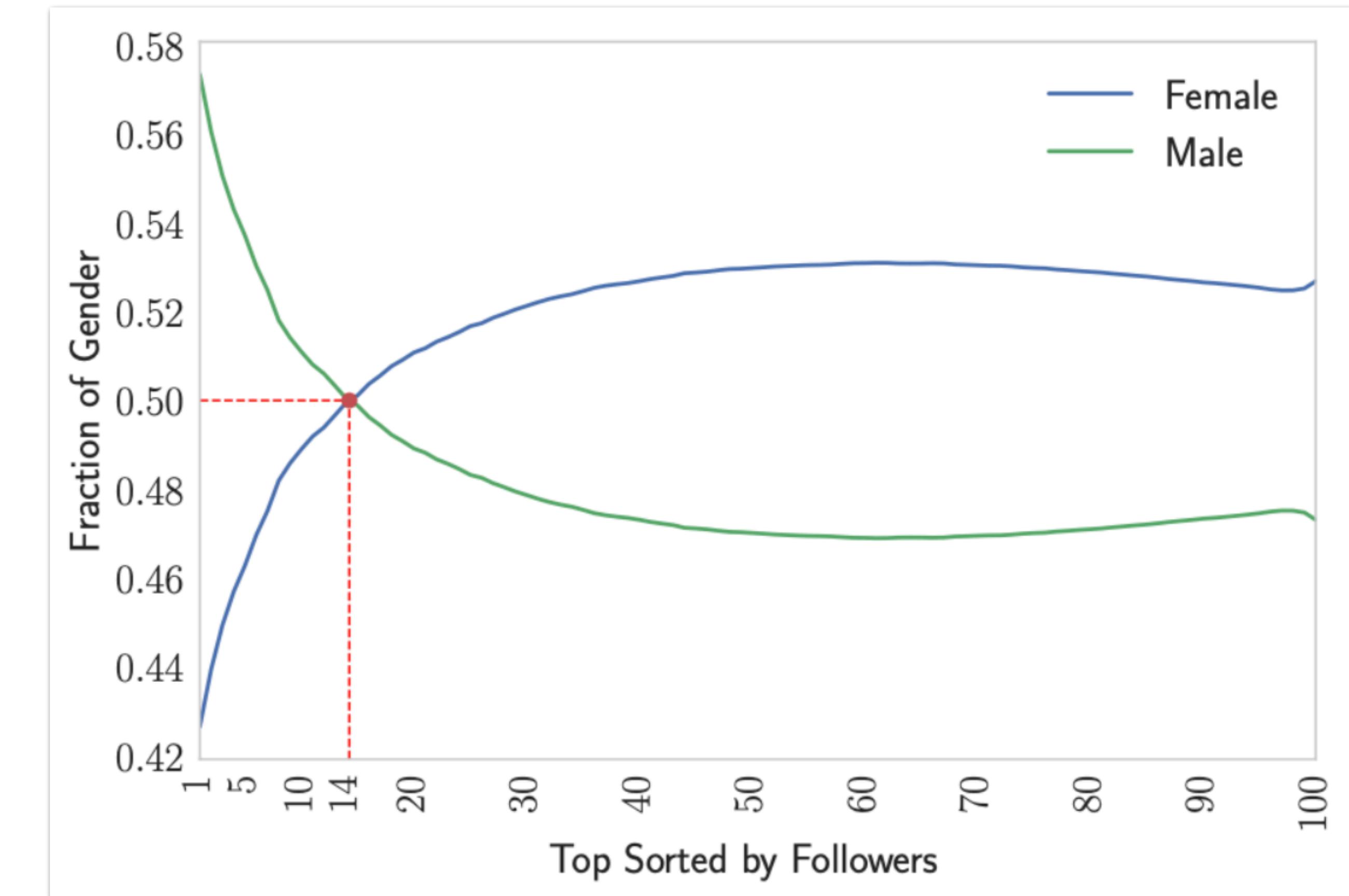
Systematic inequality and hierarchy in faculty hiring networks. Clauset et al. 2015.

Inequalities (biases) in networks

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Systematic inequality and hierarchy in faculty hiring networks. Clauset et al. 2015.



White, Man, and Highly Followed: Gender and Race Inequalities in Twitter. Messias et al. 2017.

What is inequality (bias)... ...in (machine learning) algorithms?

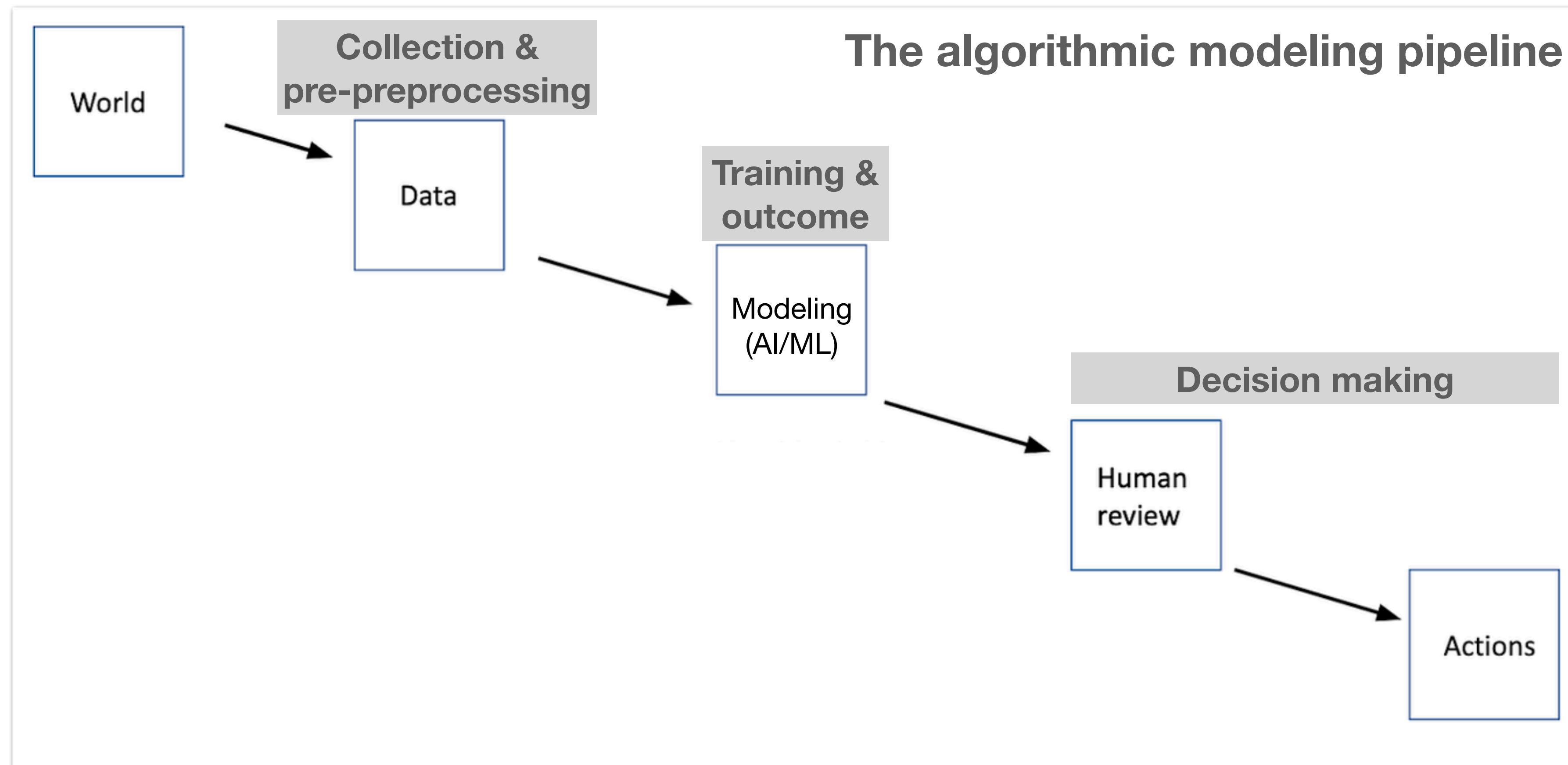


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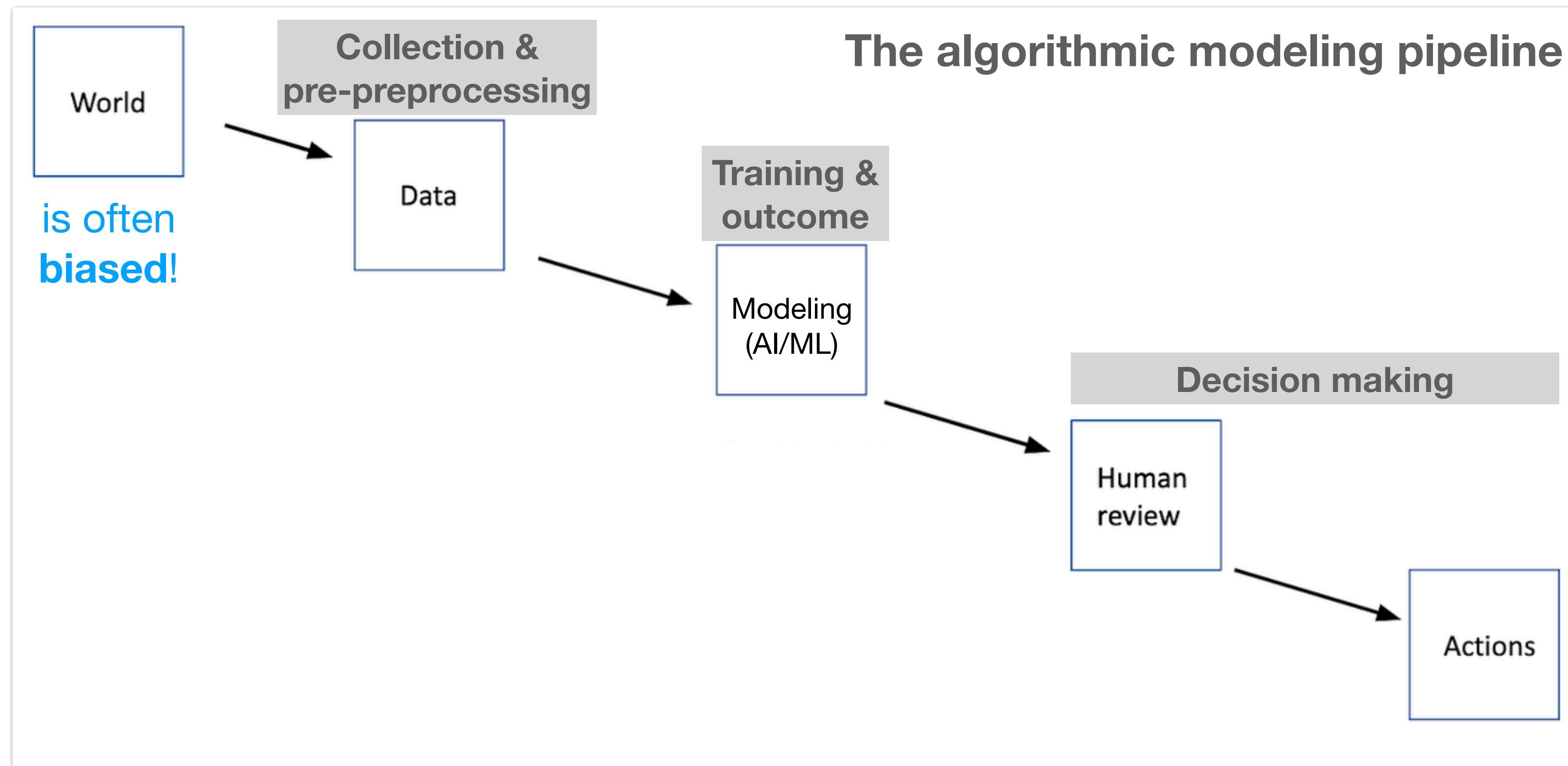


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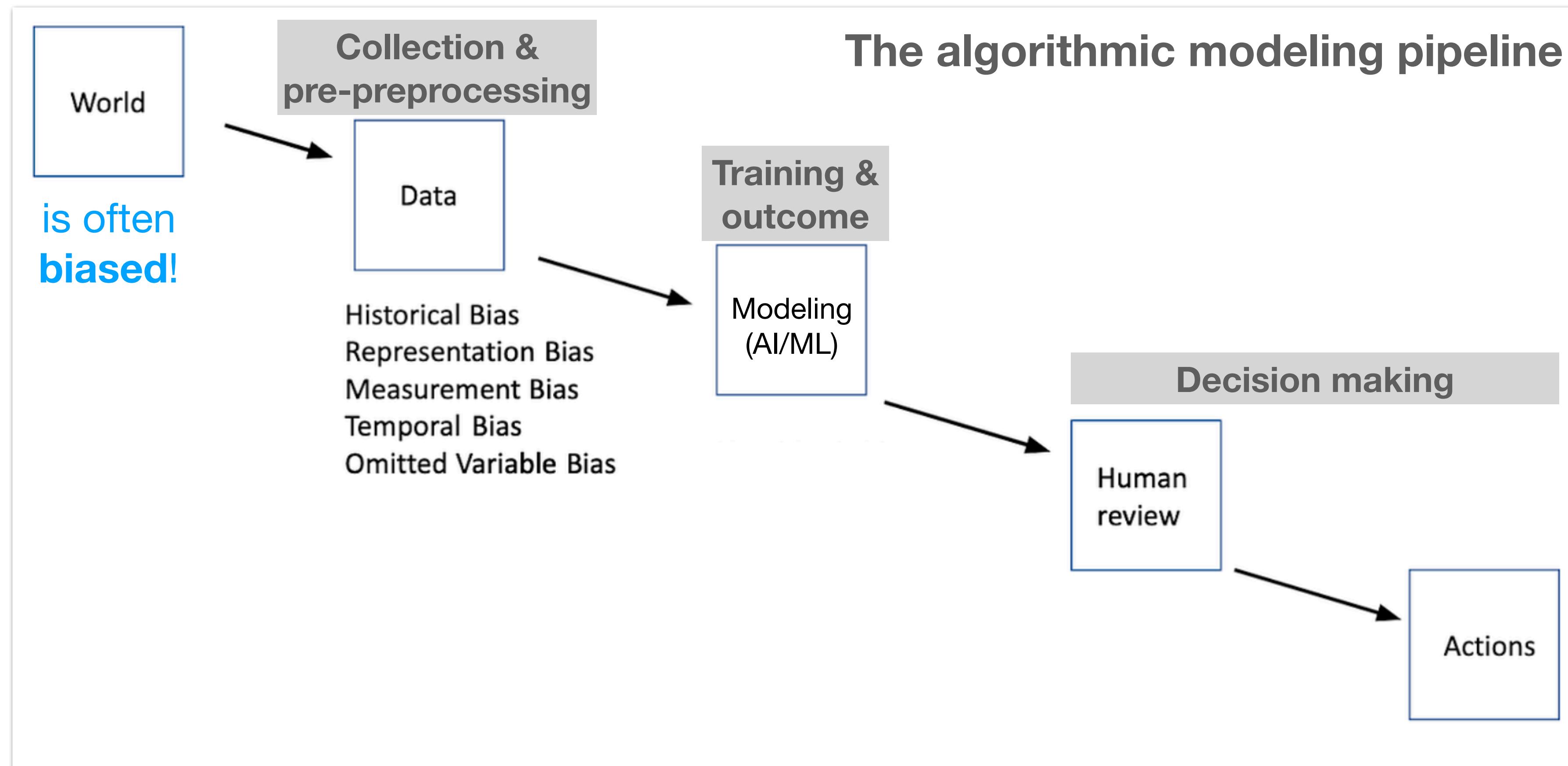


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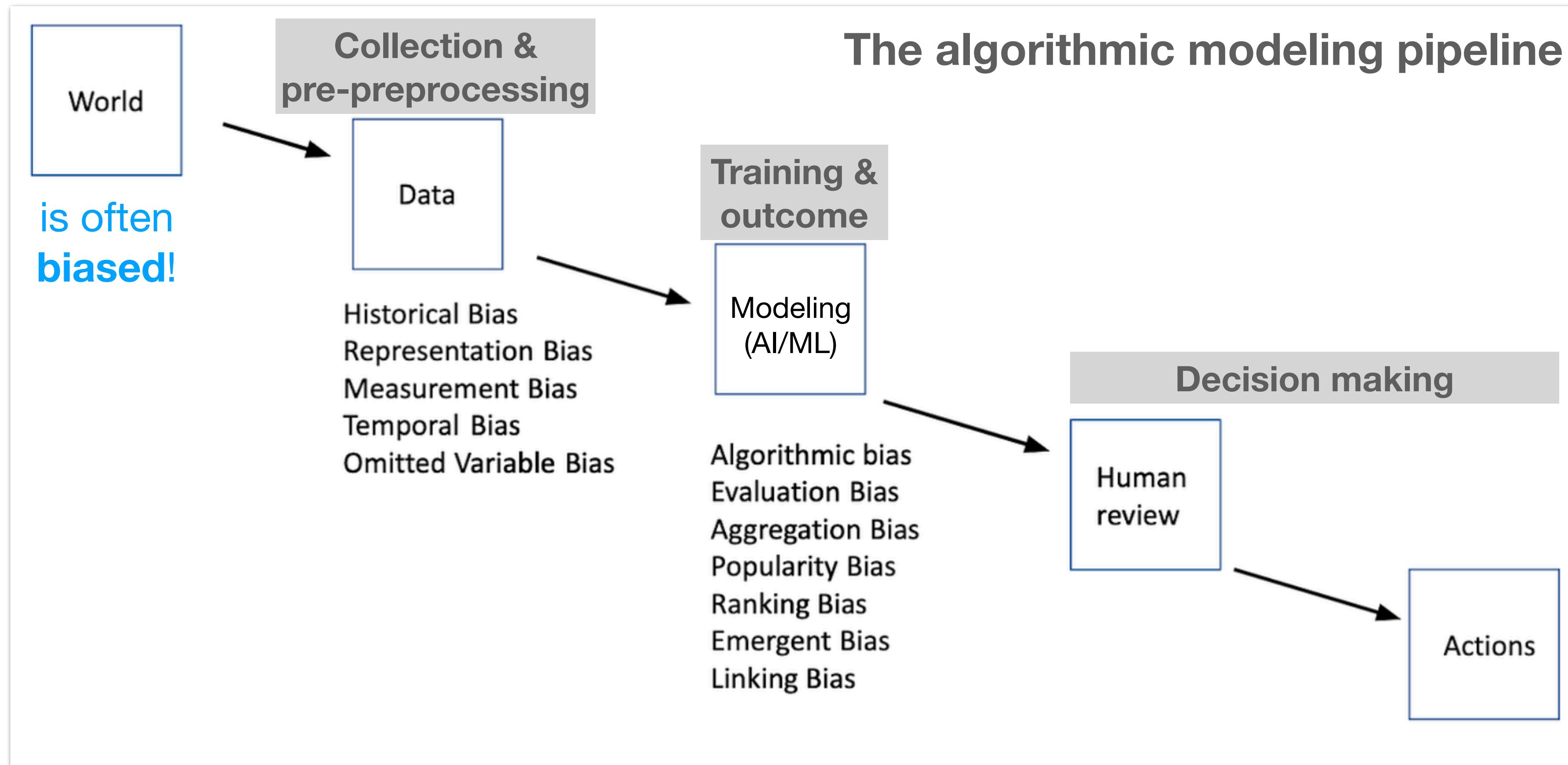


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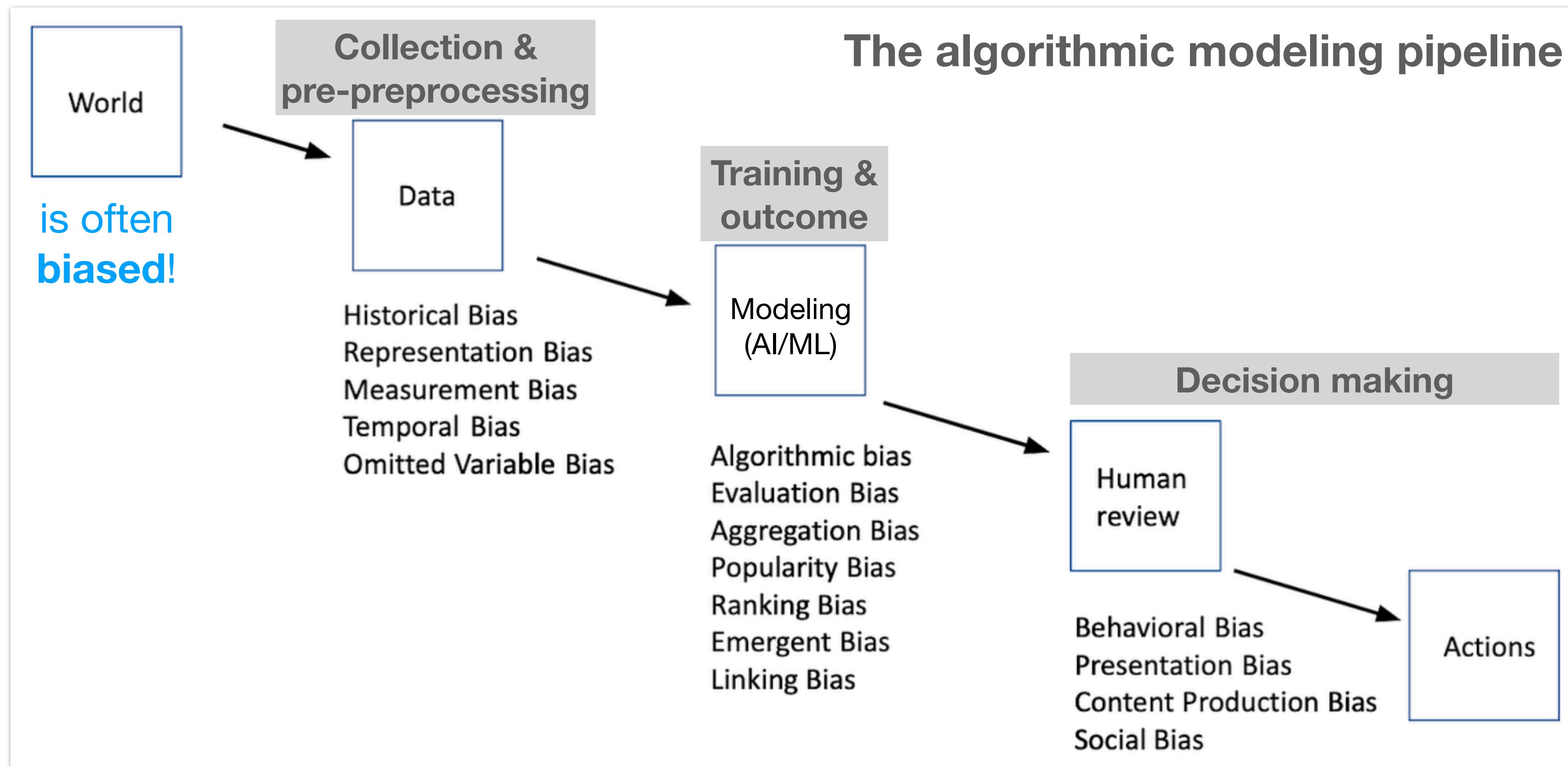


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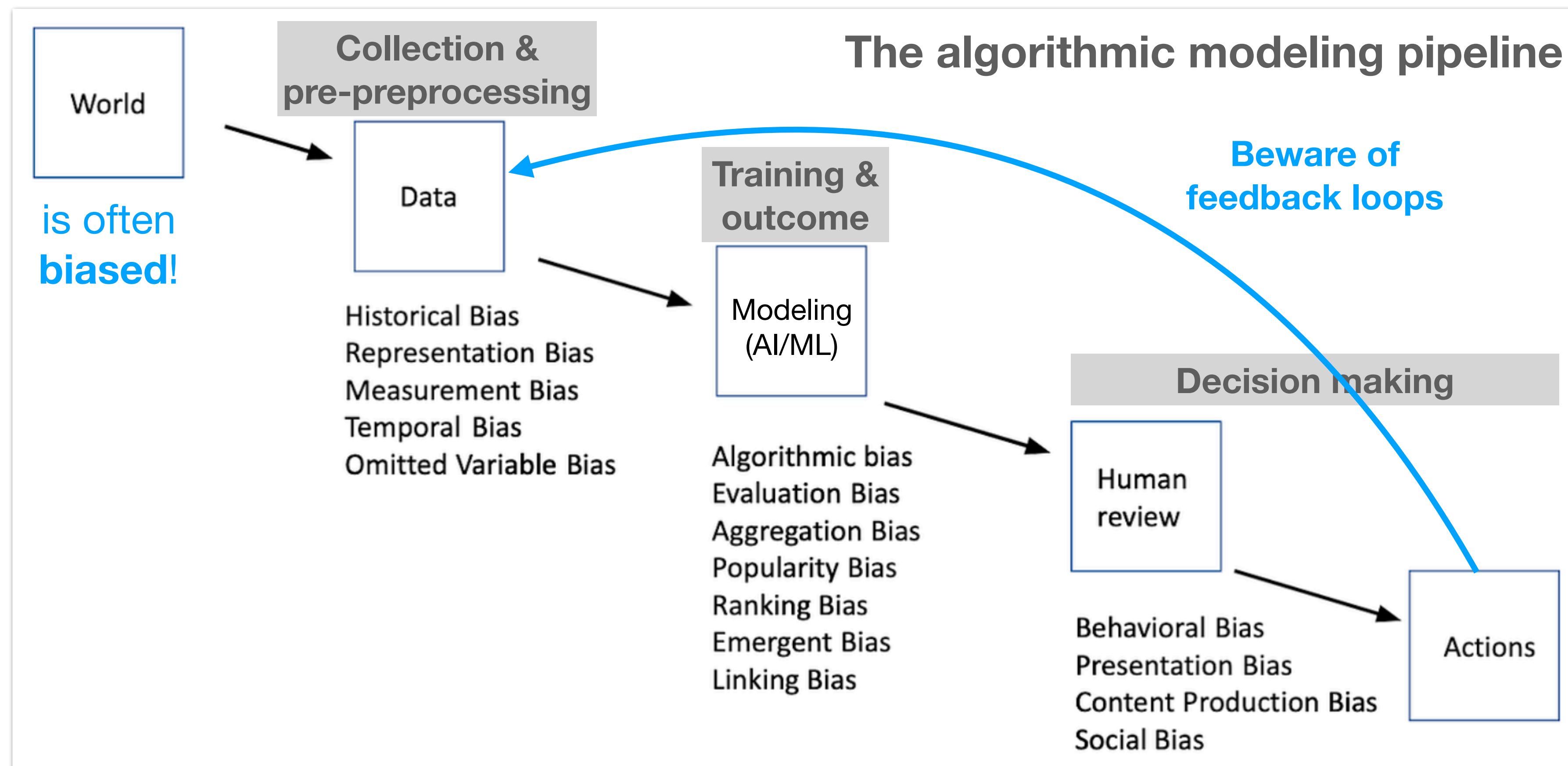
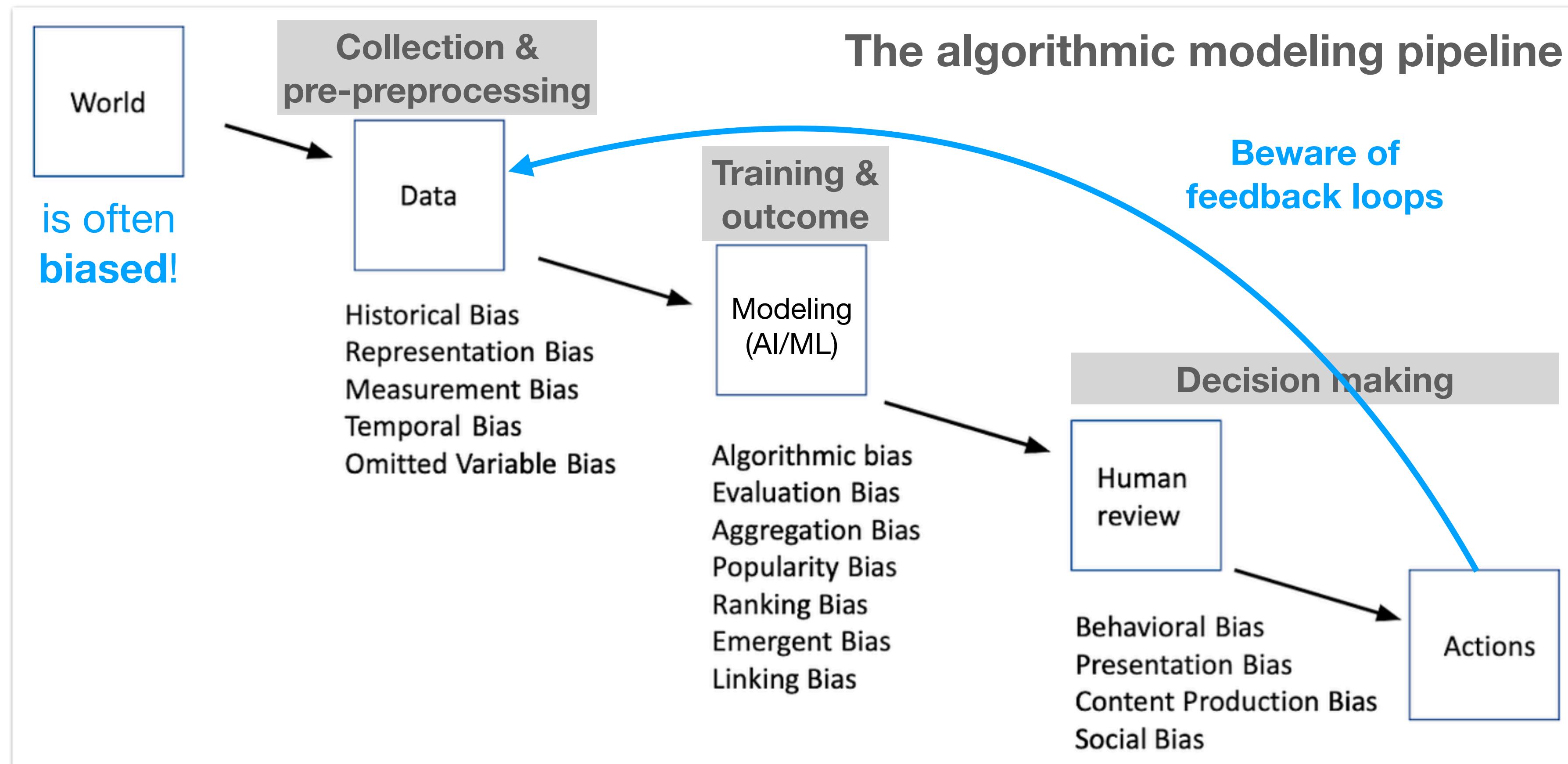


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What is inequality (bias)...

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Recommended reading:
Mehrabi et al. 2021

A Survey on Bias and Fairness in Machine Learning

NINAREH MEHRABI, FRED MORSTATTER, NRIPSUTA SAXENA, KRISTINA LERMAN, and ARAM GALSTYAN, USC-ISI

With the widespread use of artificial intelligence (AI) systems and applications in our everyday lives, accounting for fairness has gained significant importance in designing and engineering of such systems. AI systems can be used in many sensitive environments to make important and life-changing decisions; thus, it is crucial to ensure that these decisions do not reflect discriminatory behavior toward certain groups or populations. More recently some work has been developed in traditional machine learning and deep learning that address such challenges in different subdomains. With the commercialization of these systems, researchers are becoming more aware of the biases that these applications can contain and are attempting to address them. In this survey, we investigated different real-world applications that have shown biases in various ways, and we listed different sources of biases that can affect AI applications. We then created a taxonomy for fairness definitions that machine learning researchers have defined to avoid the existing bias in AI systems. In addition to that, we examined different domains and subdomains in AI showing what researchers have observed with regard to unfair outcomes in the state-of-the-art methods and ways they have tried to address them. There are still many future directions and solutions that can be taken to mitigate the problem of bias in AI systems. We are hoping that this survey will motivate researchers to tackle these issues in the near future by observing existing work in their respective fields.

CCS Concepts: • Computing methodologies → Artificial intelligence

Additional Key Words and Phrases: Fairness and bias in artificial intelligence, machine learning, deep learning, natural language processing, representation learning

ACM Reference format:

Ninareh Mehrabi, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. 2021. A Survey on Bias and Fairness in Machine Learning. *ACM Comput. Surv.* 54, 6, Article 115 (July 2021), 35 pages.
<https://doi.org/10.1145/3457607>

1 INTRODUCTION

Machine learning algorithms have penetrated every aspect of our lives. Algorithms make movie recommendations, suggest products to buy, and who to date. They are increasingly used in high-stakes scenarios such as loans [109] and hiring decisions [19, 39]. There are clear benefits to algorithmic decision-making: unlike people, machines do not become tired or bored [45, 115], and

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Authors' address: N. Mehrabi, F. Morstatter, N. Saxena, K. Lerman, and A. Galstyan, USC, Information Sciences Institute 4676 Admiralty Way, Suite 1001 Marina del Rey, CA 90292; emails: n.mehrabi@usc.edu, fredmors@isi.edu.
Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyright for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
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0360-0300/2021/07-ART115 \$15.00
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ACM Computing Surveys, Vol. 54, No. 6, Article 115. Publication date: July 2021.

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Inequalities (biases) in ML algorithms

Examples

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Many Facial-Recognition Systems Are Biased, Says U.S. Study

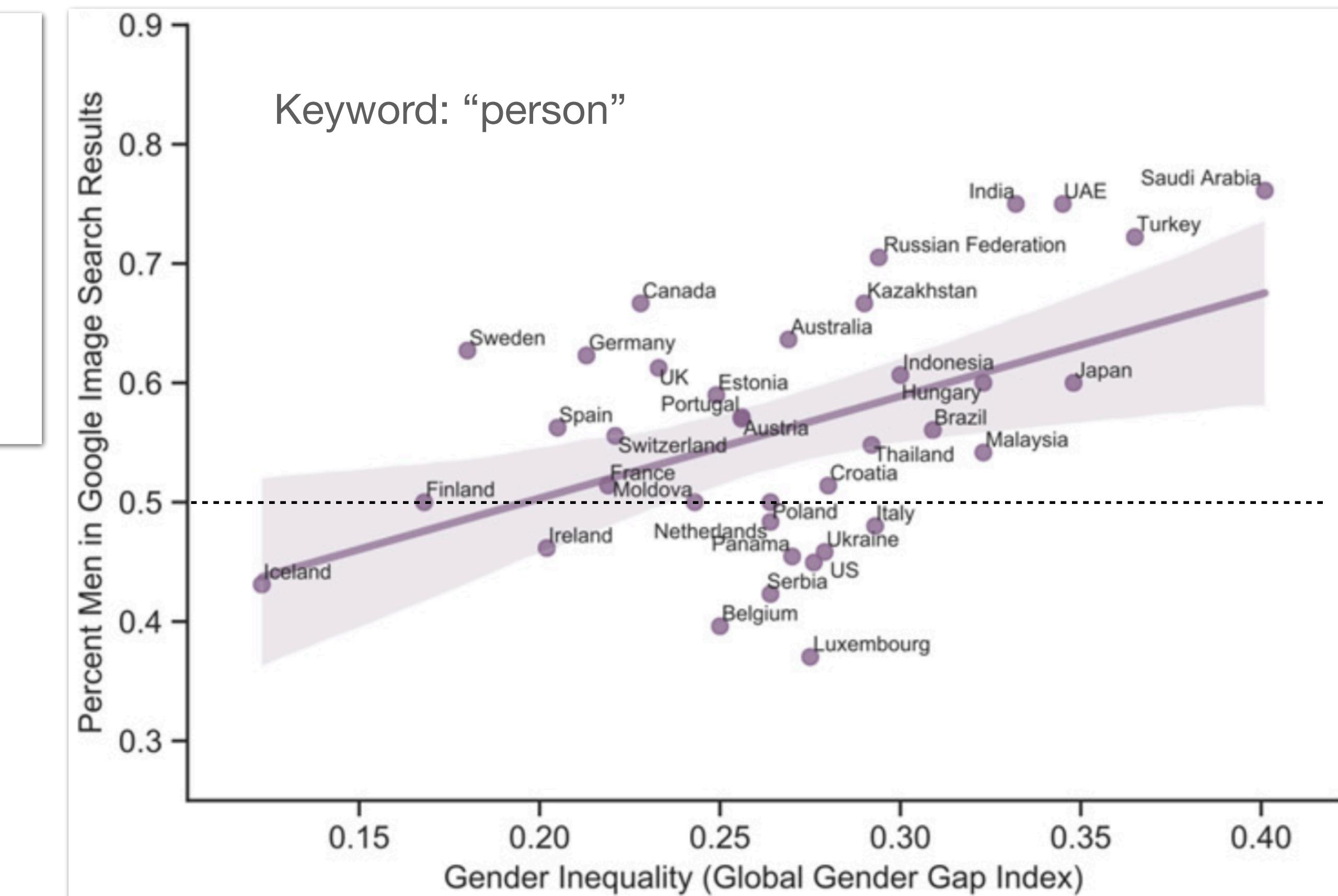
Algorithms falsely identified African-American and Asian faces 10 to 100 times more than Caucasian faces, researchers for the National Institute of Standards and Technology found.

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Propagation of societal gender inequality by internet search algorithms. Vlasceanu & Amodio 2022.

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Comparative Study > Diabet Med. 2019 Oct;36(10):1234-1242. doi: 10.1111/dme.13979.

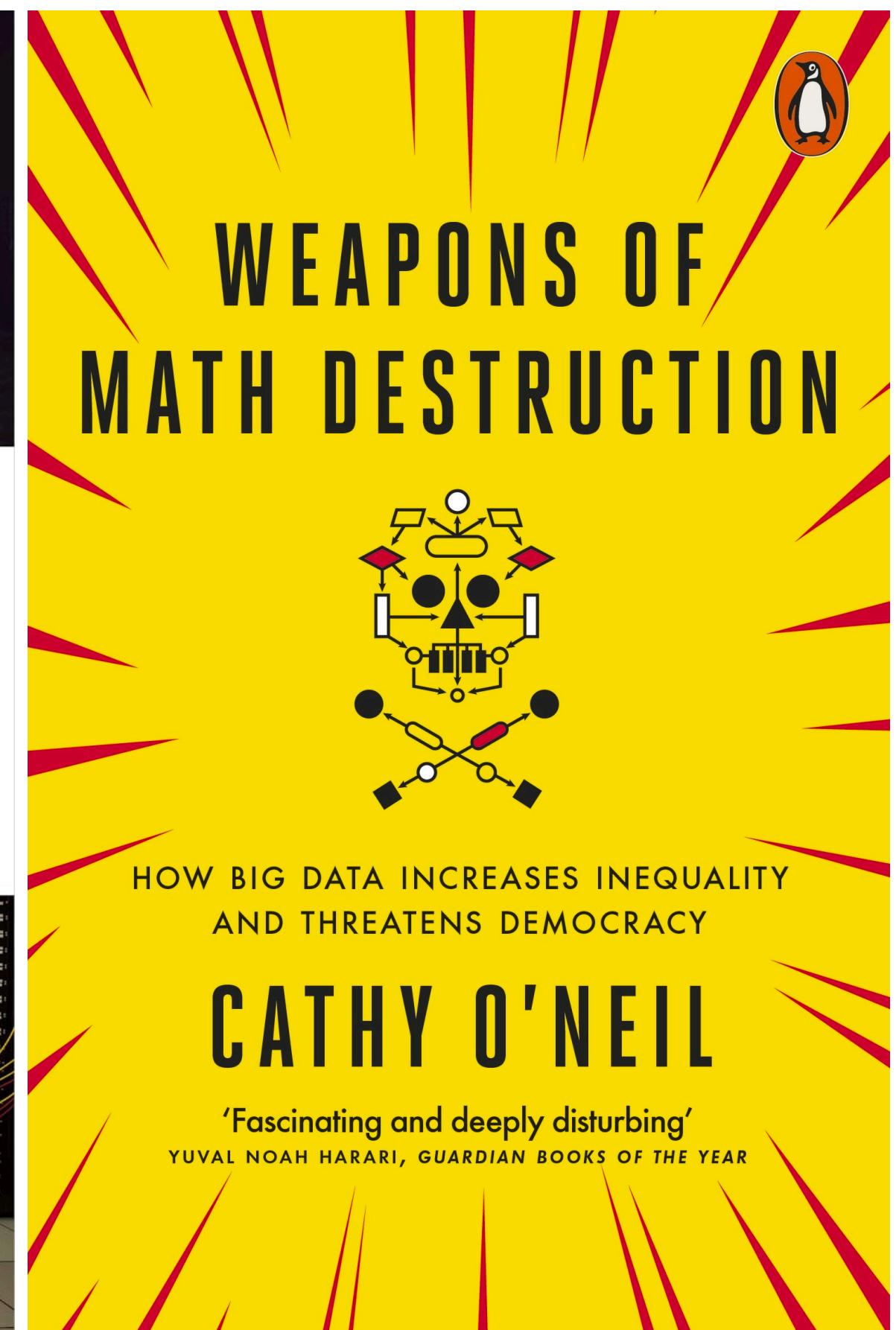
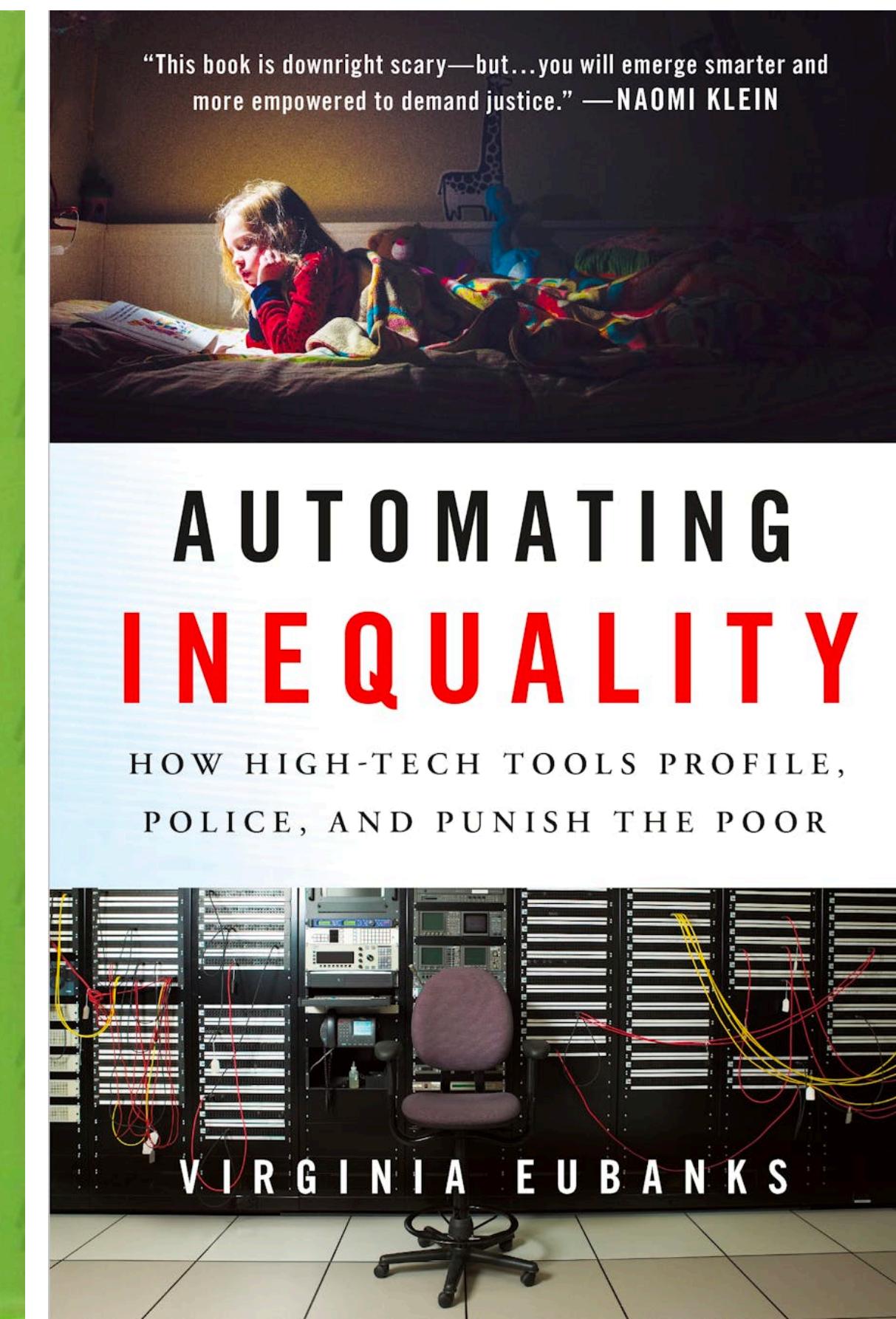
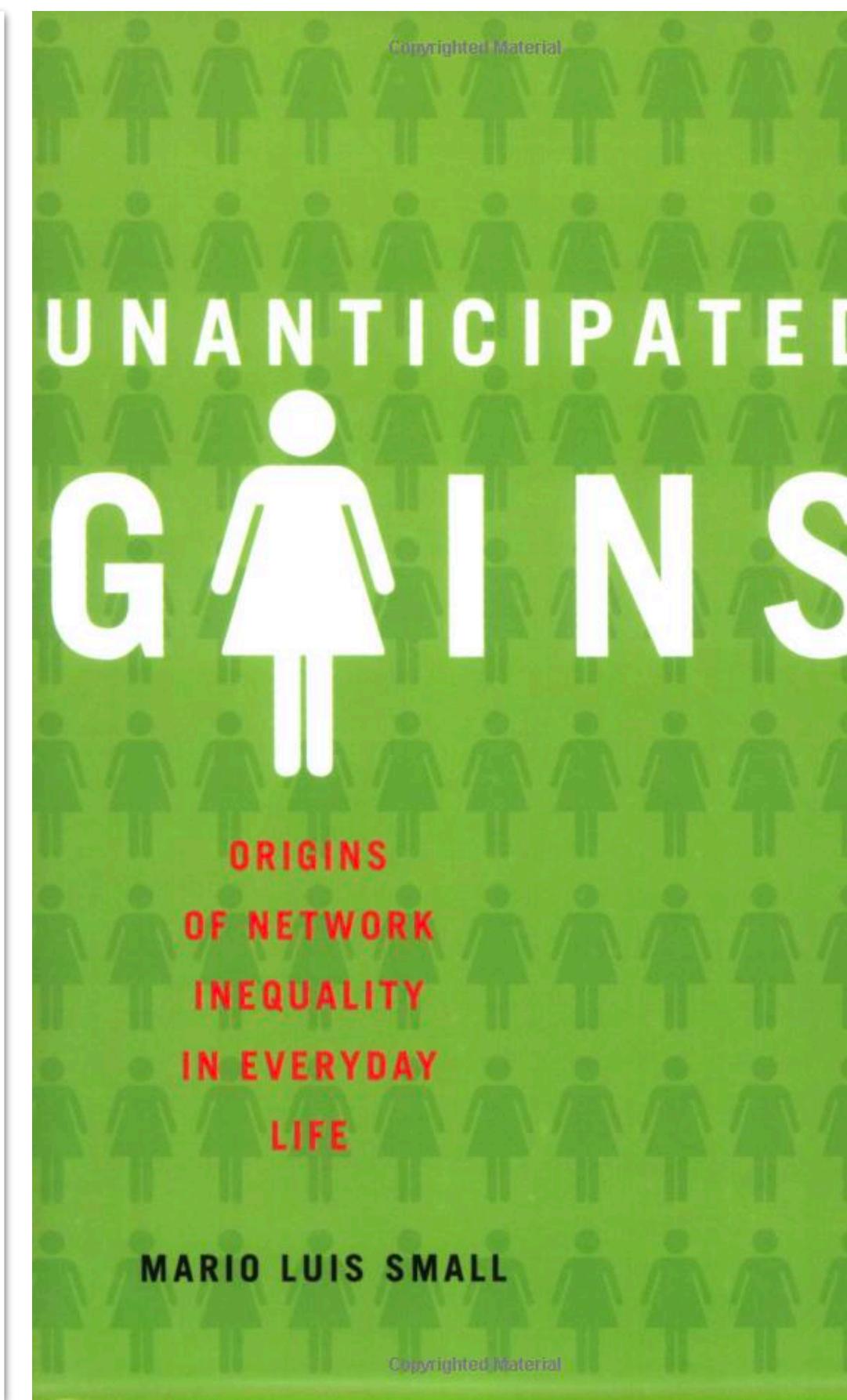
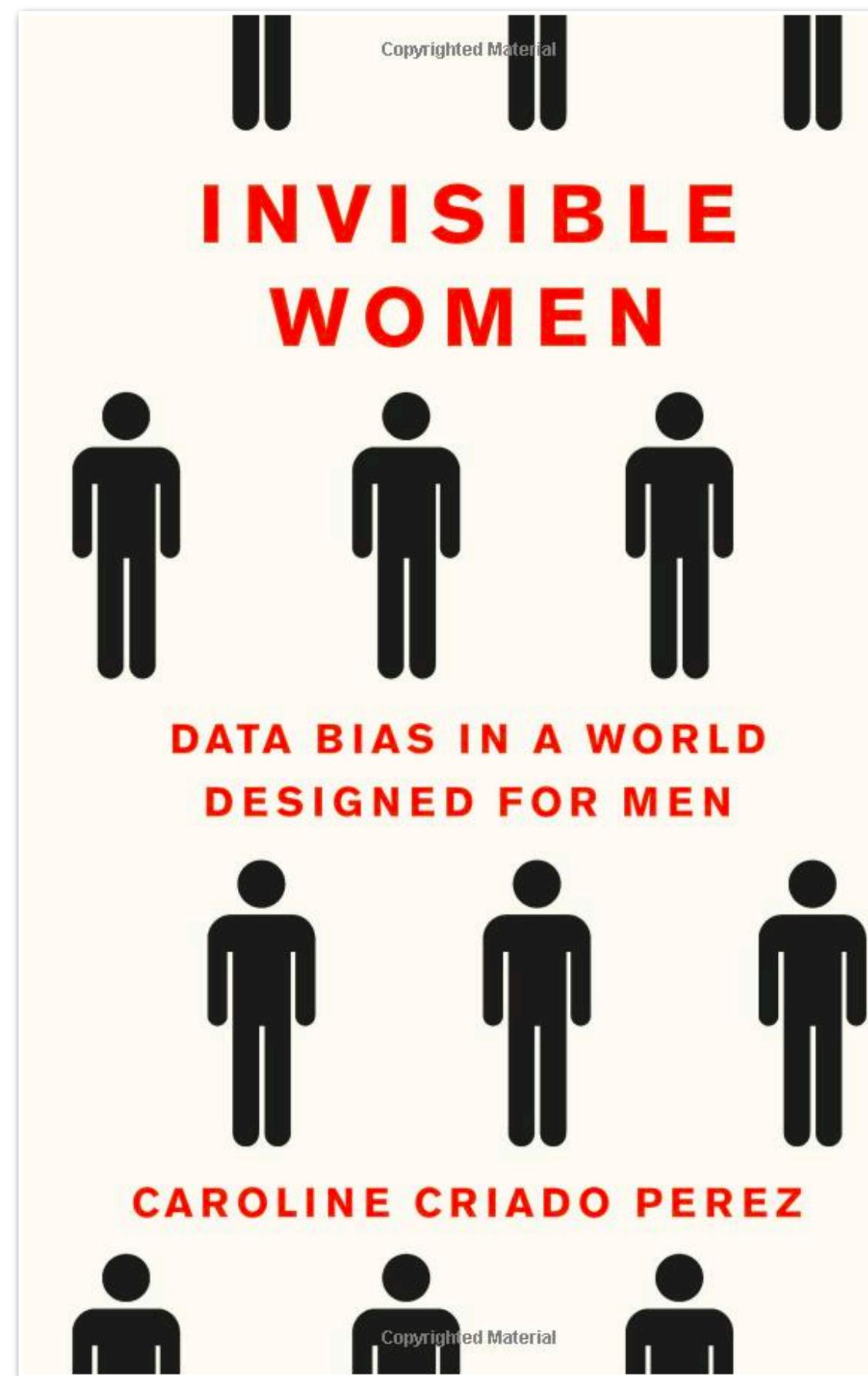
Epub 2019 Jul 15.

Racial differences in performance of HbA_{1c} for the classification of diabetes and prediabetes among US adults of non-Hispanic black and white race

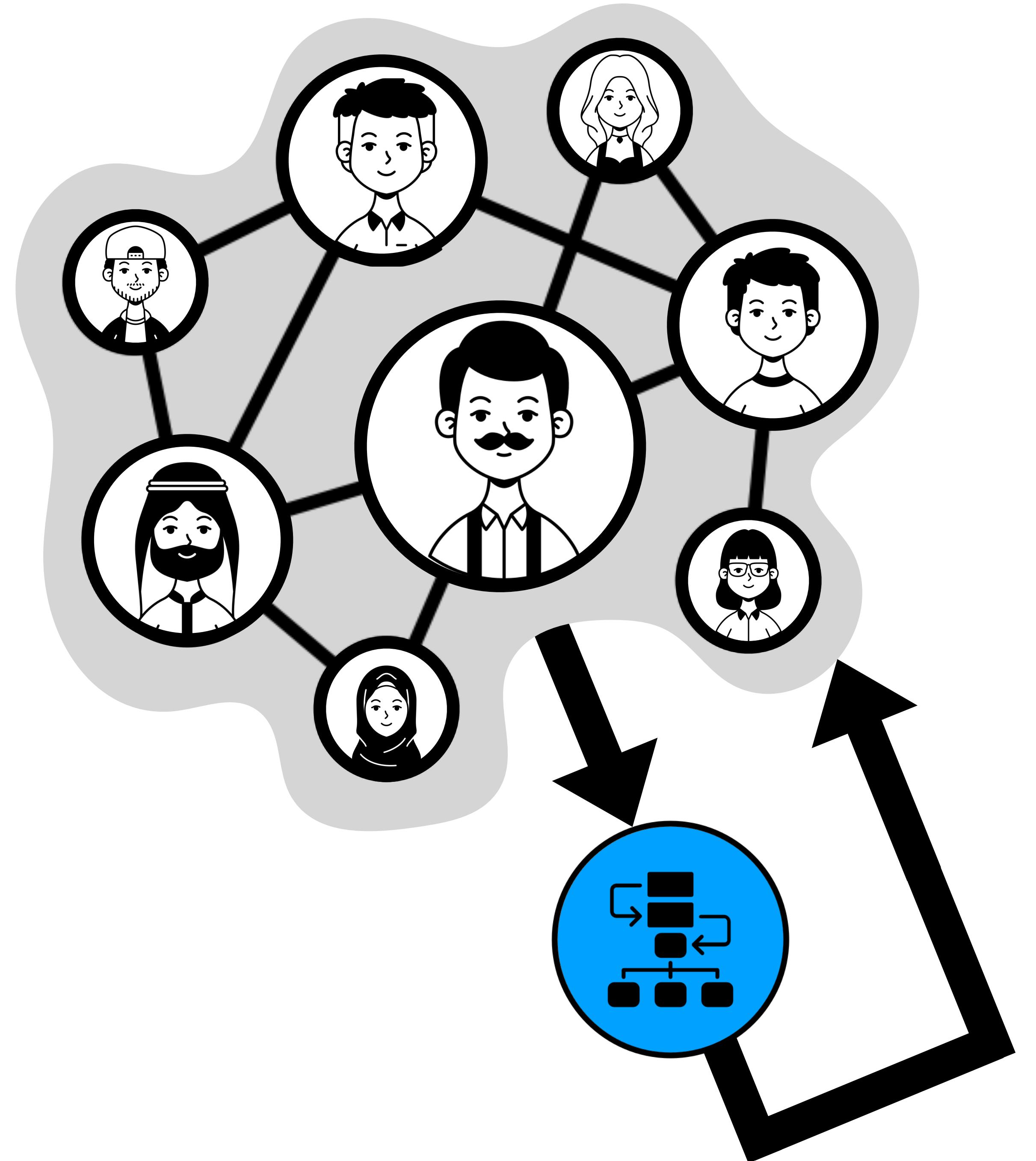
C N Ford ¹, R W Leet ^{1 2}, L M Kipling ¹, M K Rhee ^{3 4}, S L Jackson ⁵, P W F Wilson ^{3 4 6}, L S Phillips ^{3 4}, L R Staimez ^{1 2}

Data and algorithmic biases in the real world

Highly recommended books!



What about the inequalities in network-based algorithms?



Disclaimer:

A network-based algorithm is such that the data input is a network (graph).
It is NOT a deep neural network.

Network-based algorithms

Definition

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Networks are biased, thus, these algorithms can be biased too!

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Today's class

Inequality in network-based algorithms

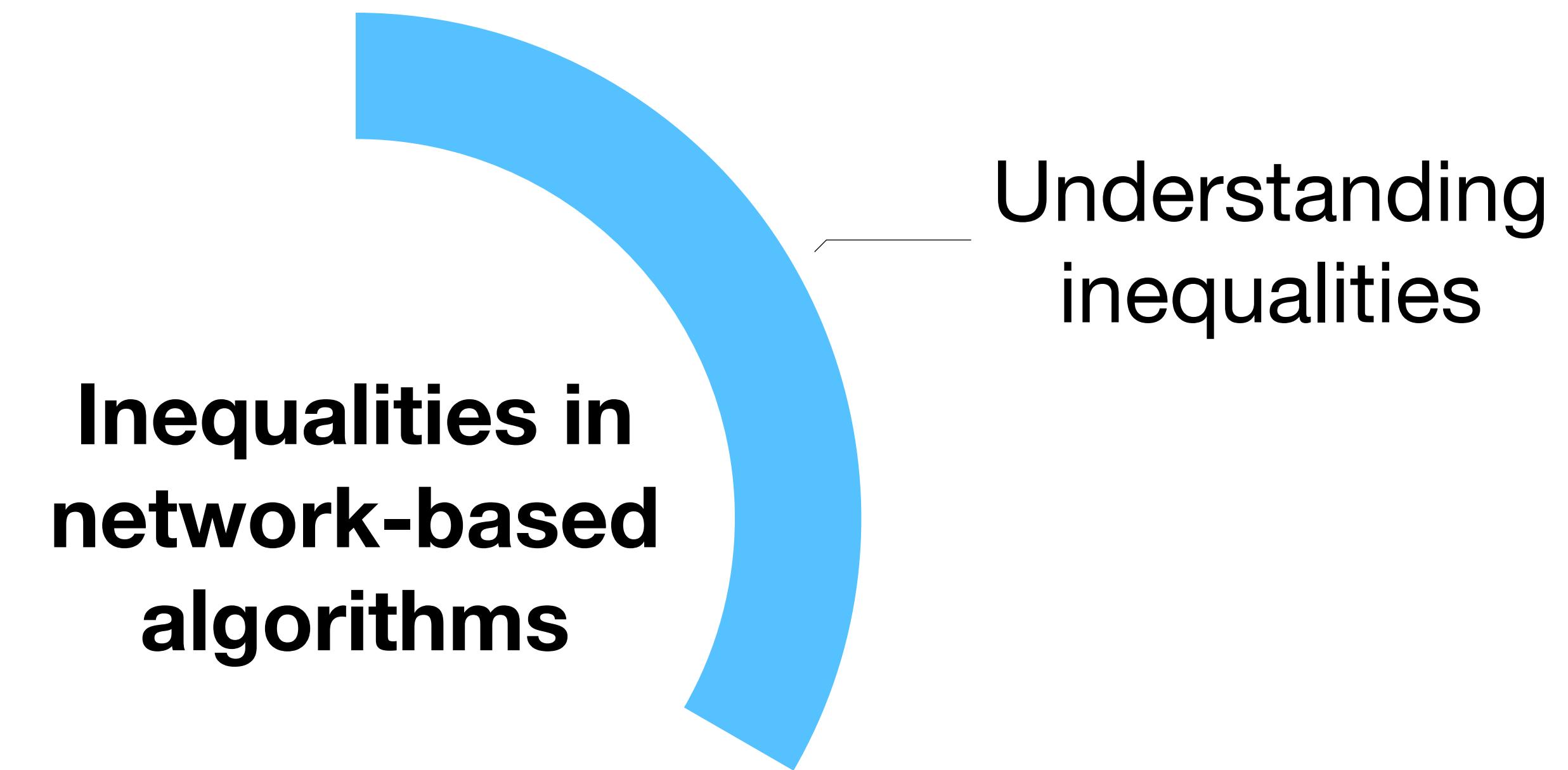
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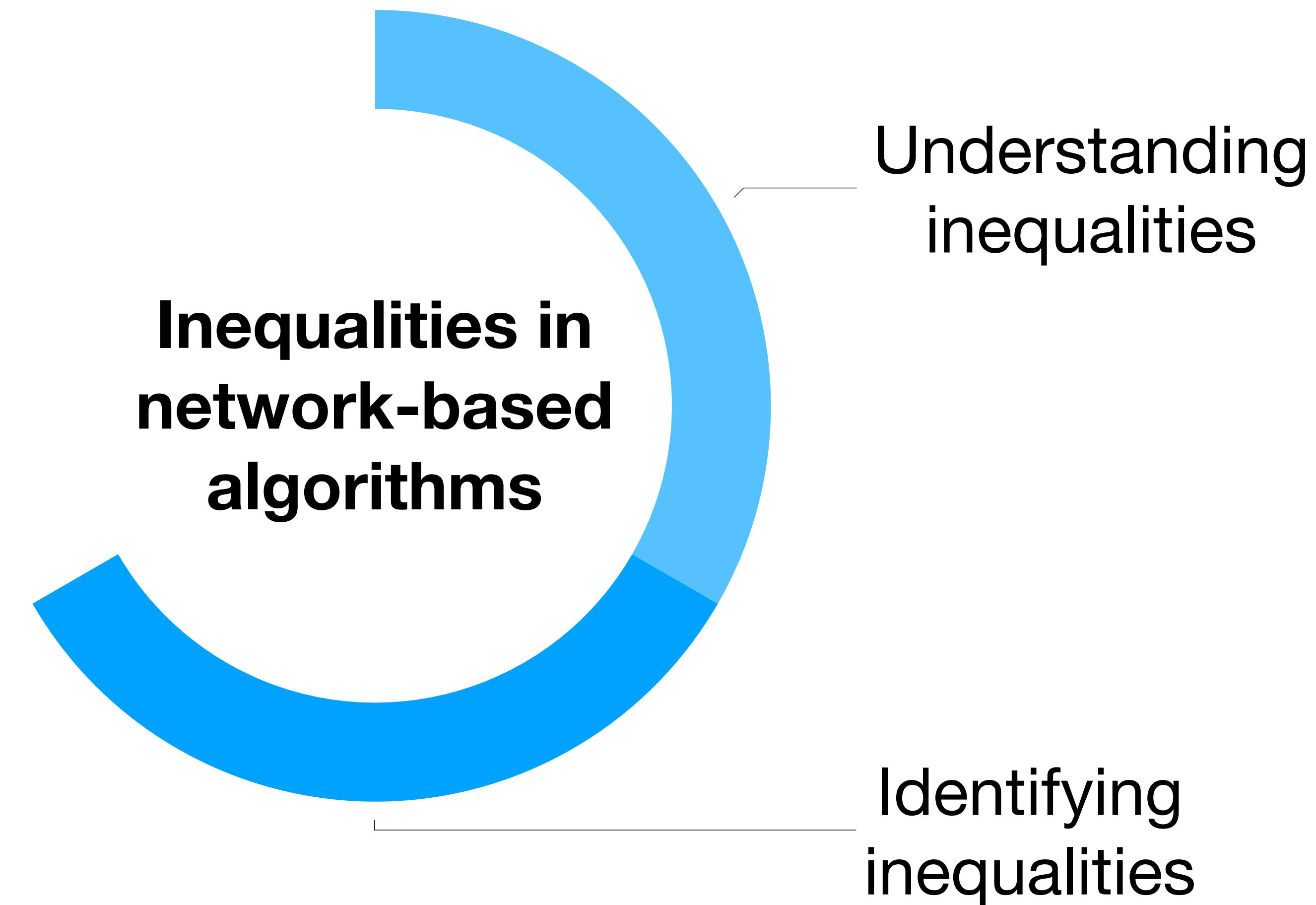
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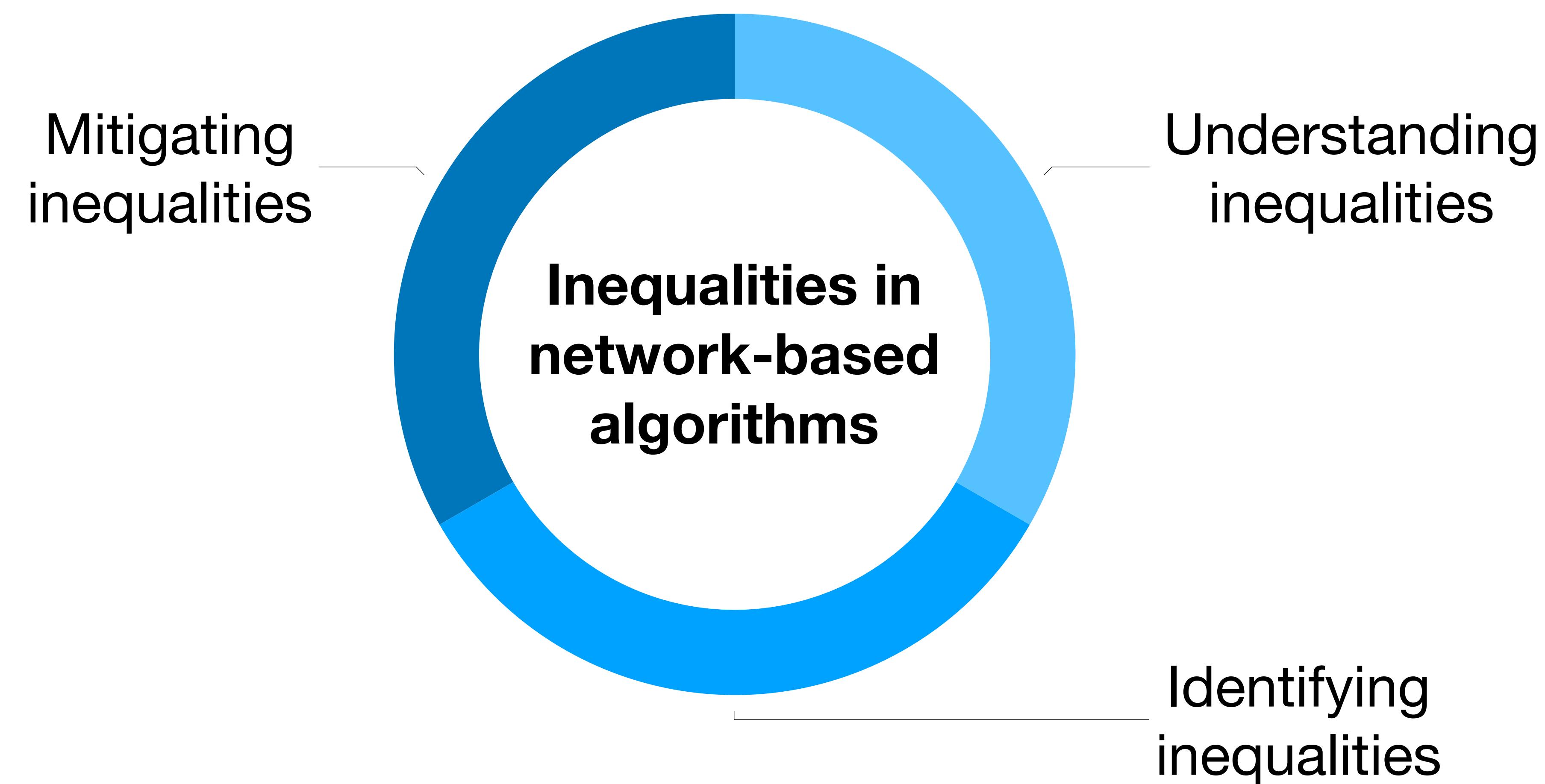
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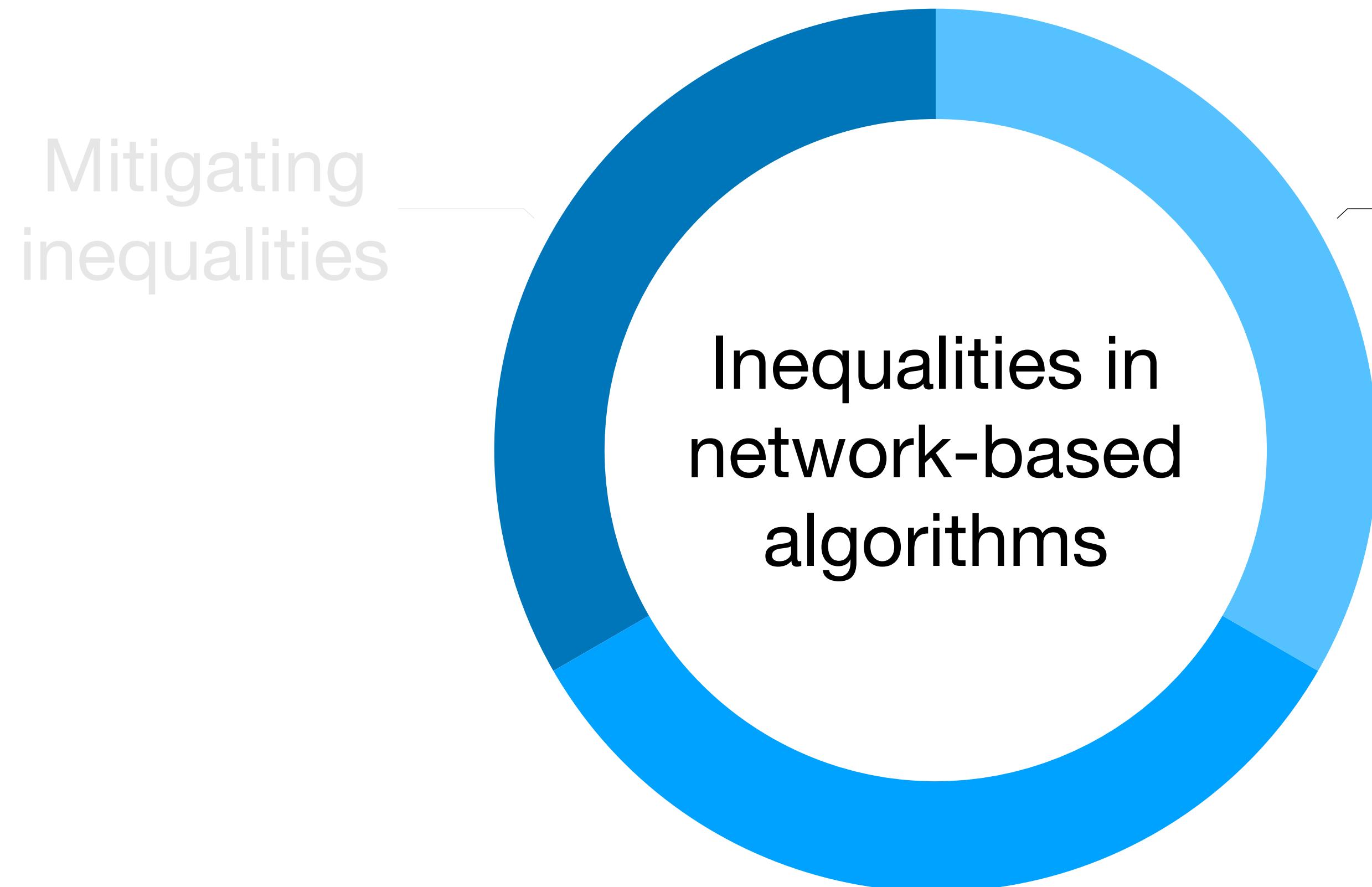
Inequality in network-based algorithms



1.

Understanding inequalities

Identifying
inequalities



Understanding Inequalities in network-based algorithms

Understanding

Inequalities in network-based algorithms

1. Understand the impact of these inequalities on society

Understanding

Inequalities in network-based algorithms

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2. Understand how these inequalities form

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Inequalities in network-based algorithms

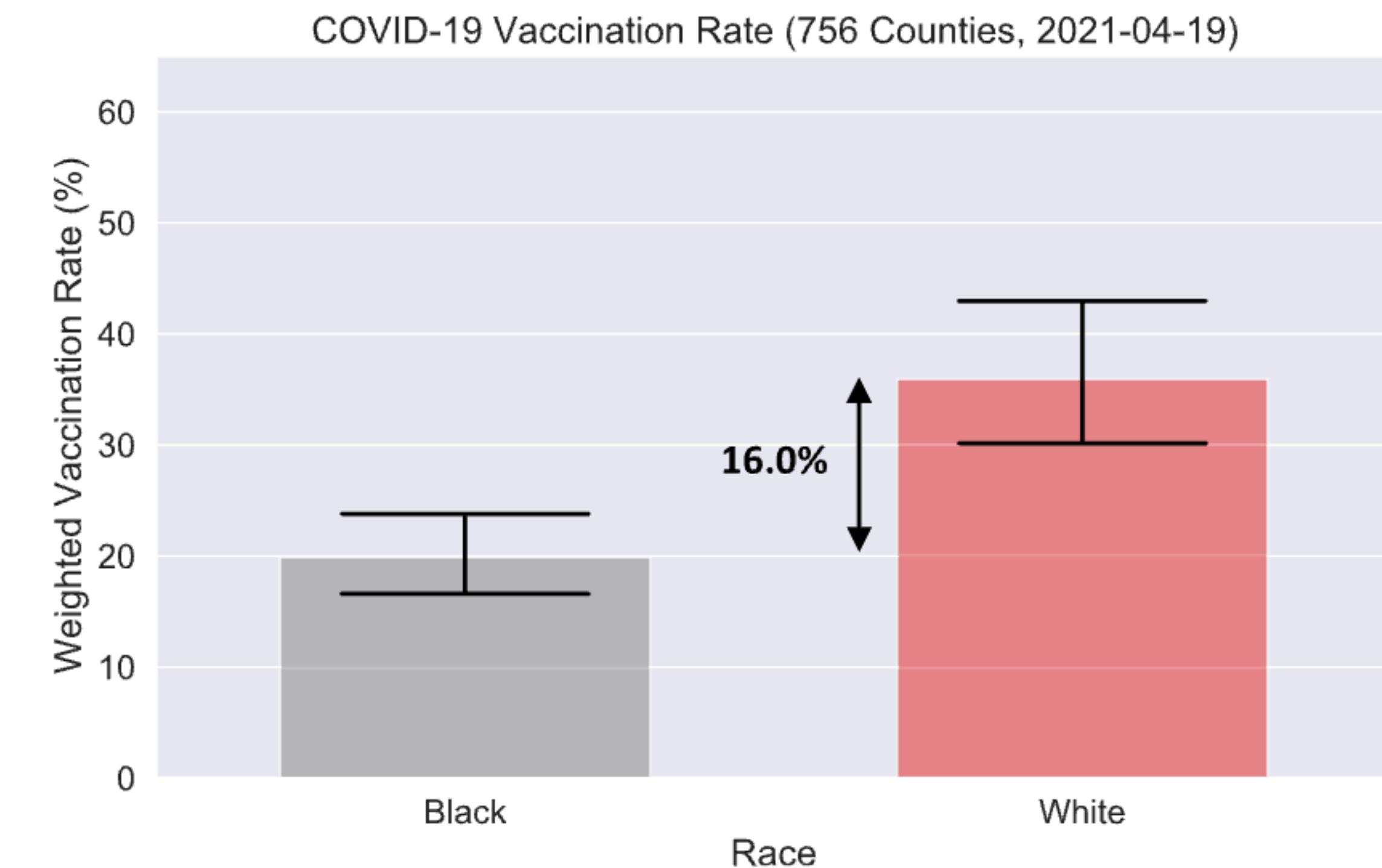
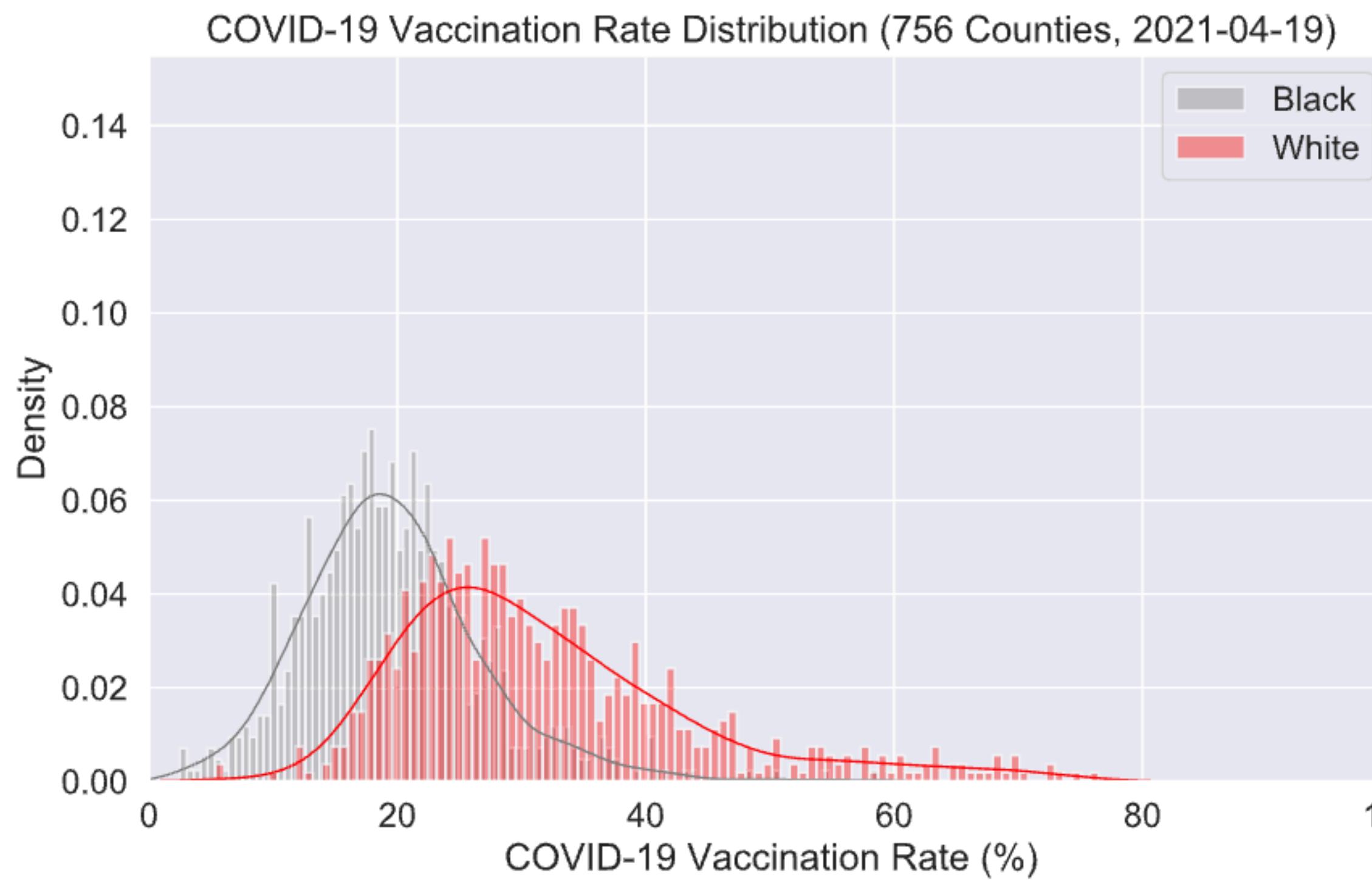
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 - a. What are the **structure characteristics** and **mechanisms of link formation** in social networks that lead to such inequalities?

Understanding

Inequalities in network-based algorithms

If we understand the impact of these inequalities on society, and the correlations with how people behave (connect with each other), we can propose better mitigation strategies to reduce such inequalities!

Why do racial disparities in vaccination persist despite the increased availability of vaccines?



Agarwal, Ritu, et al. "Socioeconomic privilege and political ideology are associated with racial disparity in COVID-19 vaccination." Proceedings of the National Academy of Sciences 118.33 (2021): e2107873118.

Why do racial disparities in vaccination persist despite the increased availability of vaccines?

Table 1. Regression estimates of relationship between social determinants and COVID-19

Variable category	Variable	CVD = V_W - V_B
Economic stability	Median income	-2.20* (0.99)
	Median income disparity	0.89 [†] (0.44)
Education access and quality	High school graduation rate	1.22 (1.19)
	High school disparity	2.01*** (0.41)
Healthcare access and quality	Health facilities per capita	0.78 (0.76)
	COVID-19 cases per capita	-0.08 (0.75)
Neighborhood and built environment	Home IT rate	0.51 (0.77)
	Home IT disparity	0.20 (0.99)
Social and community context	Urban	0.19 (1.23)
	Rate of vehicle ownership	2.07 (1.28)
Constant	Political ideology	-6.45** (1.73)
	Segregation index	1.43 [†] (0.69)
	Racial bias	1.43 [†] (0.73)
		8.286*** (1.44)

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Constant		-6.45** (1.73)
		1.43† (0.69)
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		8.286*** (1.44)

Why do racial disparities in vaccination persist despite the increased availability of vaccines?

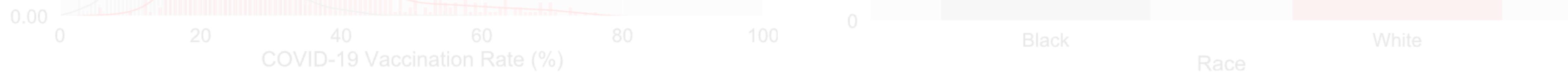
Table 1. Regression estimates of relationship between social determinants and COVID-19

Variable category	Variable	CVD = V_W - V_B
Economic stability	Median income	-2.20* (0.99)
1. More votes for the Republican candidate (Trump, 2020 elections) → less White than Black people getting the vaccine	Median income disparity	0.89† (0.44)
Education access and quality	High school graduation rate	1.22 (1.19)
2. More segregated the area (higher homophily) → more White than Black people getting the vaccine	High school disparity	2.01*** (0.41)
Healthcare access and quality	COVID-19 cases per capita	-0.08 (0.75)
Neighborhood and built environment	Home IT rate	0.51 (0.77)
3. More bias against Black people → more White than Black people getting the vaccine	Home IT disparity	0.20 (0.99)
Social and community context	Urban	0.19 (1.23)
	Rate of vehicle ownership	2.07 (1.28)
Political ideology		
Segregation index		
Racial bias		
Constant		8.286*** (1.44)

Why do racial disparities in vaccination persist despite the increased availability of vaccines?

If we don't control for these disparities in network-based algorithms, we can exacerbate discrimination against already marginalized groups.

Density



Agarwal, Ritu, et al. "Socioeconomic privilege and political ideology are associated with racial disparity in COVID-19 vaccination." Proceedings of the National Academy of Sciences 118.33 (2021): e2107873118.

Optimization vs. Fairness

In influence maximization

Rahmatalabi, Aida, et al. "Fair influence maximization: A welfare optimization approach." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 35. No. 13. 2021.

Optimization vs. Fairness

In influence maximization

- Public health interventions, such as COVID-19 or suicide/HIV prevention, and community preparedness against natural disasters, leverage social network information to maximize outreach.

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Optimization vs. Fairness

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- **Algorithmic influence maximization** techniques have been proposed to aid with the choice of “peer leaders” or “influencers” in such interventions.
- Yet, traditional algorithms for influence maximization have not been designed with fair / diversity interventions in mind. As a result, they may **disproportionately exclude minority communities from the benefits of the intervention.**

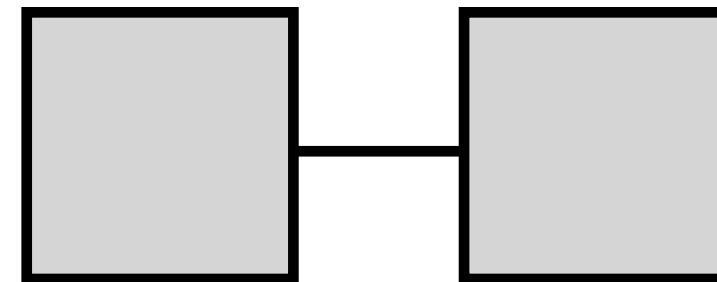
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Optimization vs. Fairness

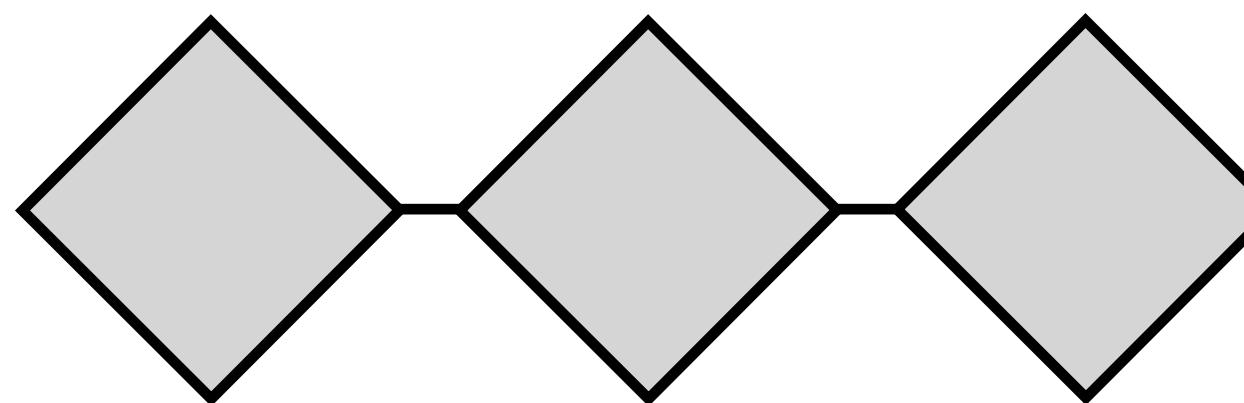
In influence maximization (example)

High segregation
(Like in the example before)

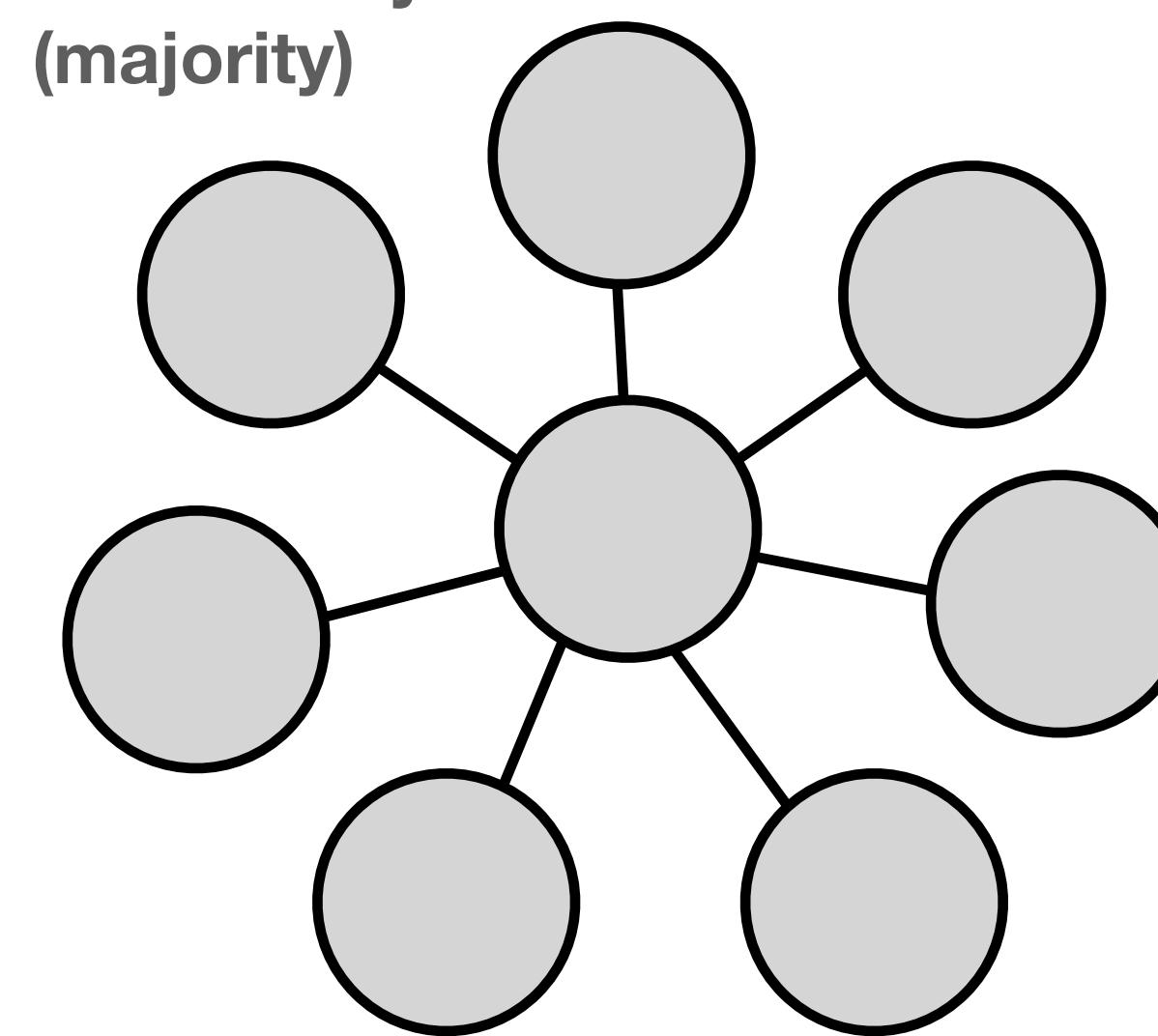
Community 2
(minority)



Community 3
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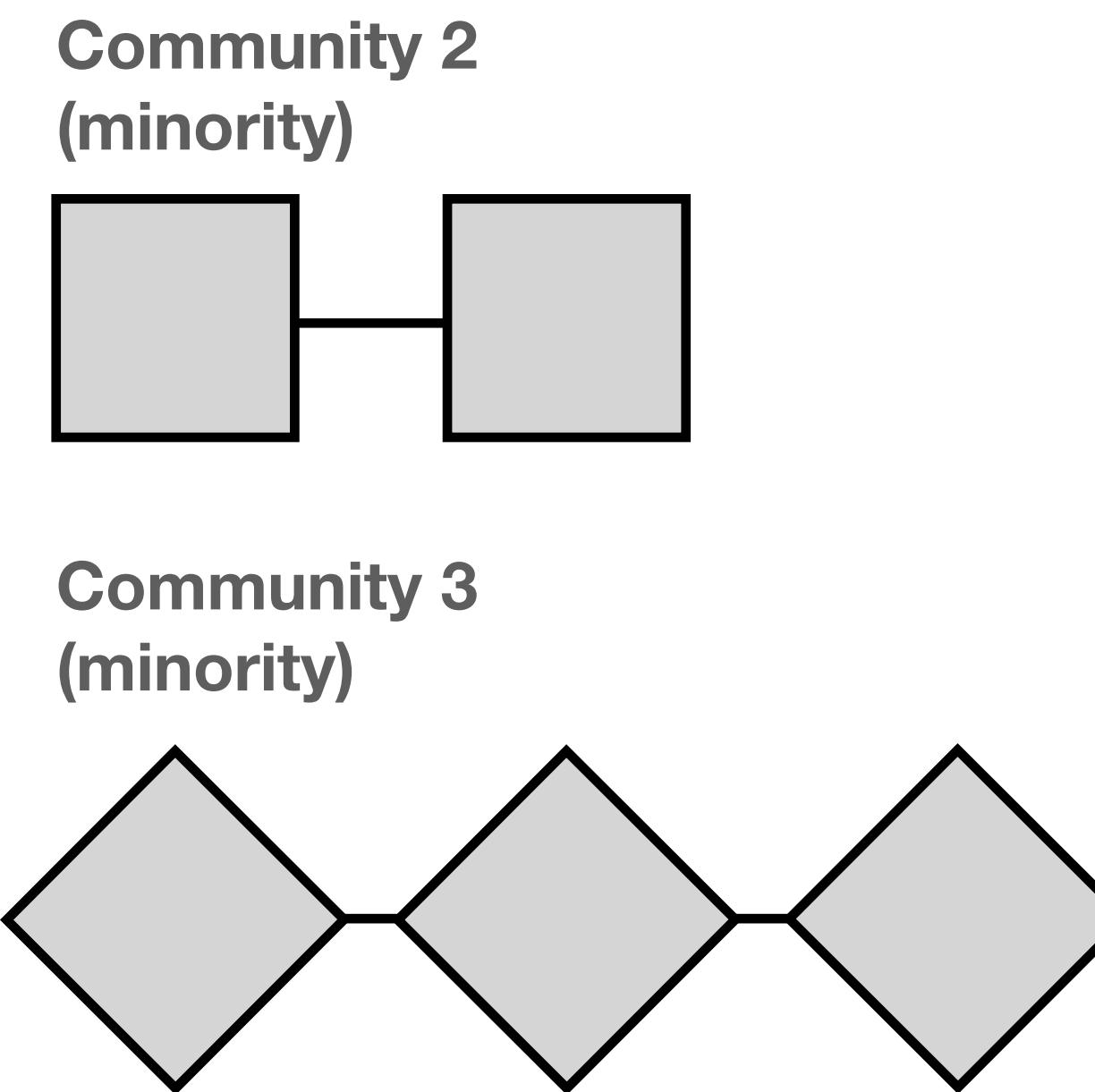
Community 1
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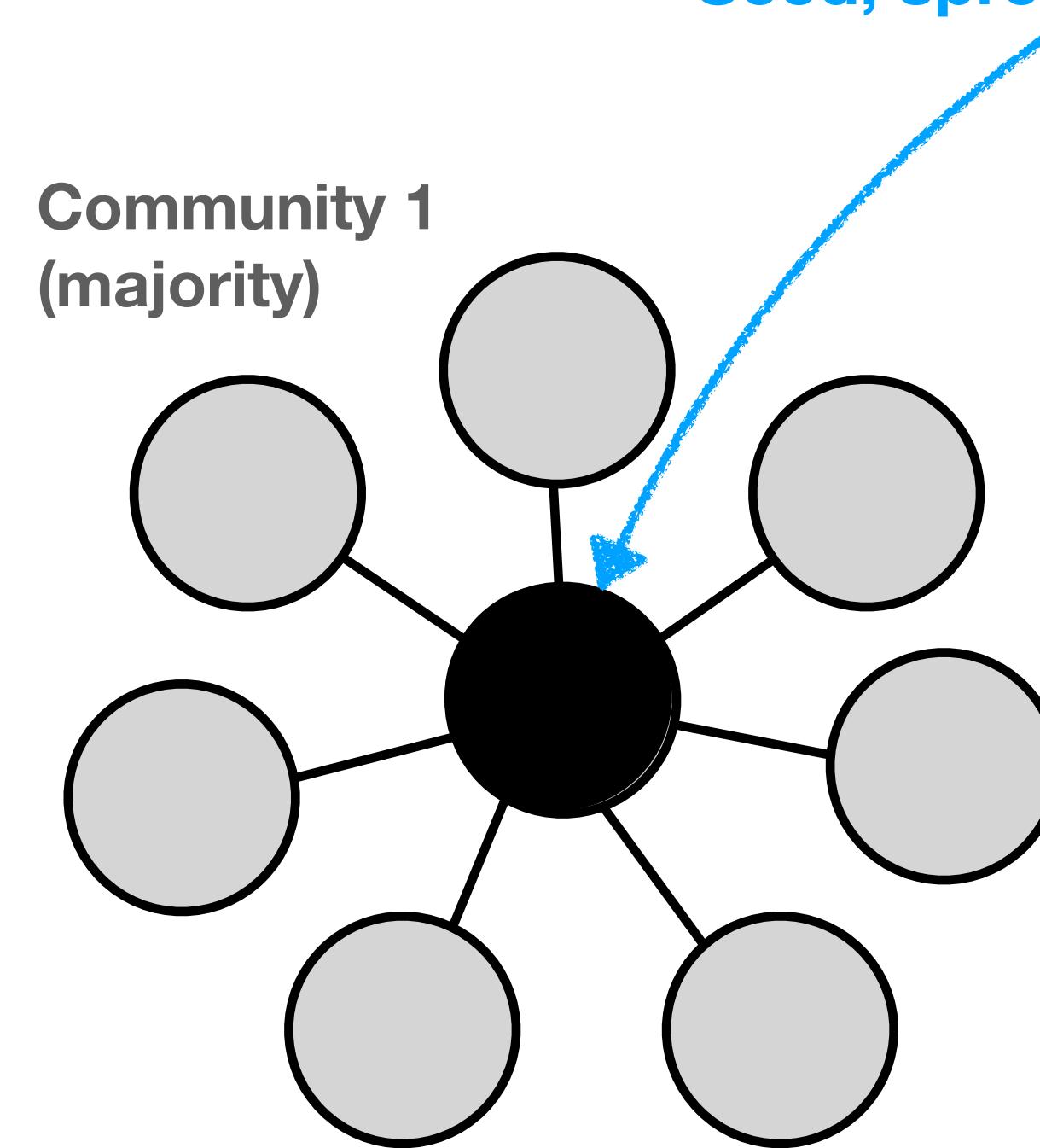
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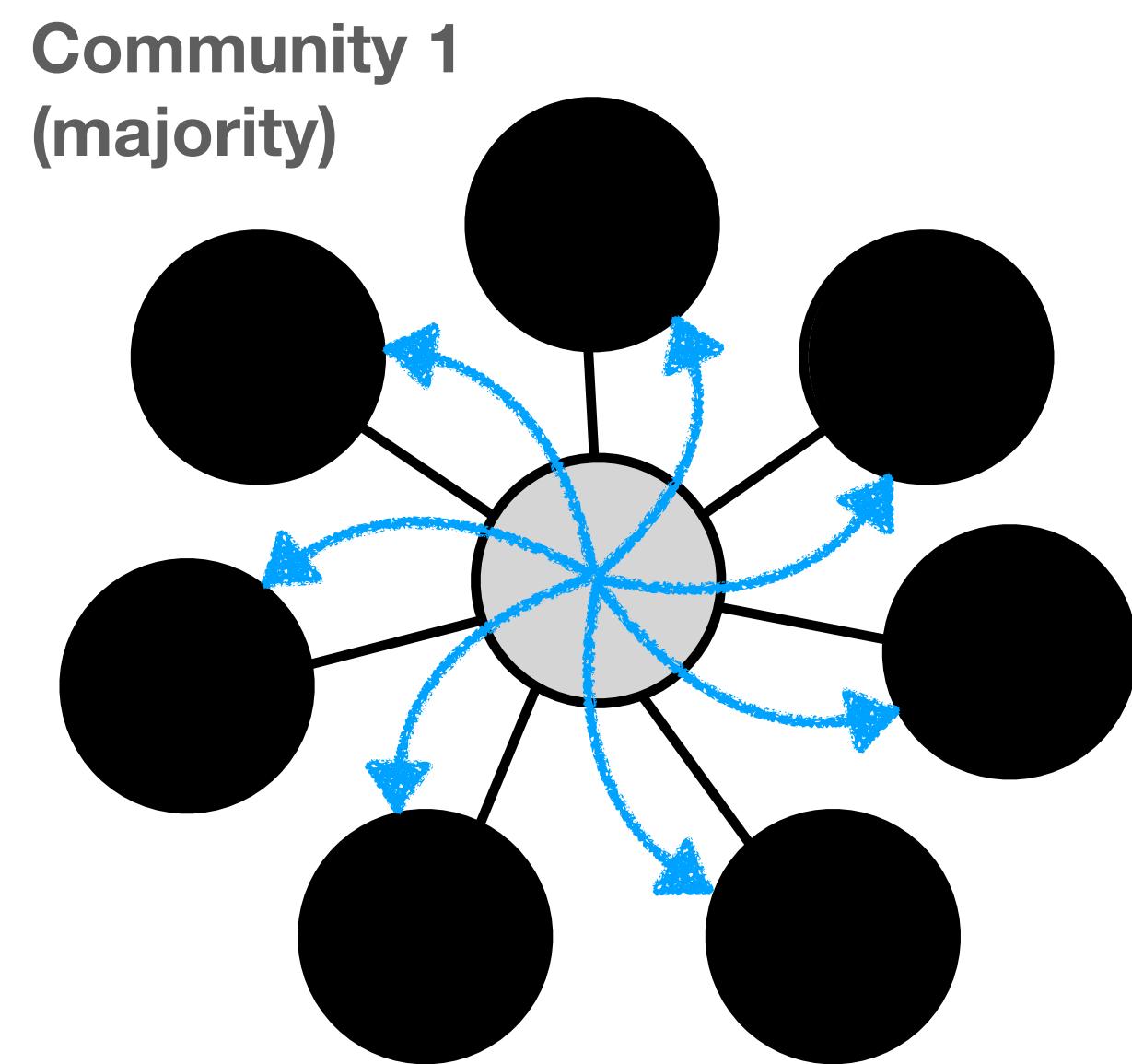
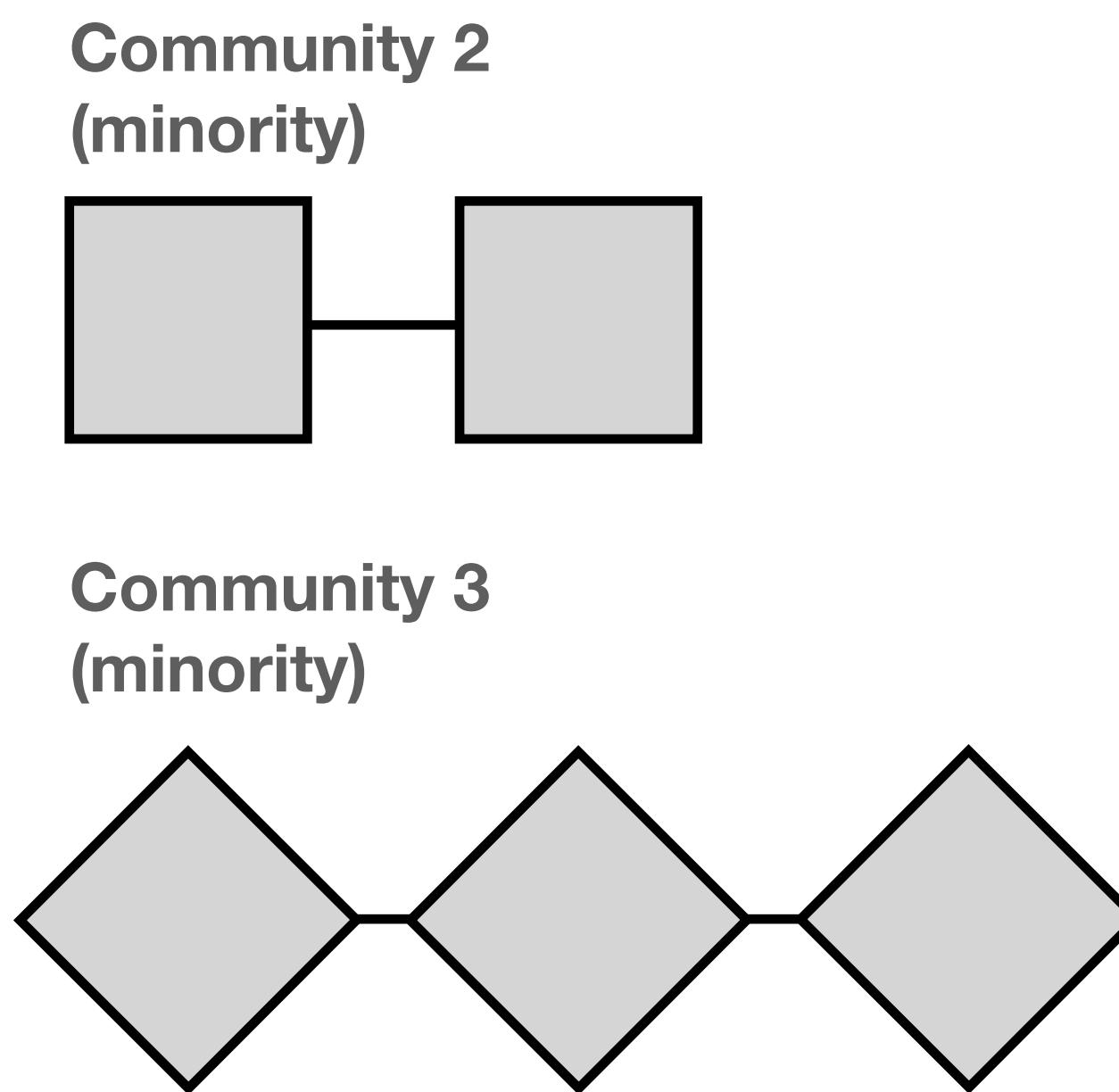
STEP 1: Select seed nodes
Seed, spreader, influential node



Optimization vs. Fairness

In influence maximization (example)

High segregation
(Like in the example before)



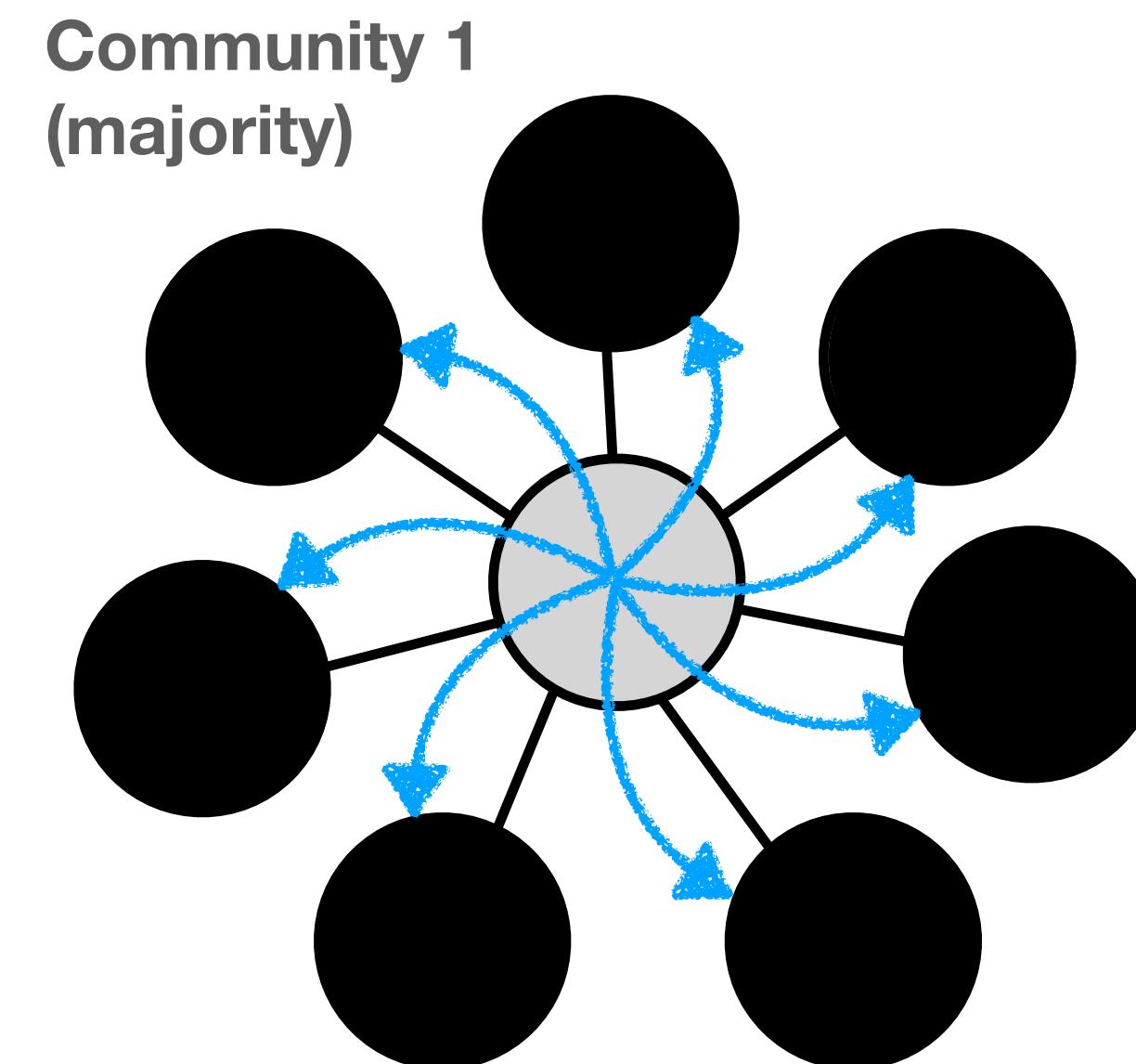
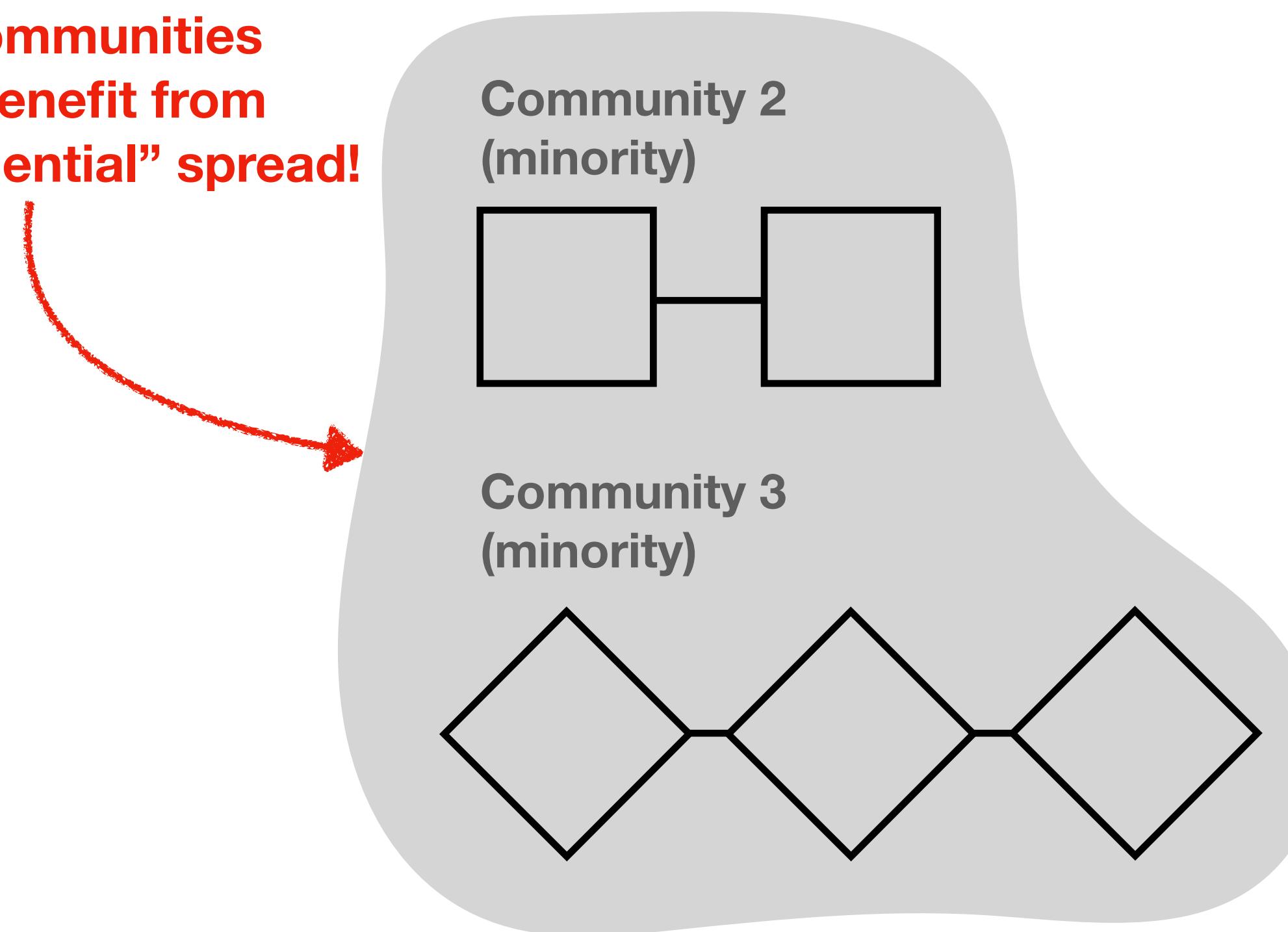
- STEP 2: Spread influence
- Not getting infected
 - Sharing a resource / info

Optimization vs. Fairness

In influence maximization (example)

High segregation
(Like in the example before)

These communities did not benefit from the “influential” spread!



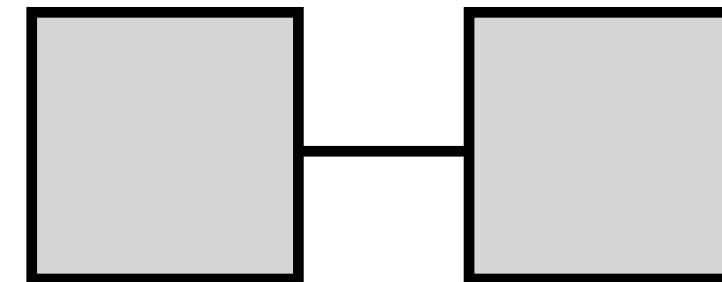
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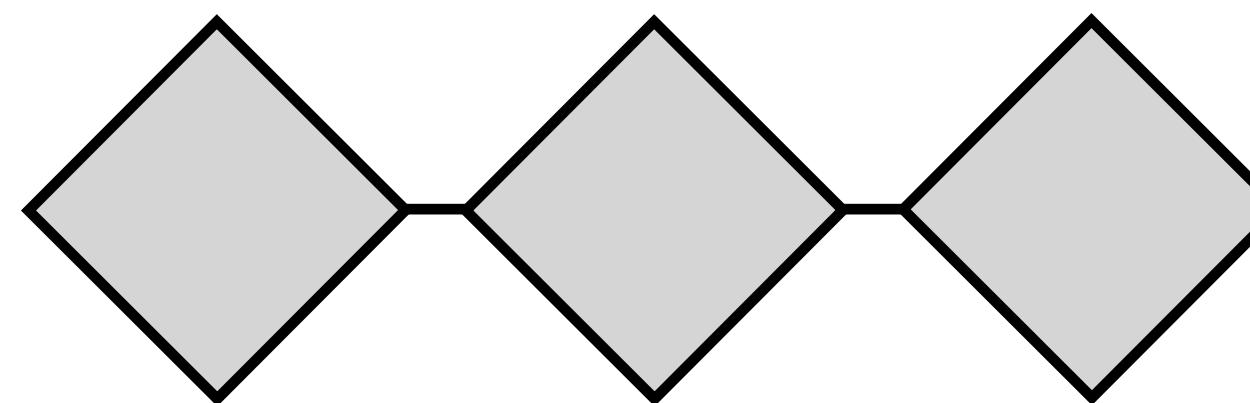
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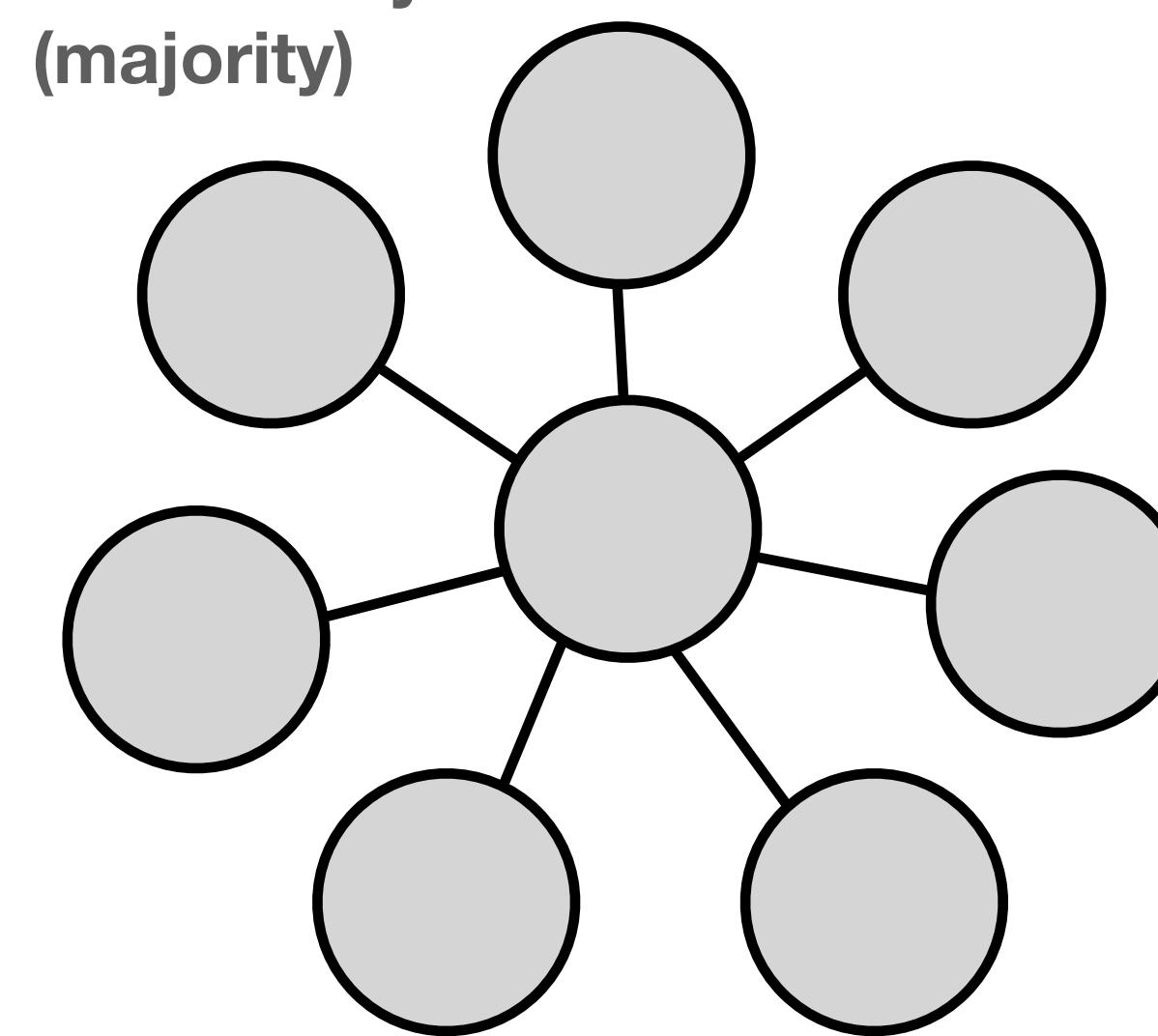
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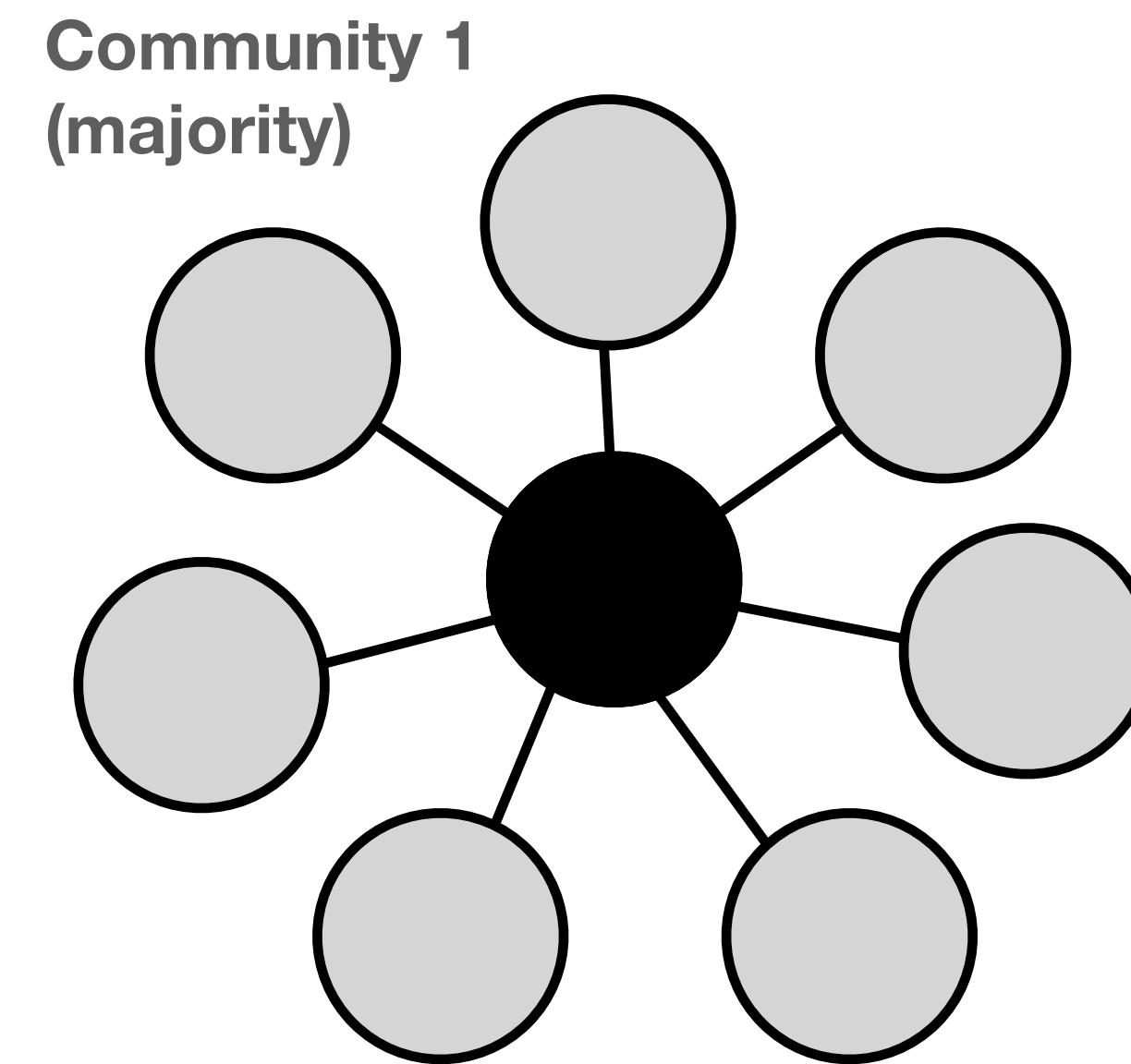
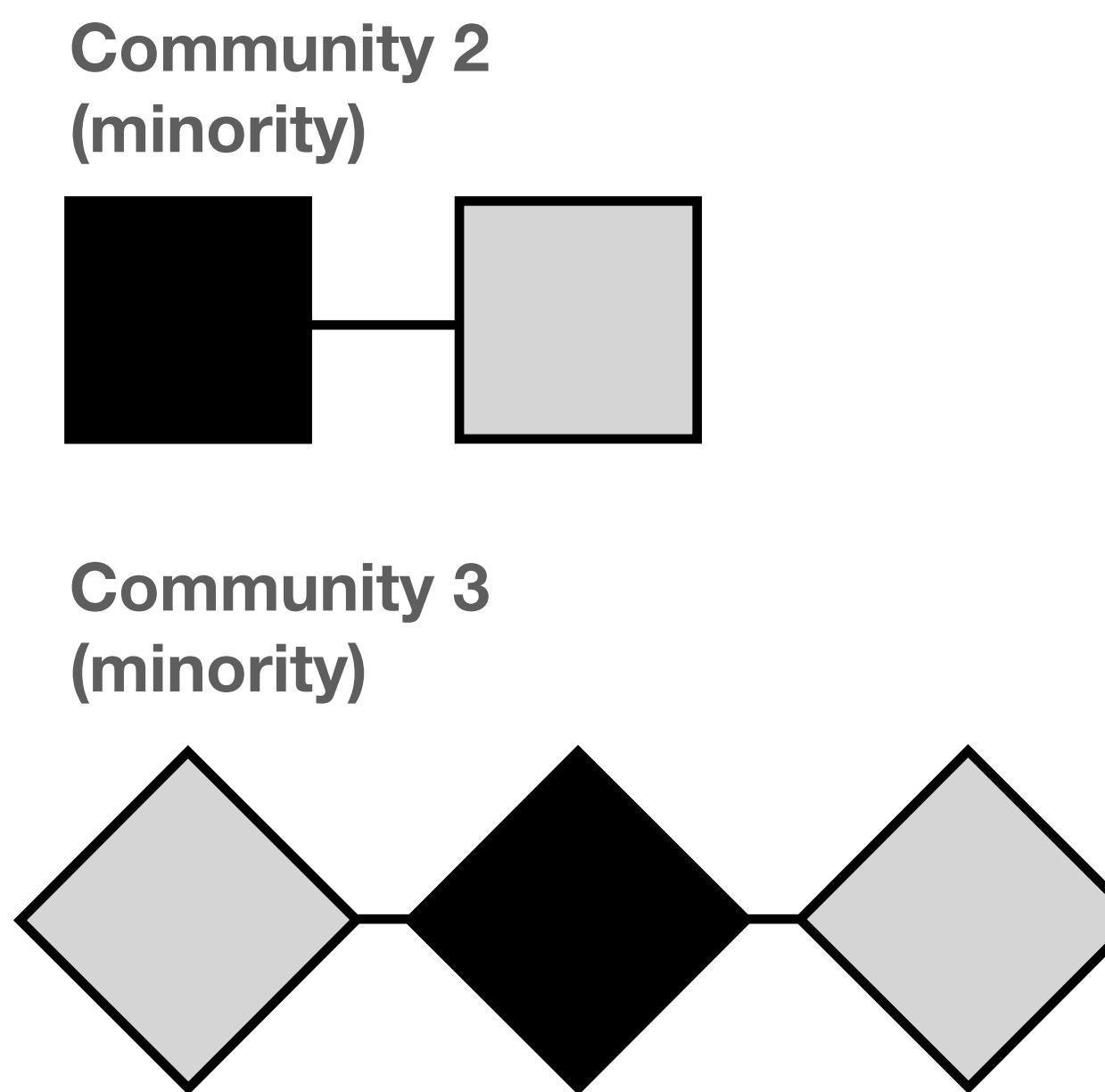
Optimization vs. Fairness

In influence maximization (example)

Mitigation strategy #1

Group fairness (more diverse outreach)

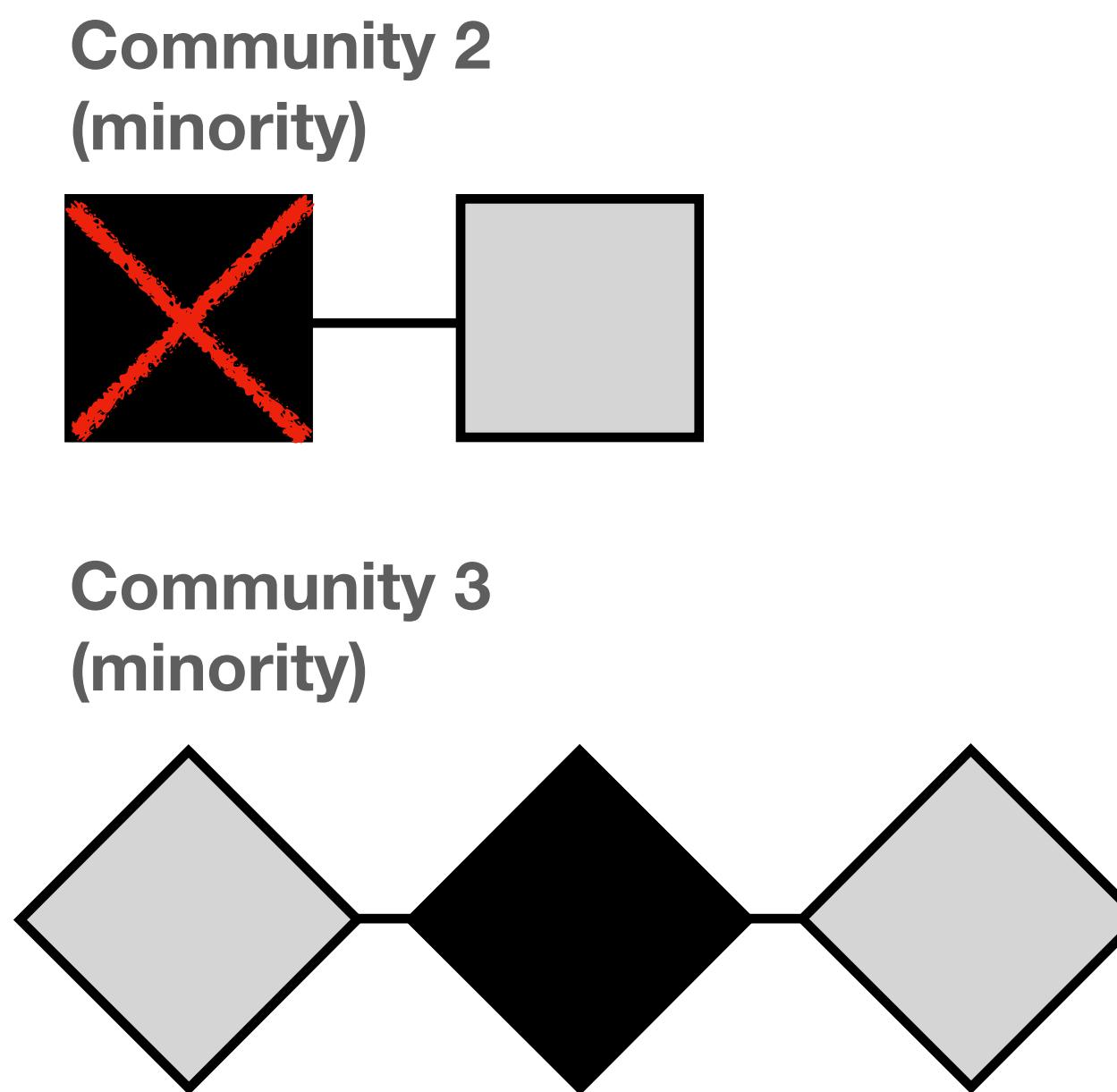
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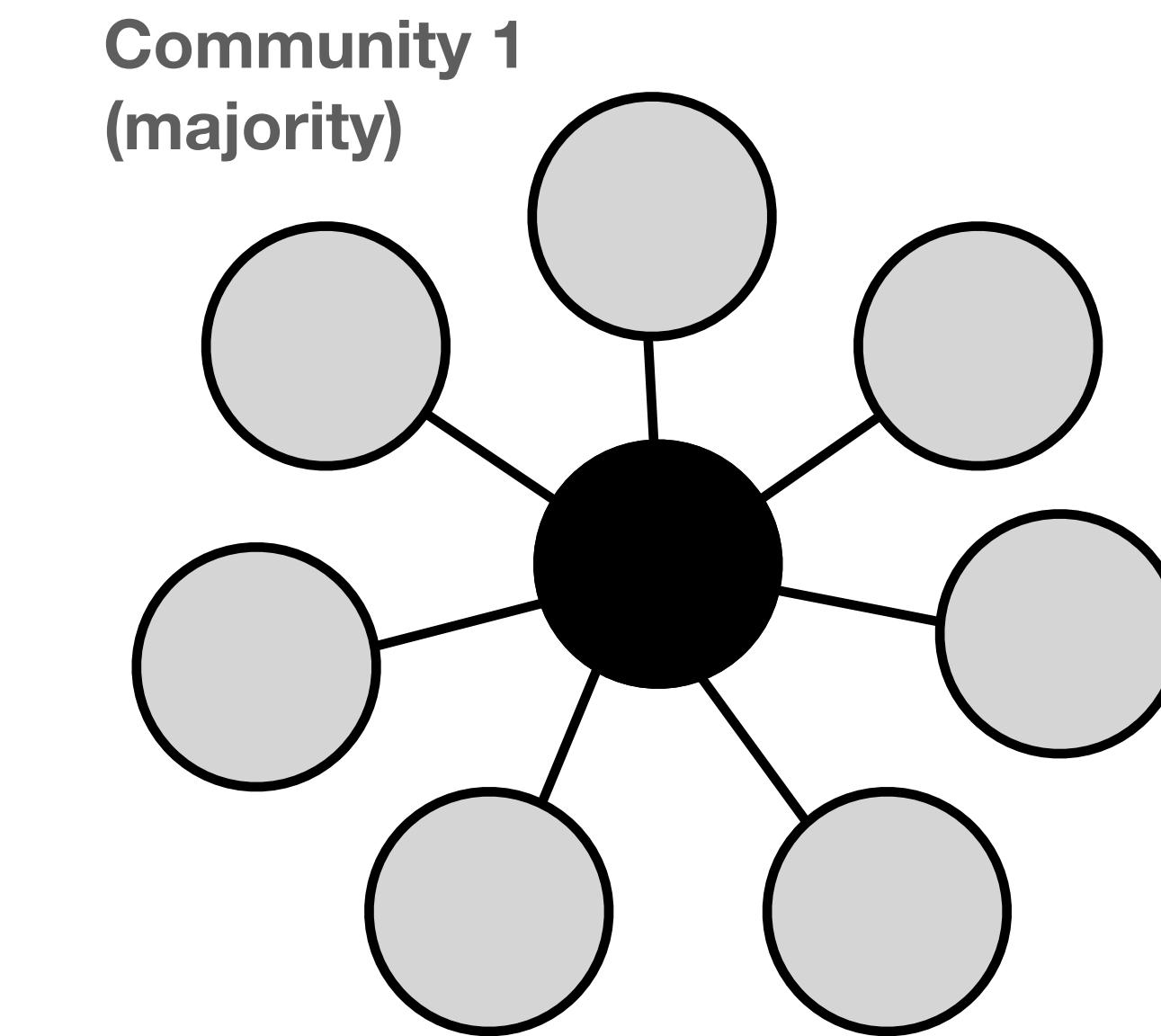
In influence maximization (example)

High segregation
(Like in the example before)



Mitigation strategy #1
Group fairness (more diverse outreach)

Trade-off between
- budget (number of seeds to be selected)
- And utility (outreach)

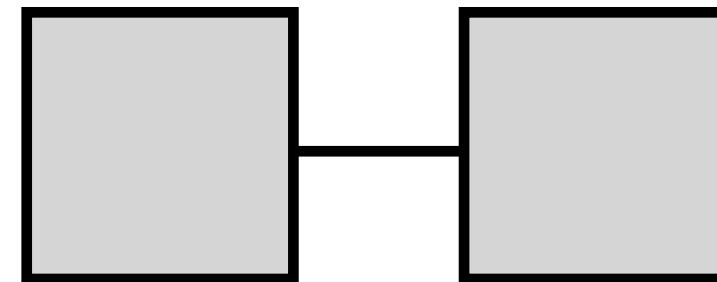


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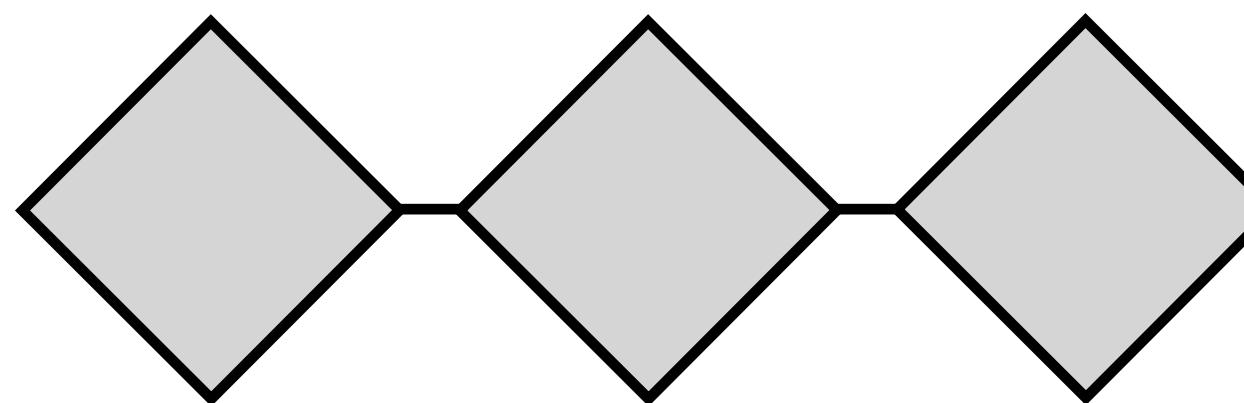
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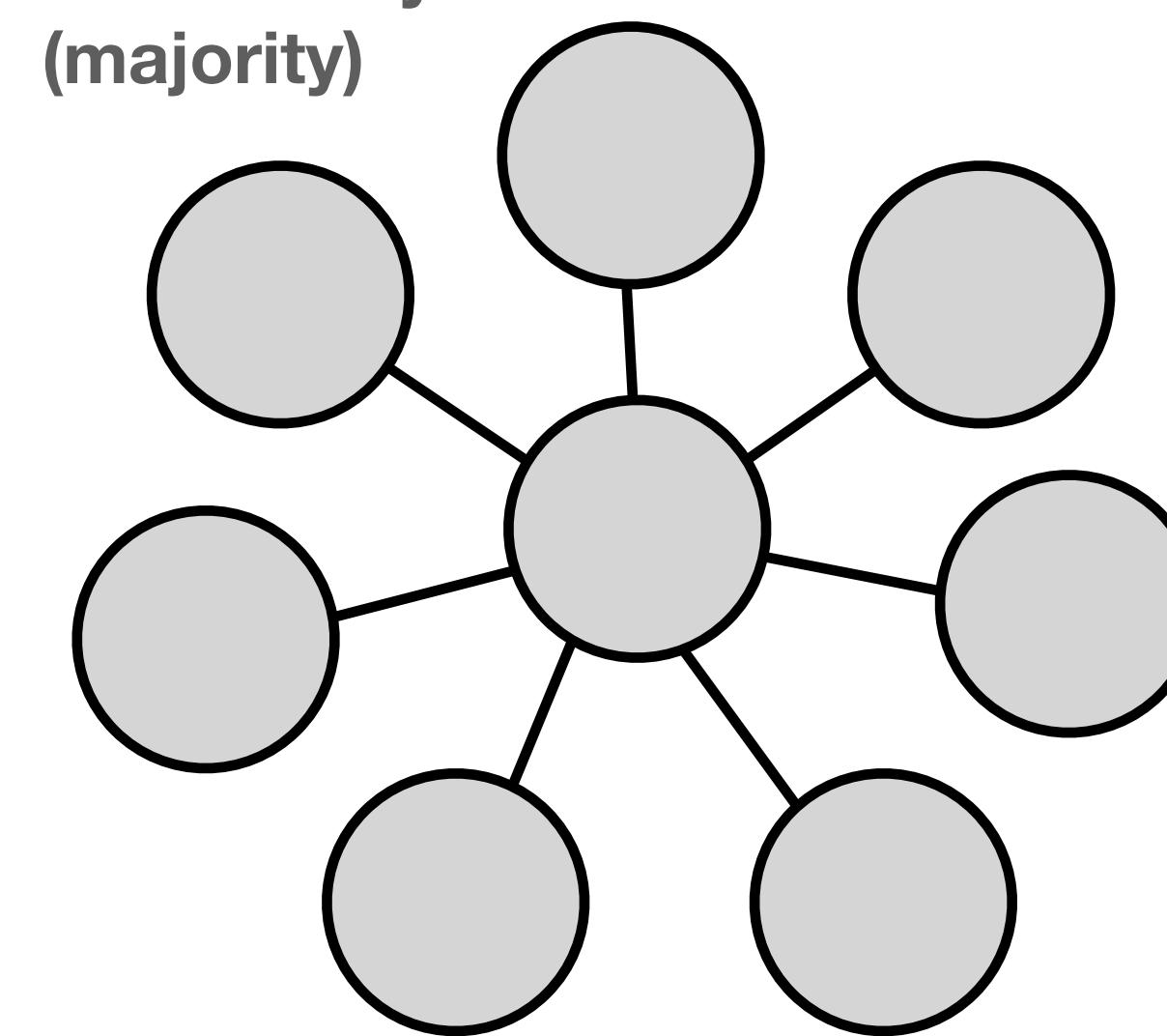
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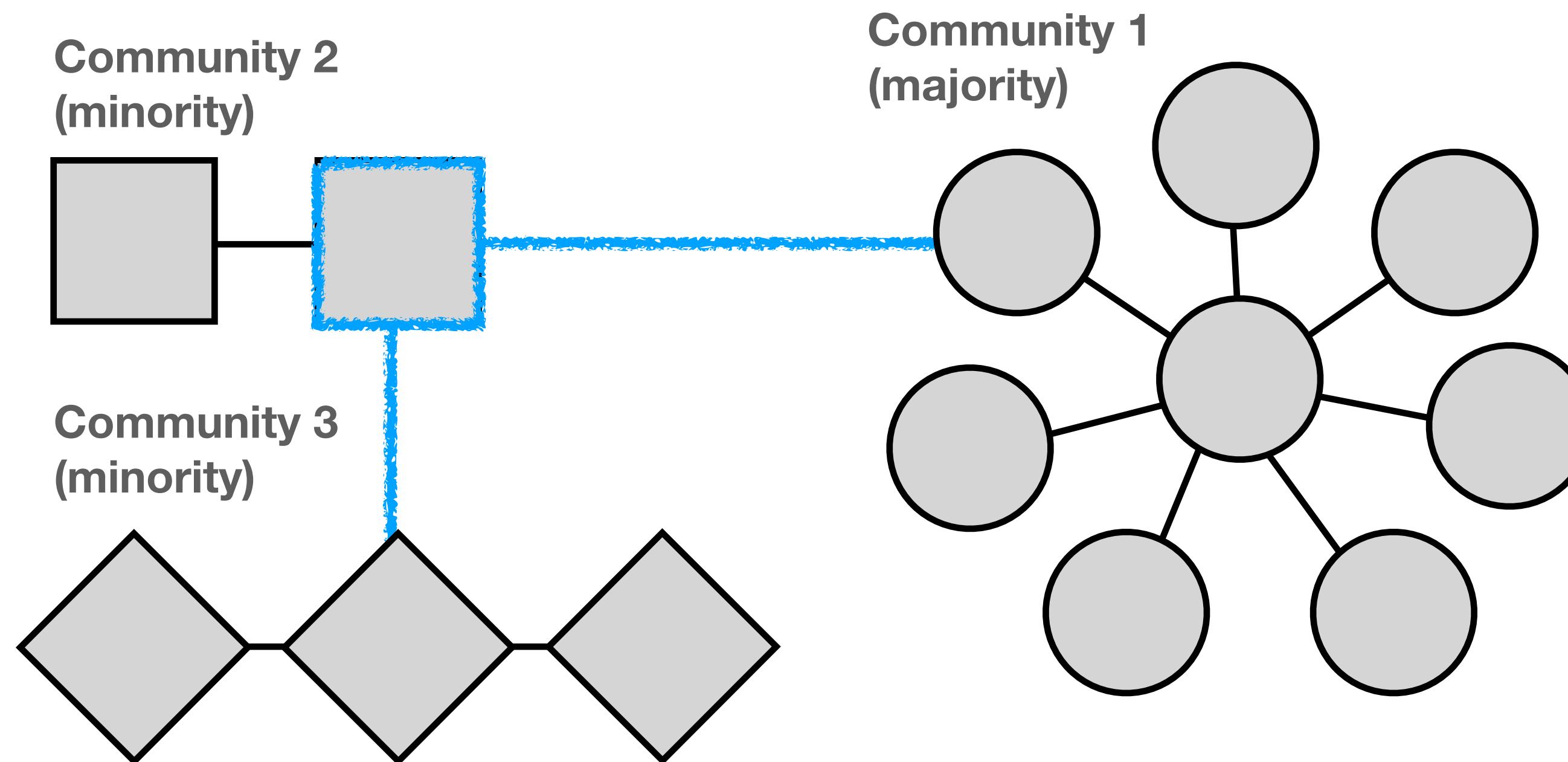
Optimization vs. Fairness

In influence maximization (example)

Mitigation strategy #2

Reducing segregation
by changing the structure of the network

High segregation
(Like in the example before)



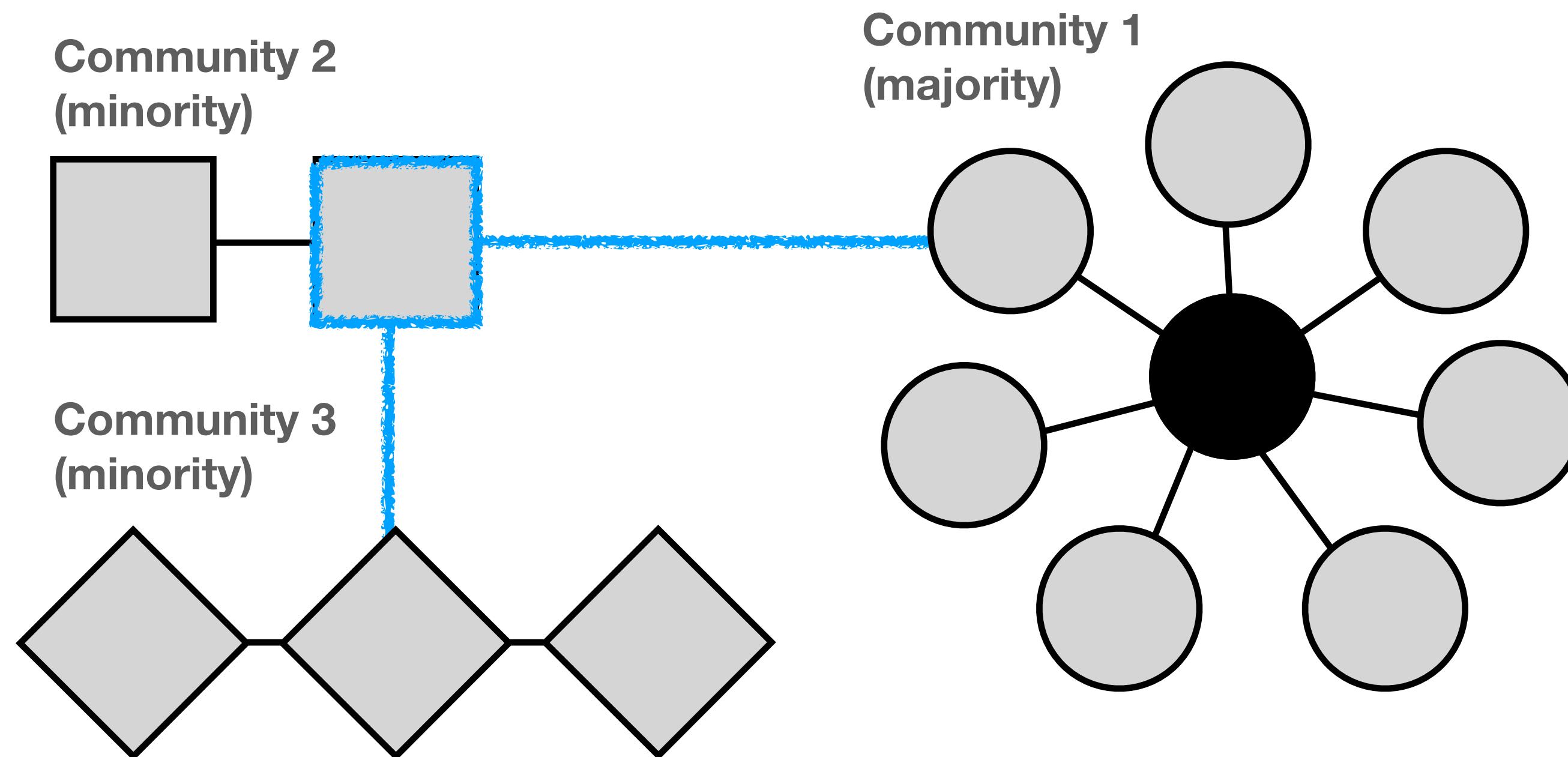
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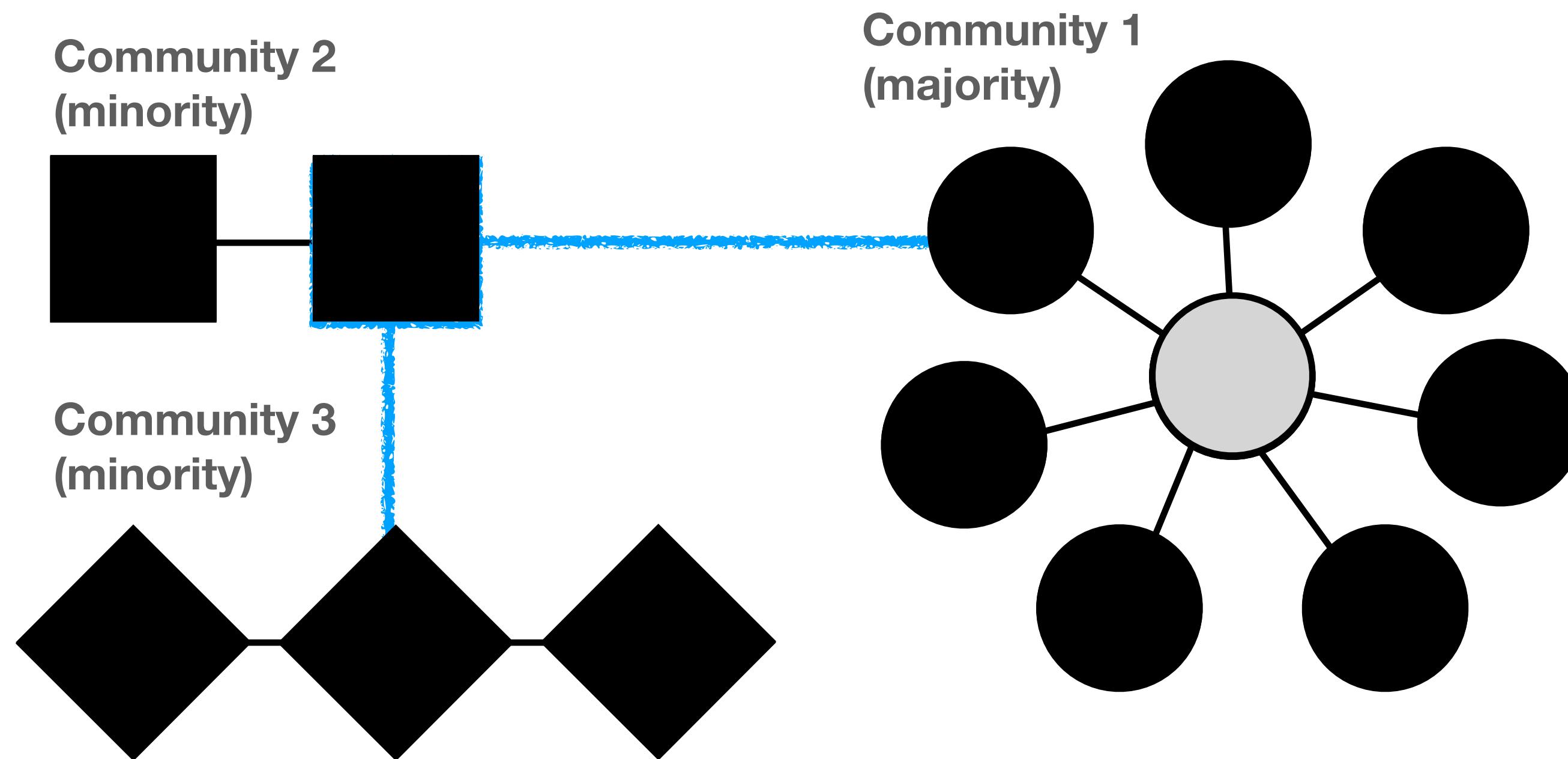
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Tools to understand...

...how inequalities in network-based algorithms emerge

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 - Or 19% are female, 80% are men, 1% are non-binary
 - Where do we get all these different networks?
 - Using **synthetic data** (random network generators)

Synthetic networks

...and where to find them

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- What are synthetic networks?

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 - Biased links towards: popular nodes, similar nodes, friends-of-friends, etc.
 - (We can also model completely random non-attributed graphs)

Model Class	Examples	Characteristics
Static Models	Erdos-Renyi Watts-Strogatz	<ul style="list-style-type: none"> • N fixed • p_k exponentially bounded • Static, time independent topologies
Generative Models	Configuration Model Hidden Parameter Model	<ul style="list-style-type: none"> • Arbitrary pre-defined p_k • Static, time independent topologies
Evolving Network Models	Barabasi-Albert Model Bianconi-Barabasi Model Initial Attractiveness Model Internal Links Model Node Deletion Model Accelerated Growth Model Aging Model	<ul style="list-style-type: none"> • p_k is determined by the processes that contribute to the network's evolution. • Time-varying network topologies

Table 6.1
Classes of Models in Network Science
The table summarizes the three main modeling frameworks used in network science, together with their distinguishing features.

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The table summarizes the three main modeling frameworks used in network science, together with their distinguishing features.

Today, we will cover this graph model and some variations

Mechanisms of edge formation

Found in real-world social networks

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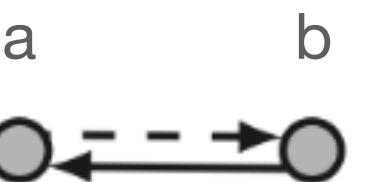
Reciprocity



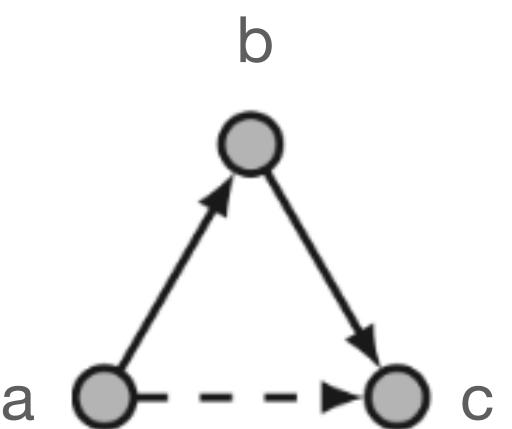
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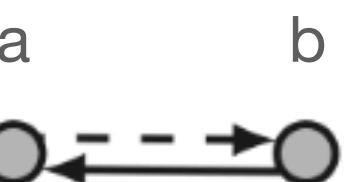
Transitivity



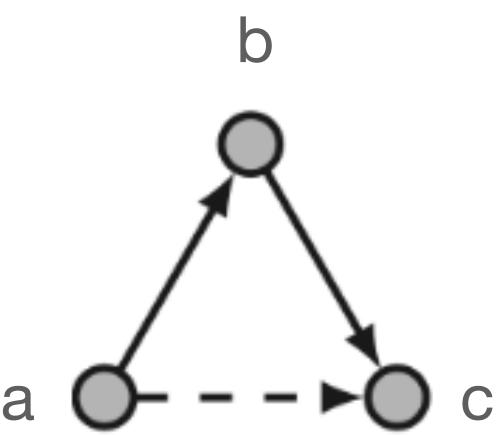
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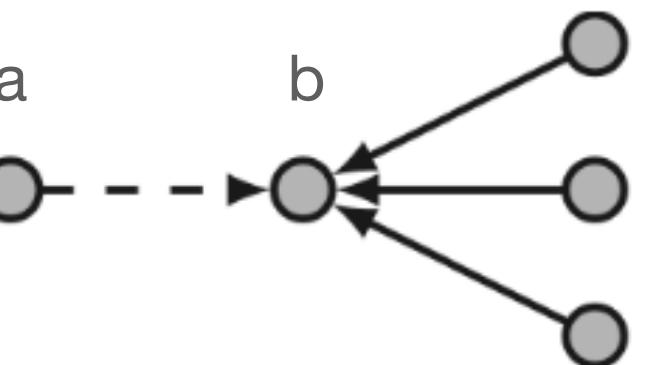
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Popularity



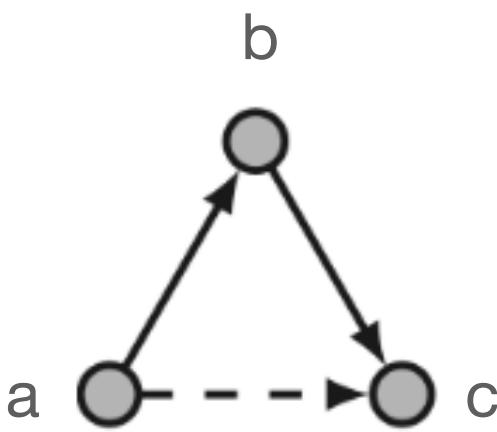
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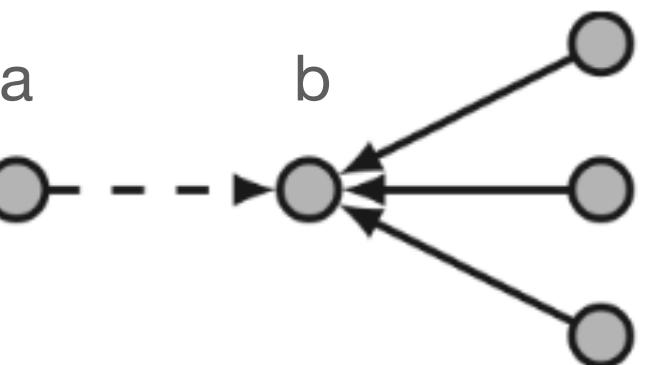
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Transitivity



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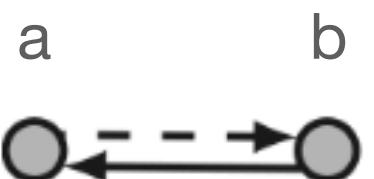
Activity



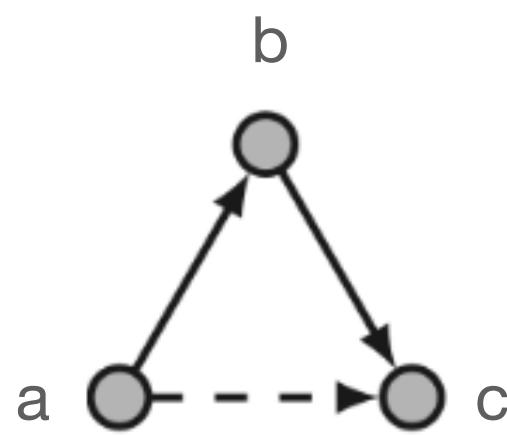
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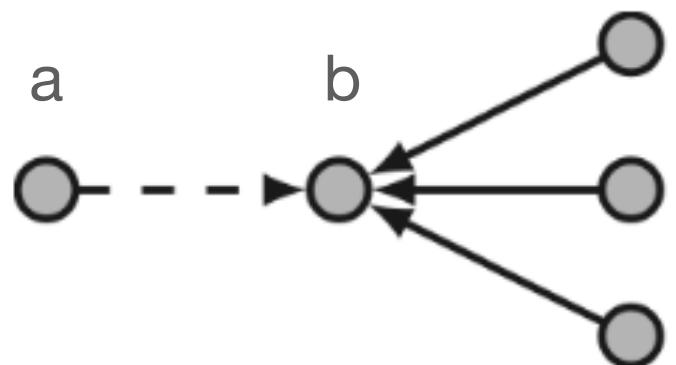
Reciprocity



Transitivity



Popularity



Activity



Attraction



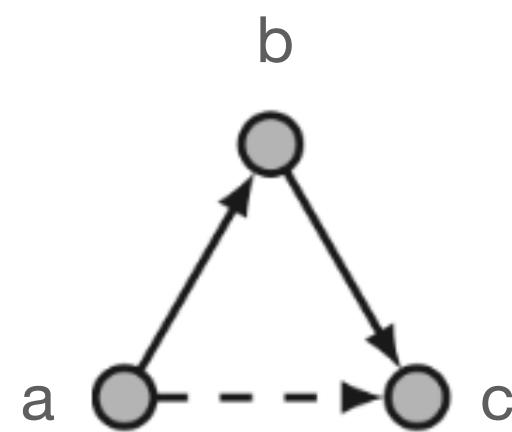
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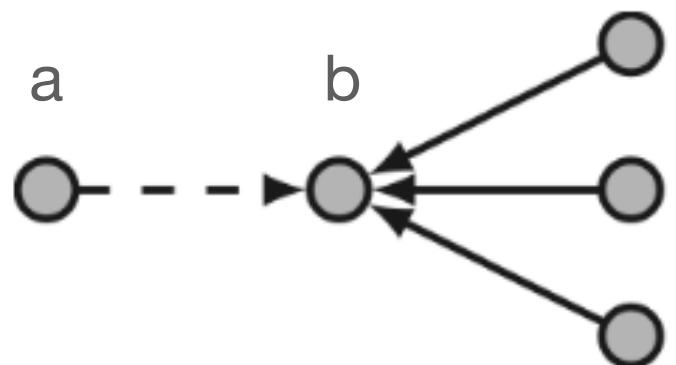
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Activity



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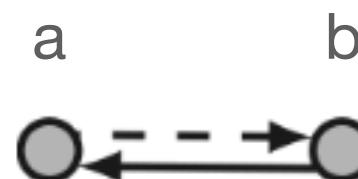
Homophily



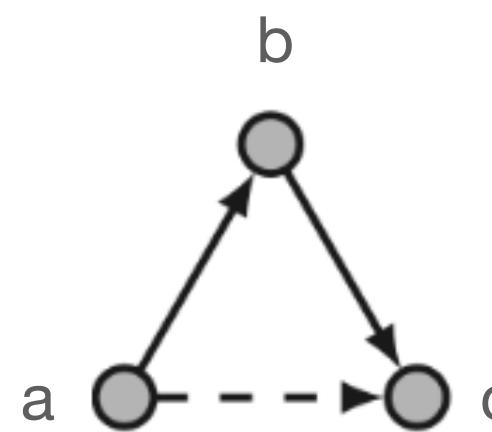
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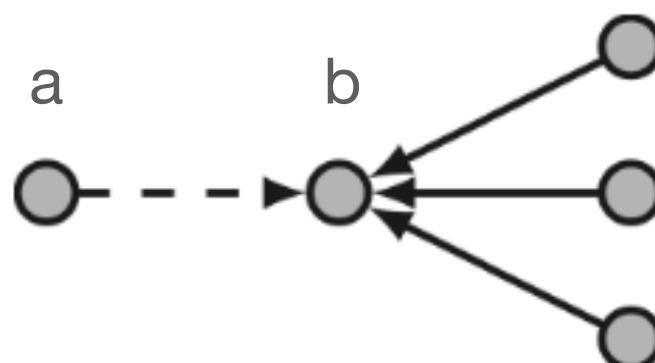
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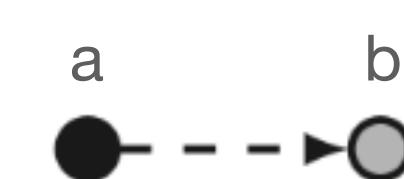
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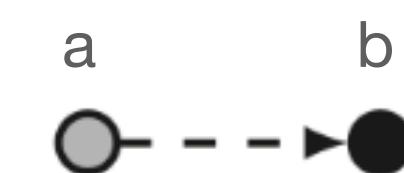
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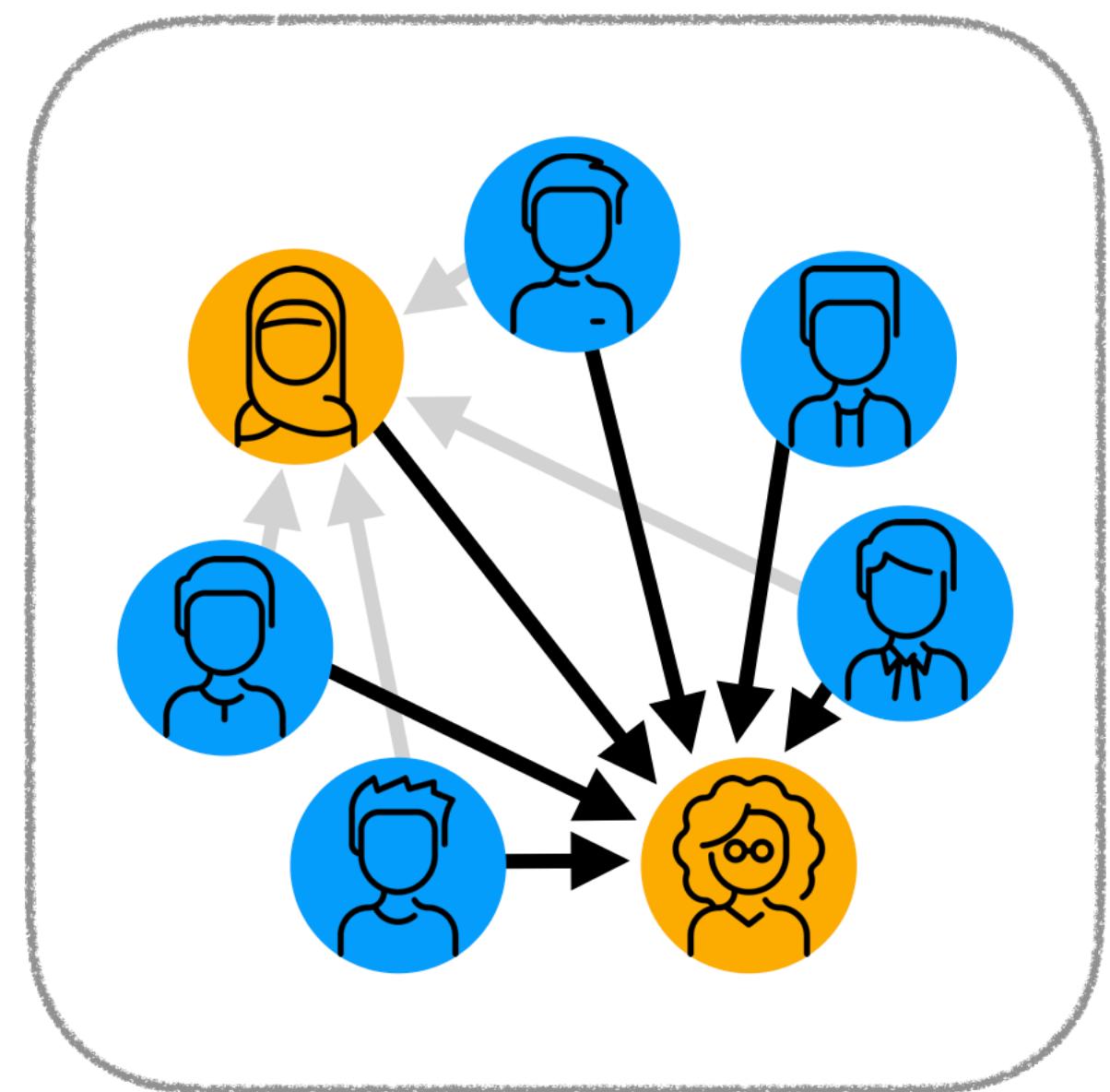
Homophily



We'll cover this
today!

Popularity

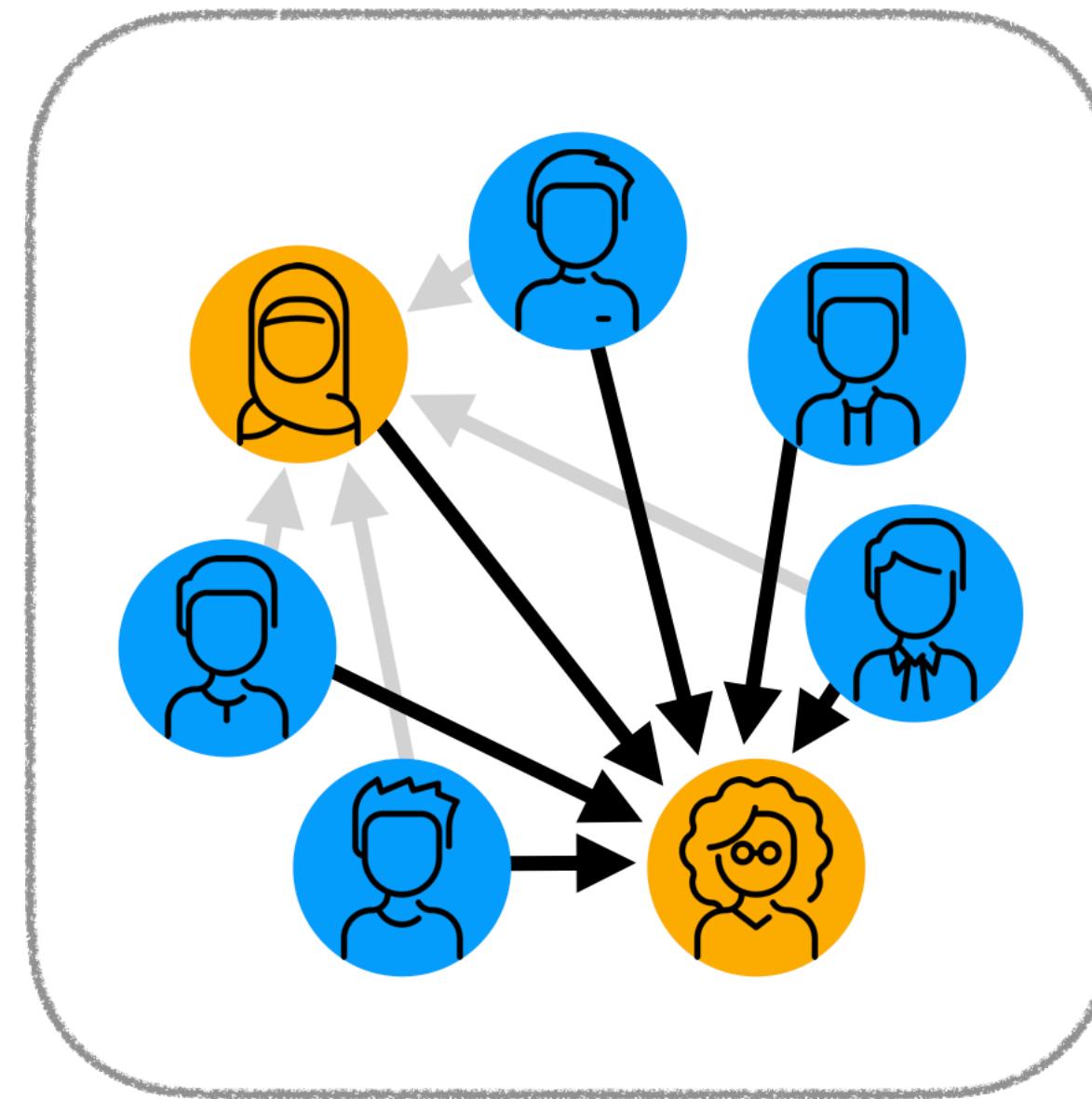
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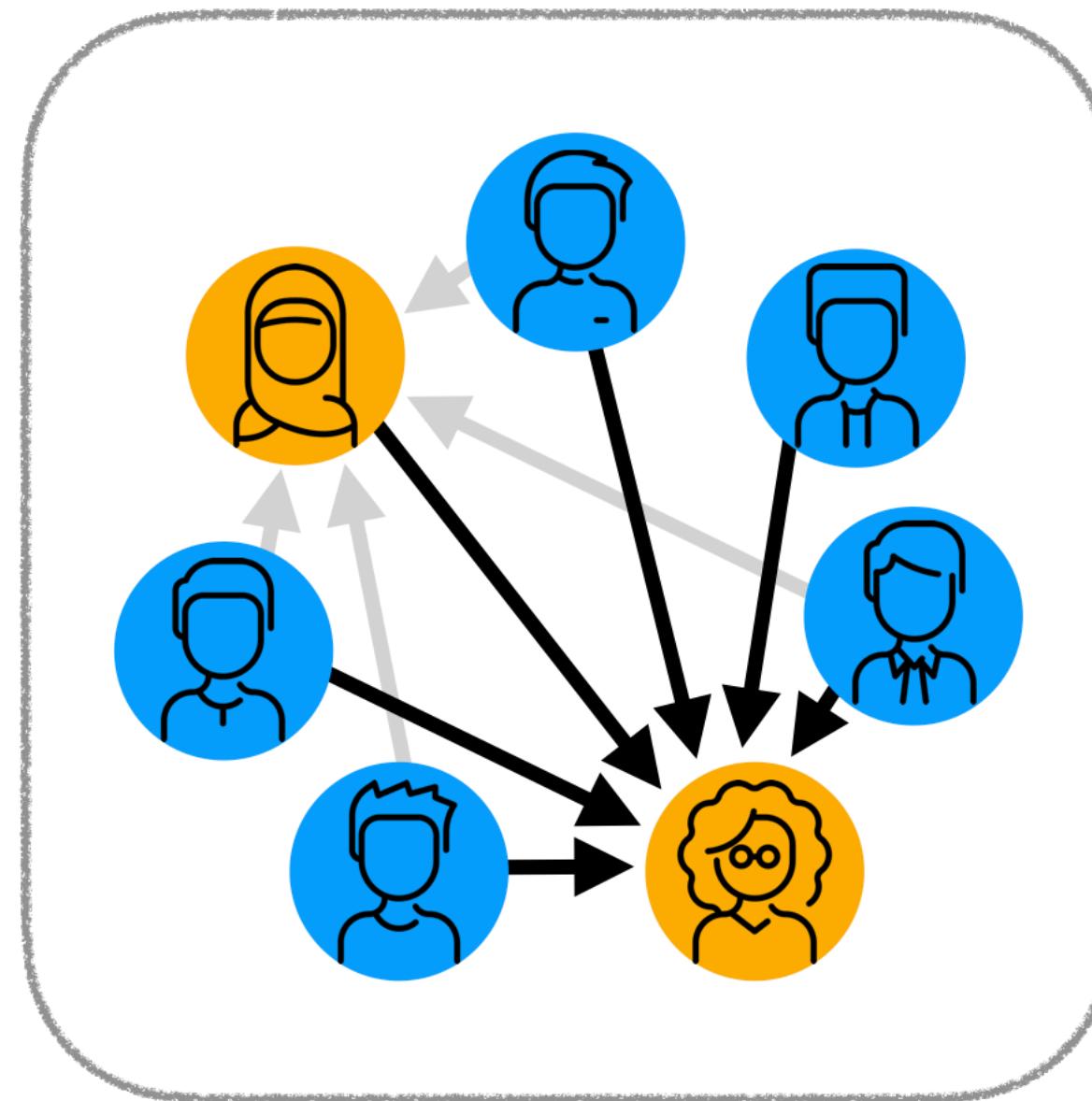


Popularity

- The tendency of actors to **connect to those who receive links from many others**. The structural position is defined by the **in-degree** of the receiver (target node) of an explained tie.

Popularity

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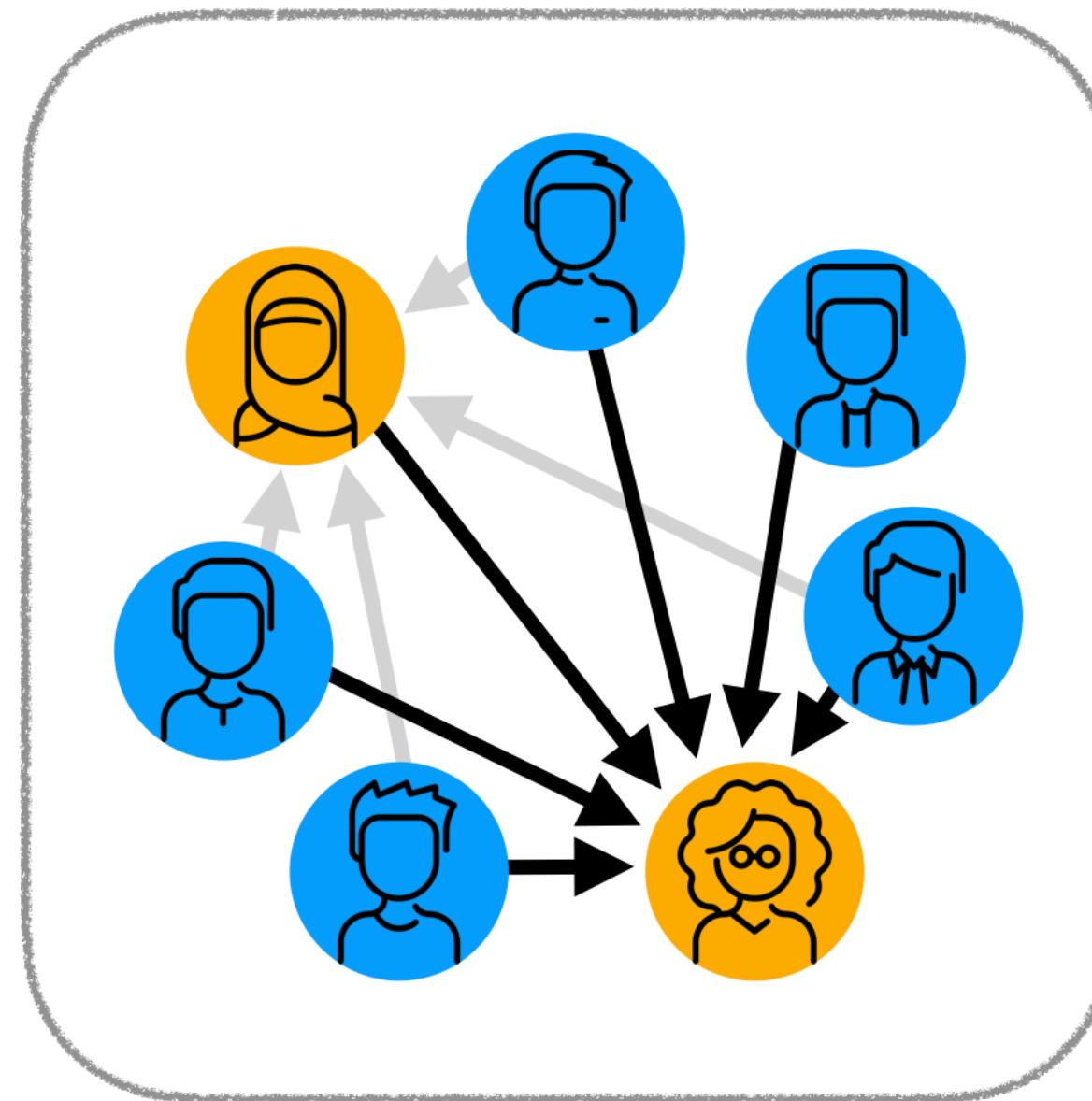


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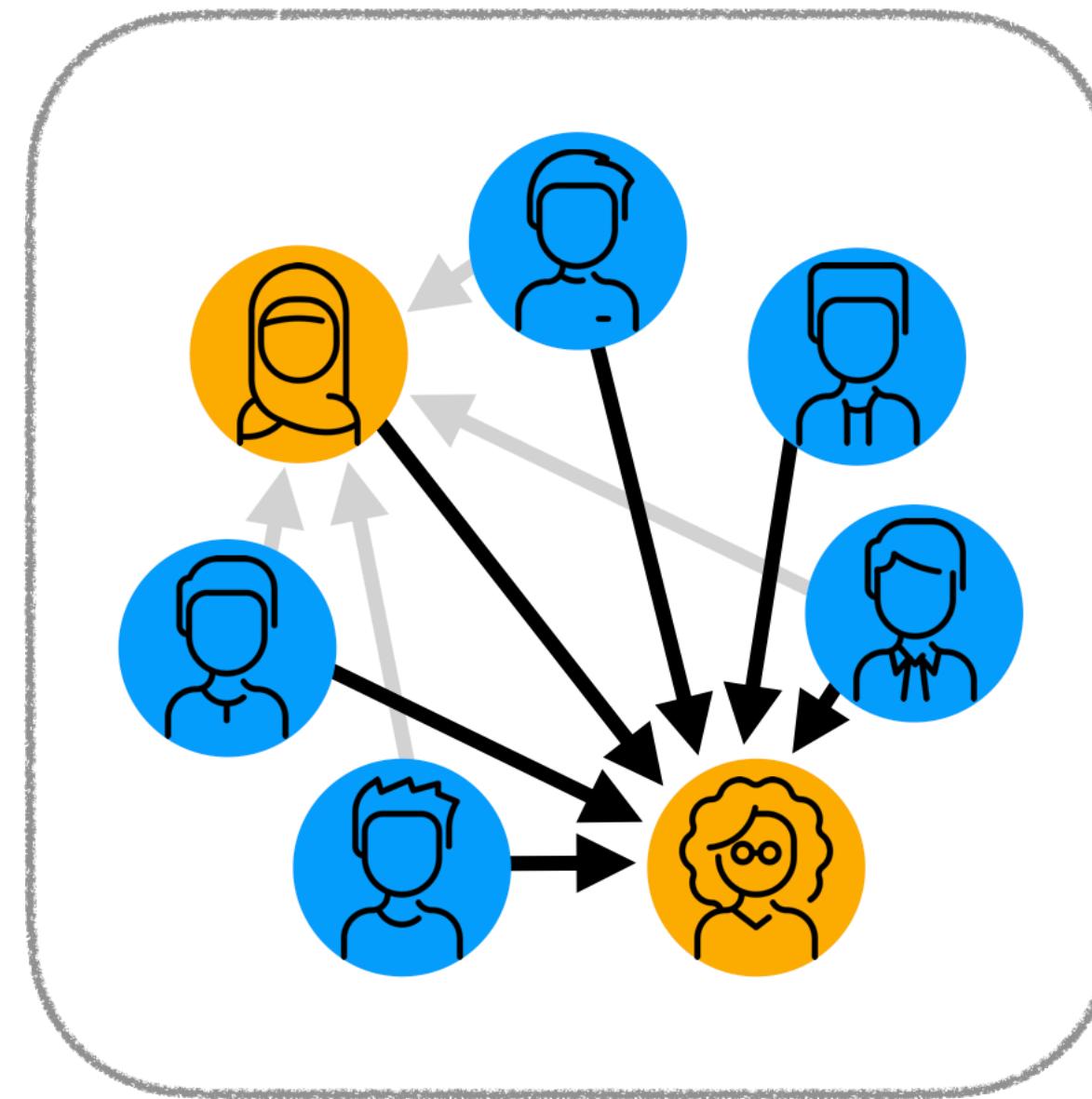
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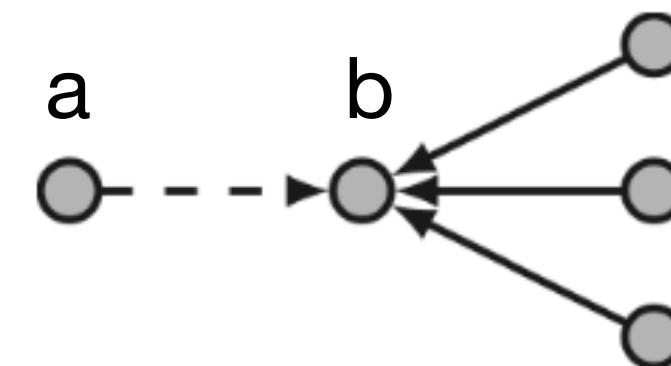
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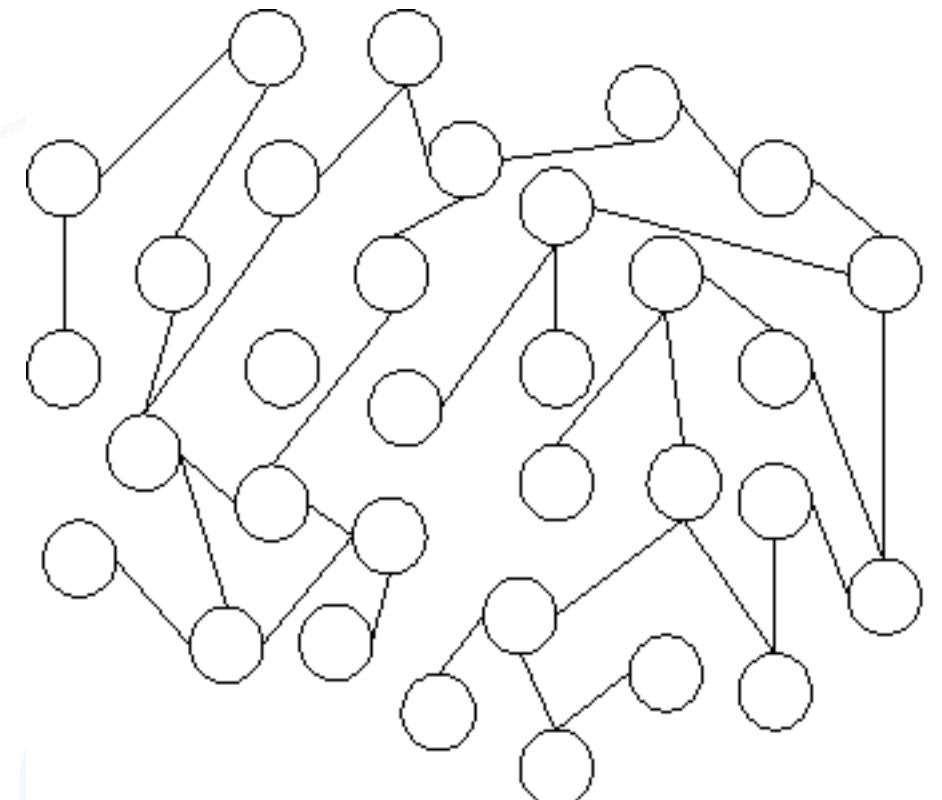
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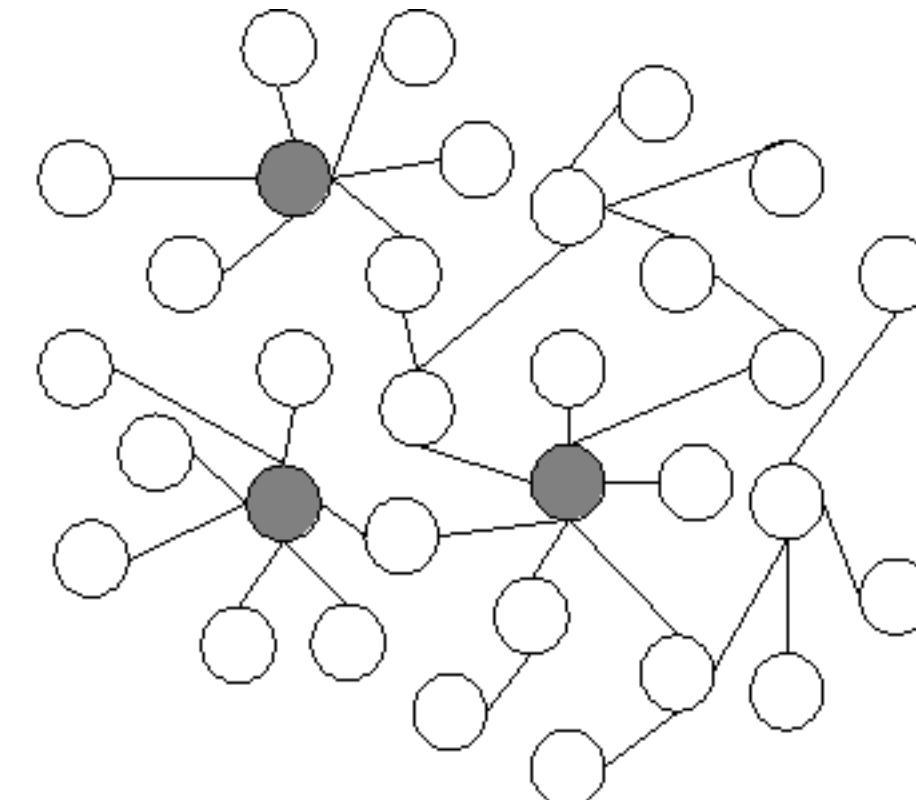
$$P(a \rightarrow b) = P(b|a) = p_{ab} = \frac{k_b}{\sum_c k_c}$$

Popularity

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(a) Random network

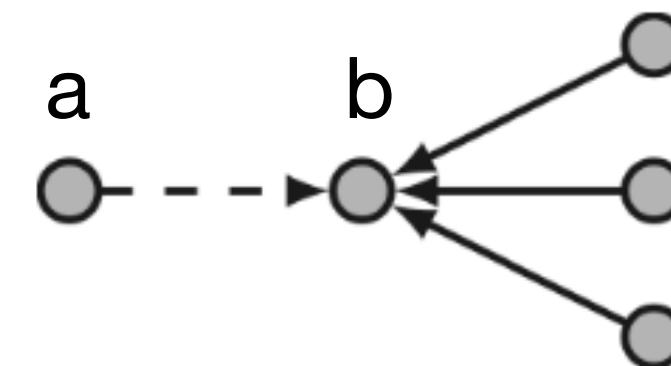


(b) Scale-free network

of actors to connect to those who receive any others. The structural position is defined by the degree of the receiver (target node) of an explained tie.

Effect or rich-gets-richer effect mechanism in discussed by Merton (1968), Price (1976) and easing recognition of an actor's scientific work (number of ties in a citation network).

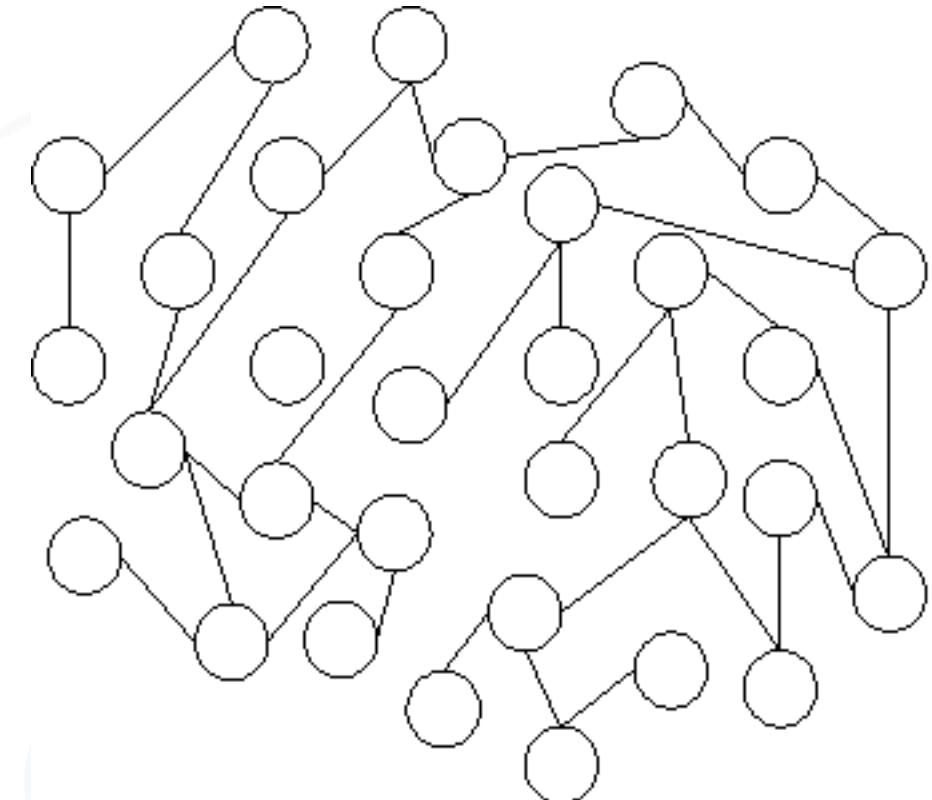
- Preferential attachment in the work of Barabási and Albert (1999) operationalised this mechanism in networks.



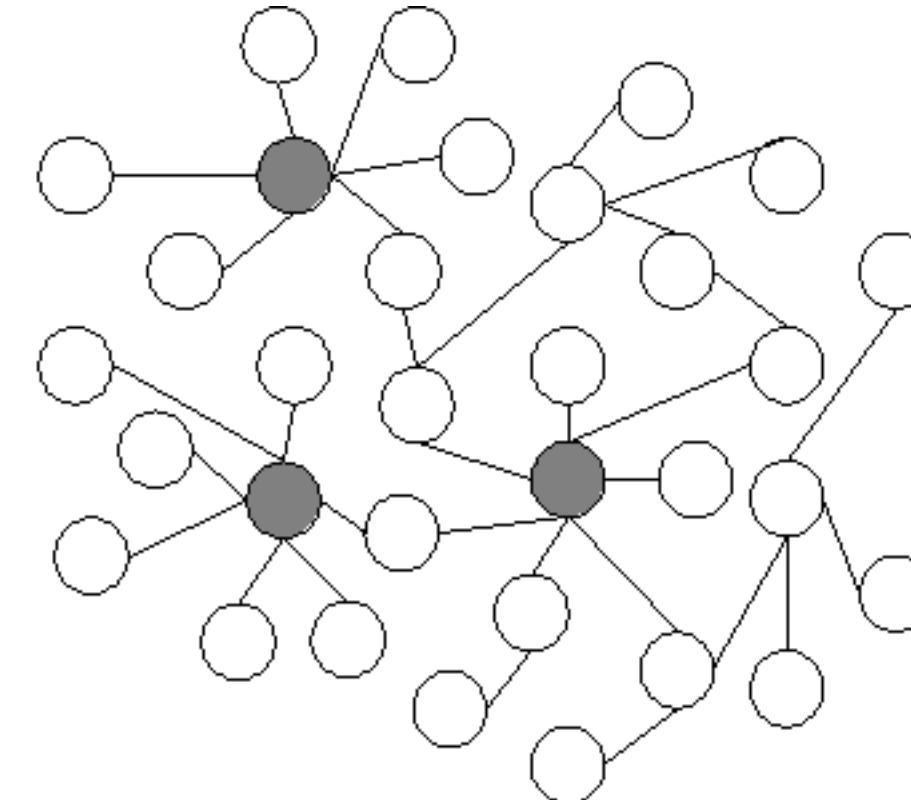
$$P(a \rightarrow b) = P(b|a) = p_{ab} = \frac{k_b}{\sum_c k_c}$$

Popularity

a.k.a. preferential attachment

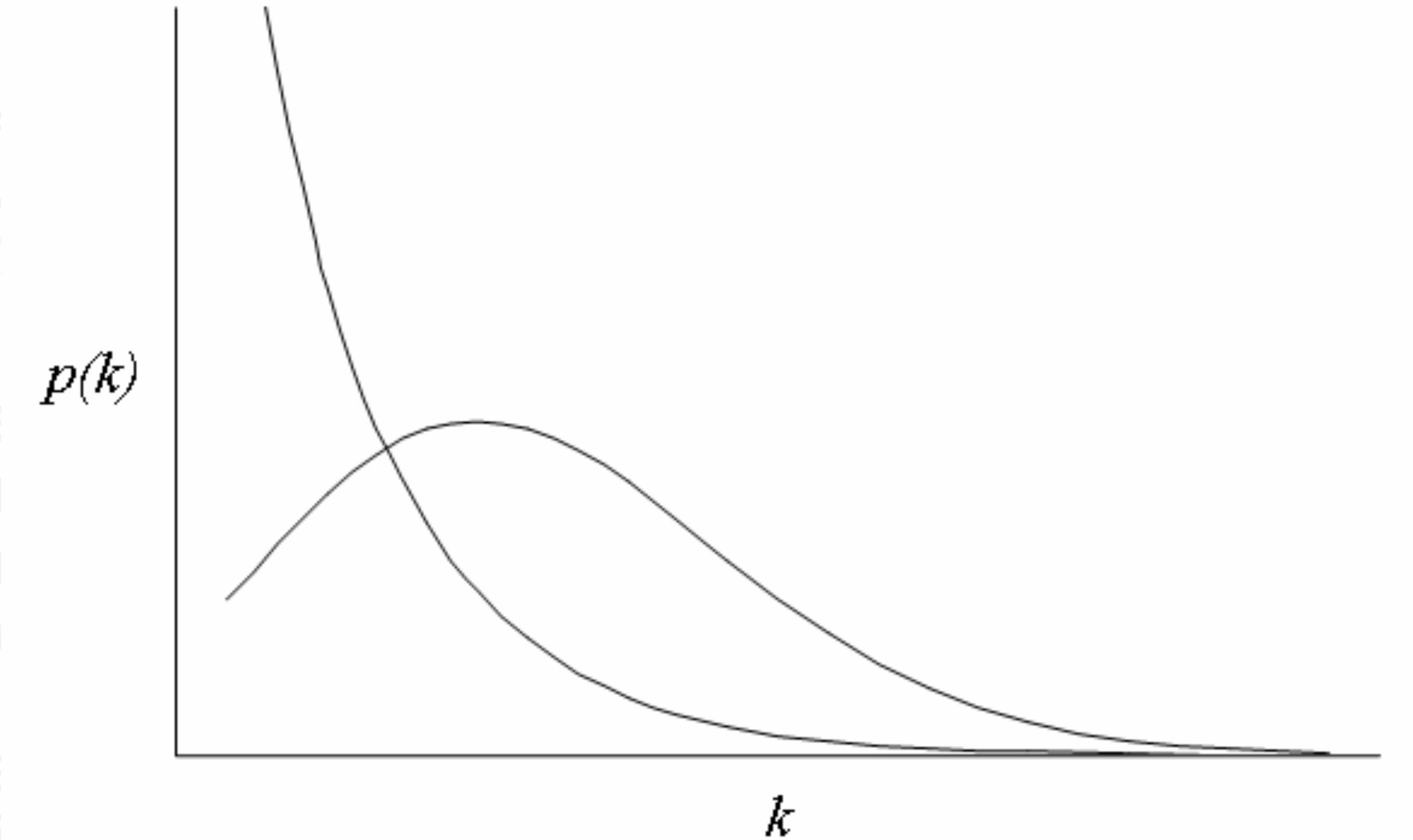


(a) Random network

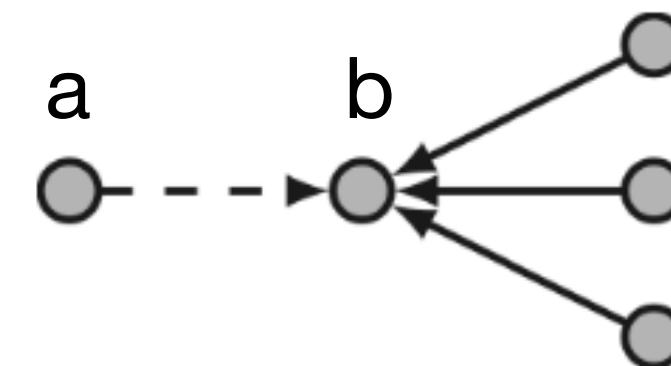


(b) Scale-free network

Degree distribution plot



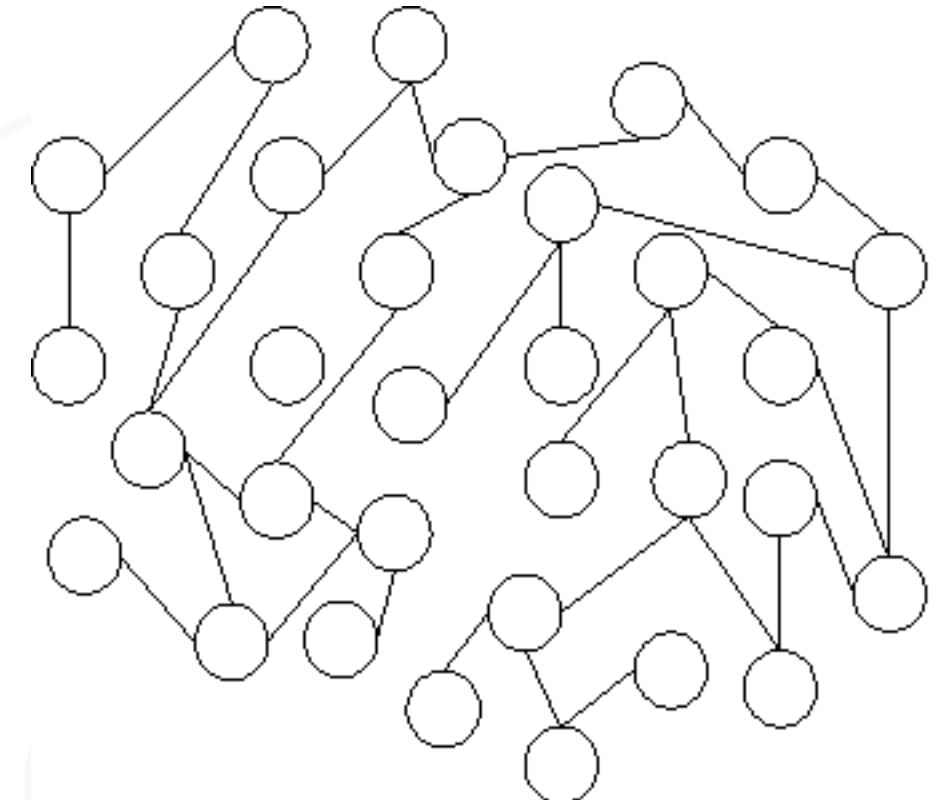
- Preferential attachment (1999) operation



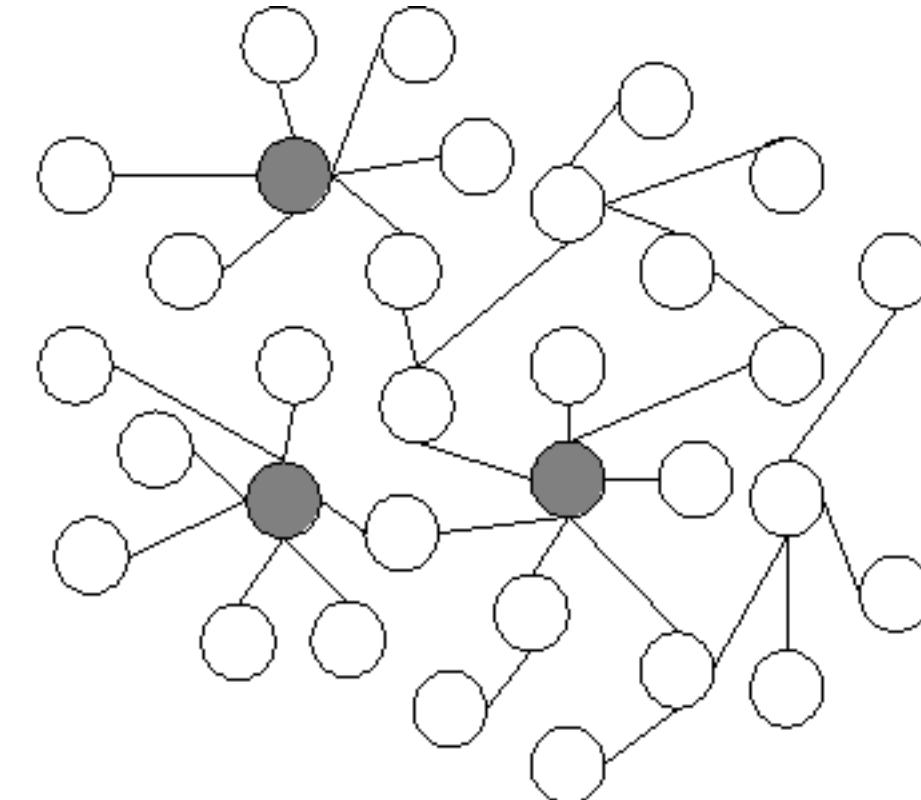
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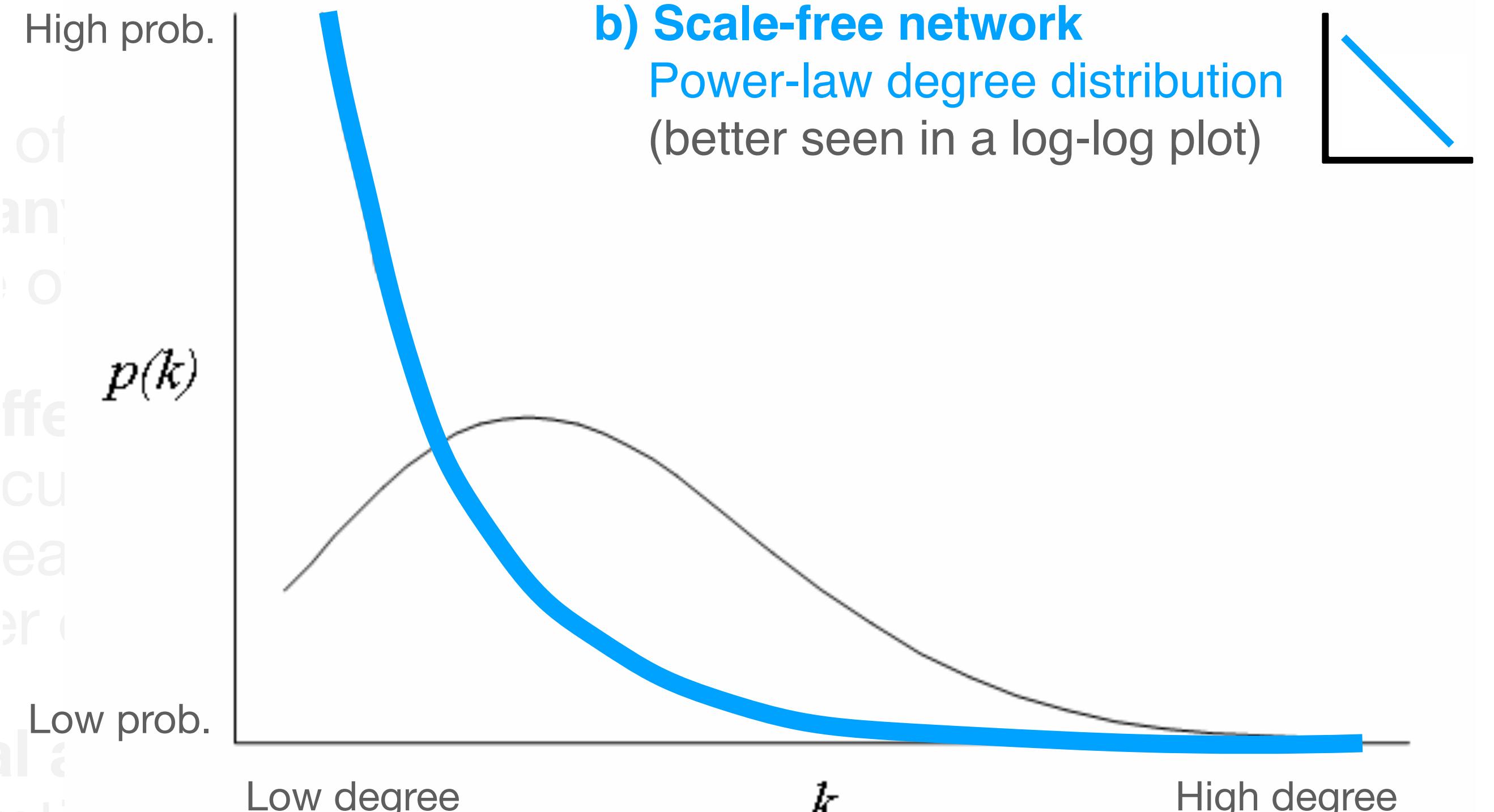


(a) Random network



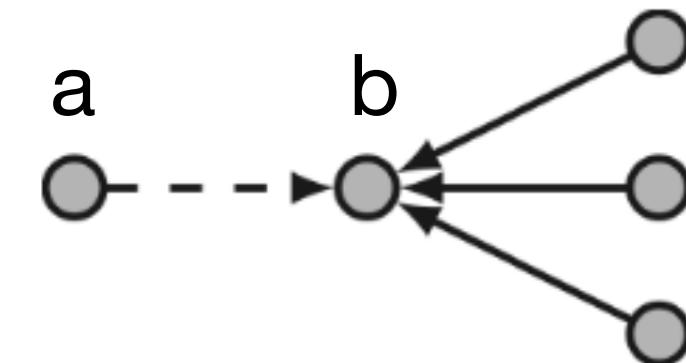
(b) Scale-free network

Degree distribution plot



b) Scale-free network

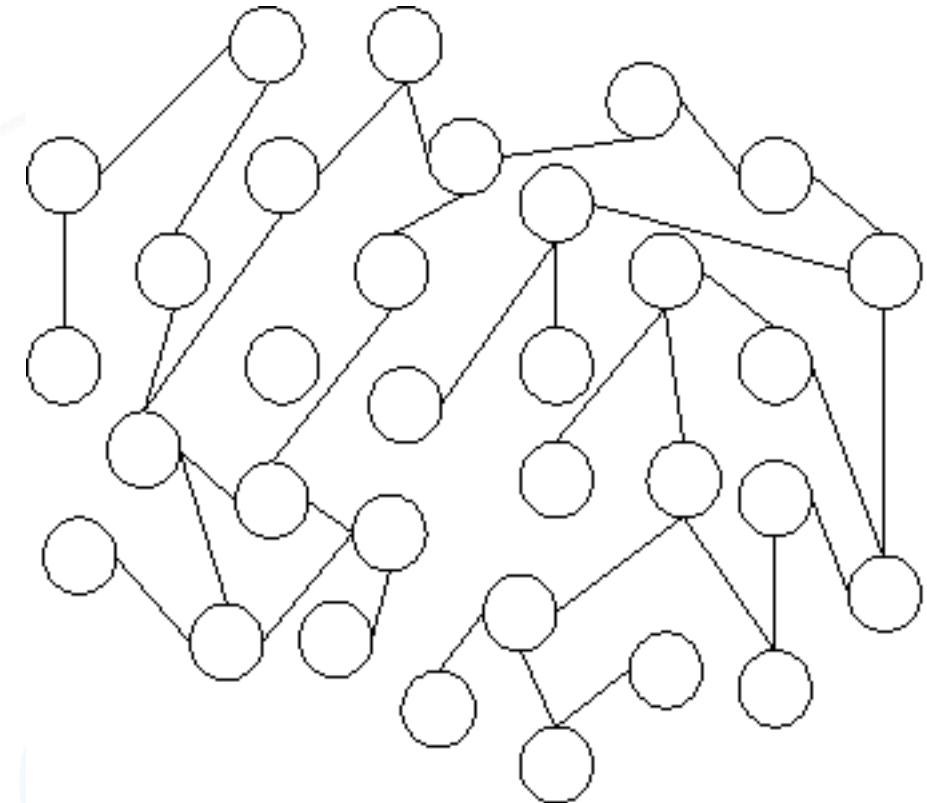
Power-law degree distribution
(better seen in a log-log plot)



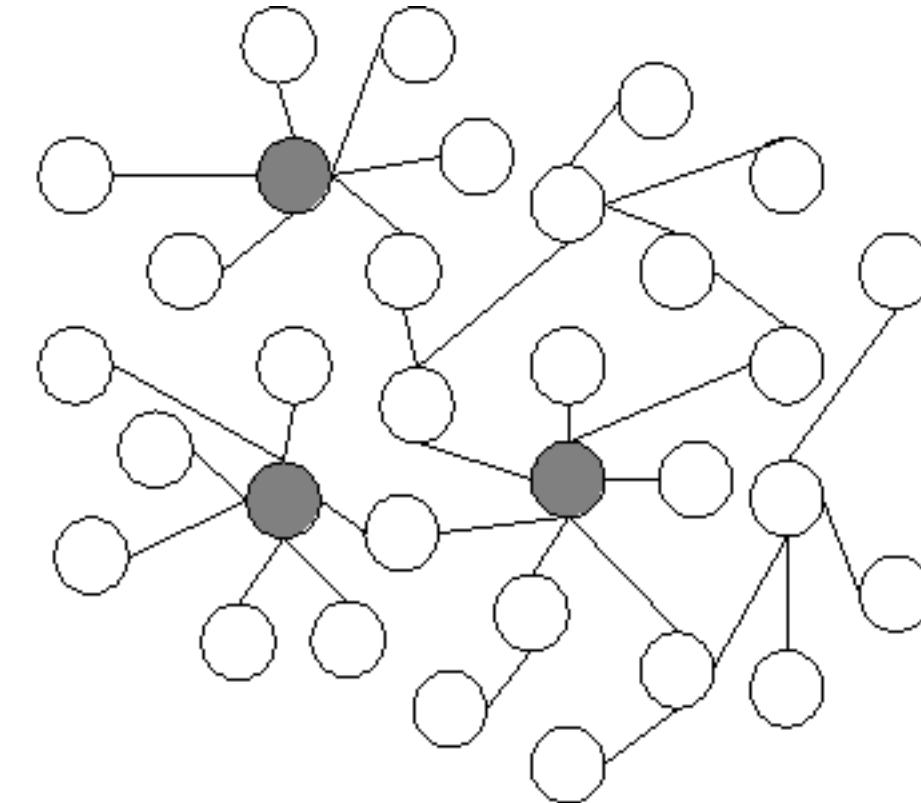
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Popularity

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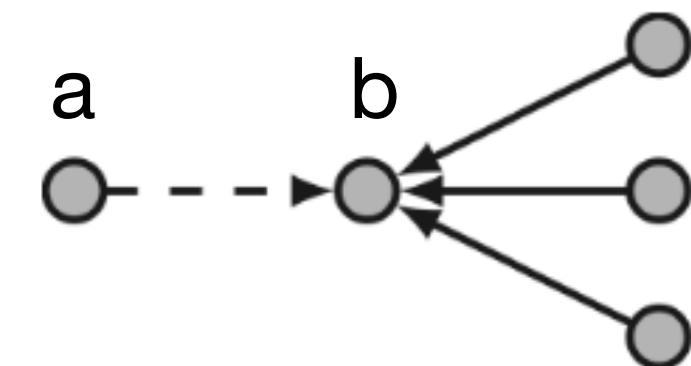
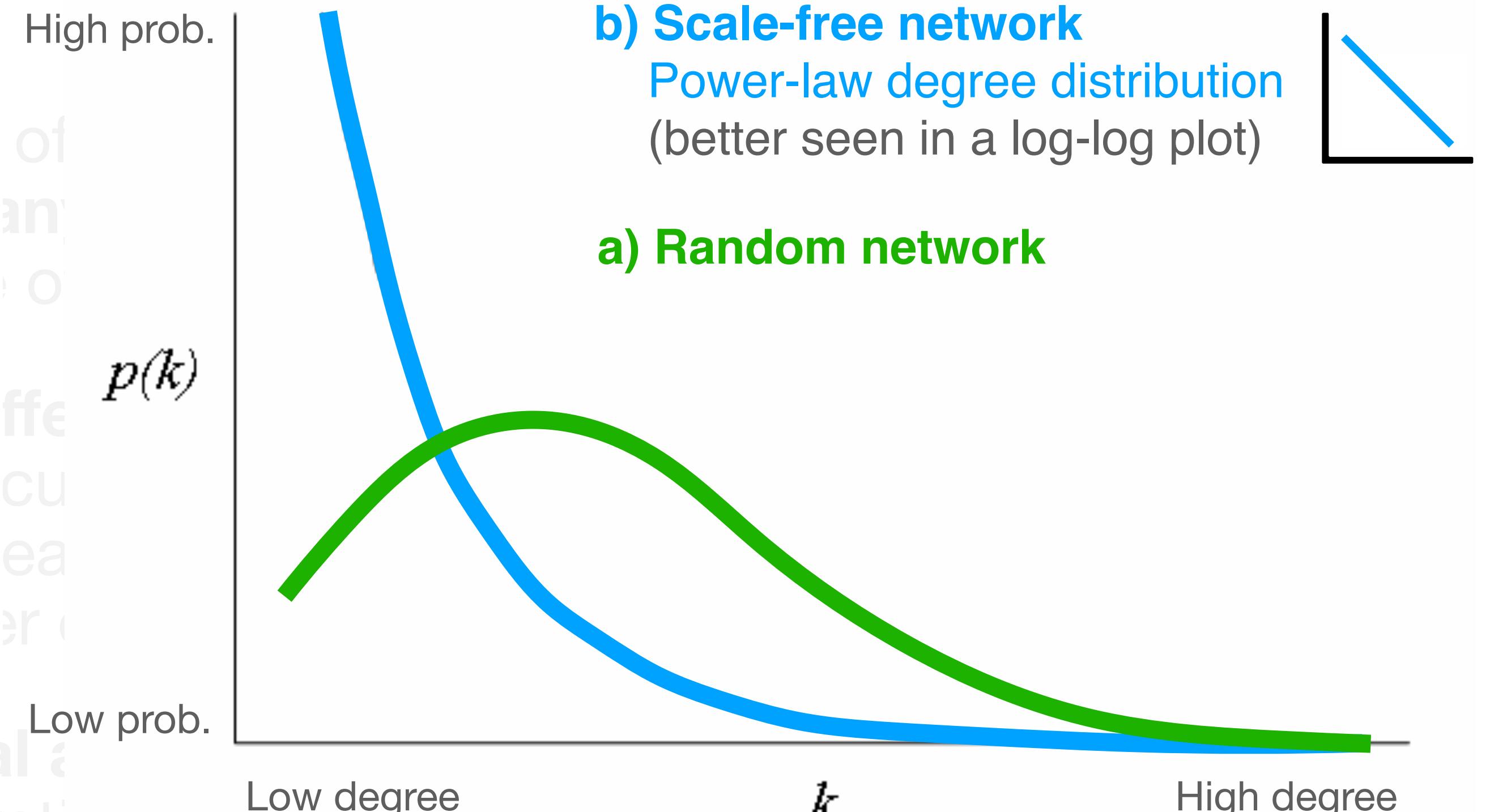


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Degree distribution plot



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Modeling “preferential attachment” in node-attributed undirected networks

Karimi, Fariba, et al. "Homophily influences ranking of minorities in social networks."
“ Scientific reports 8.1 (2018): 11077.

Modeling “preferential attachment” in node-attributed undirected networks



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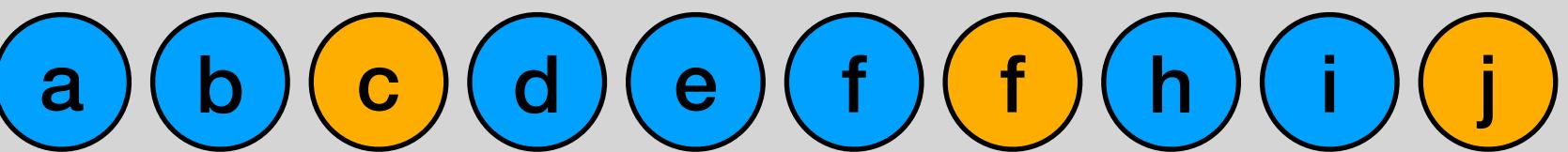
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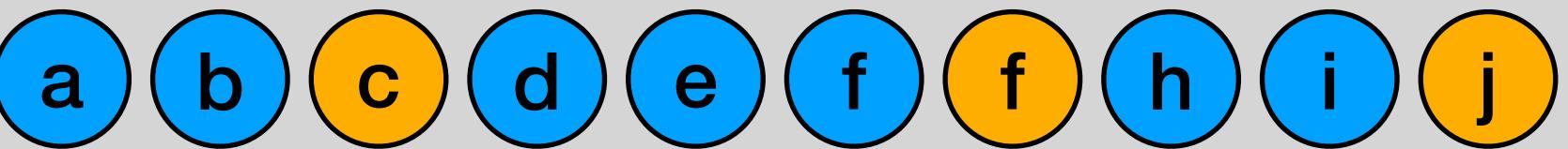
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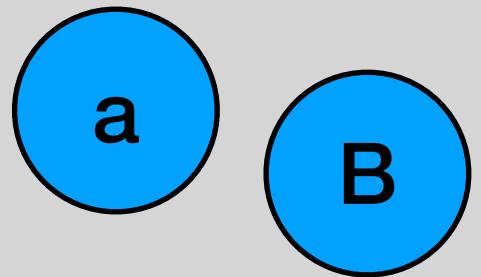
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STEP 2: Add k nodes

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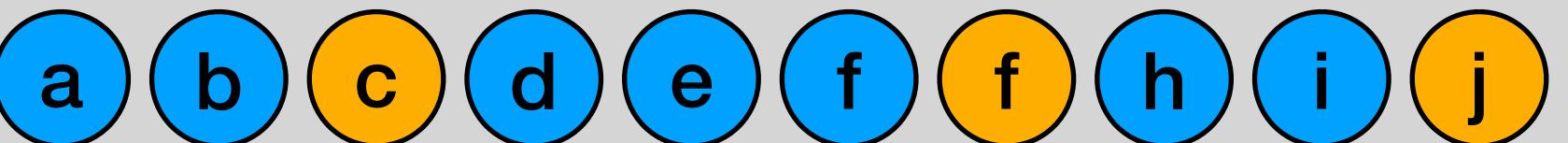
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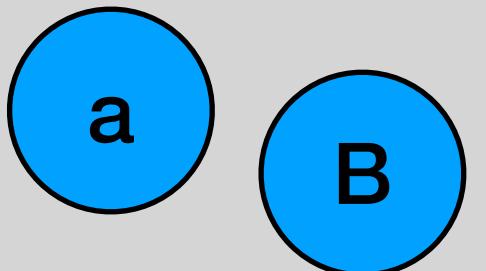
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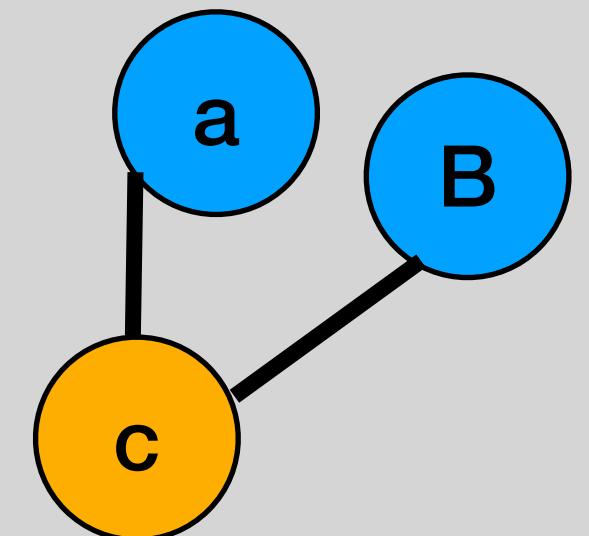


STEP 2: Add k nodes

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STEP 3: Add 1 new node and connect to k existing nodes.



Modeling “preferential attachment”

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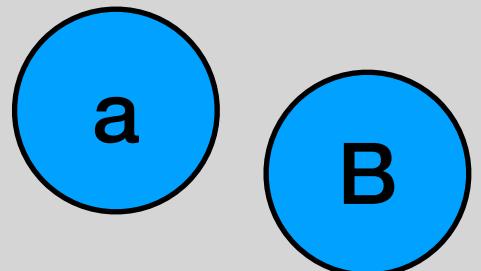
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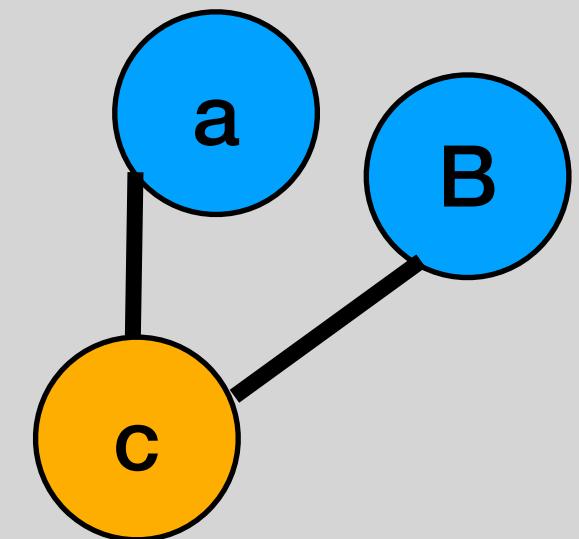


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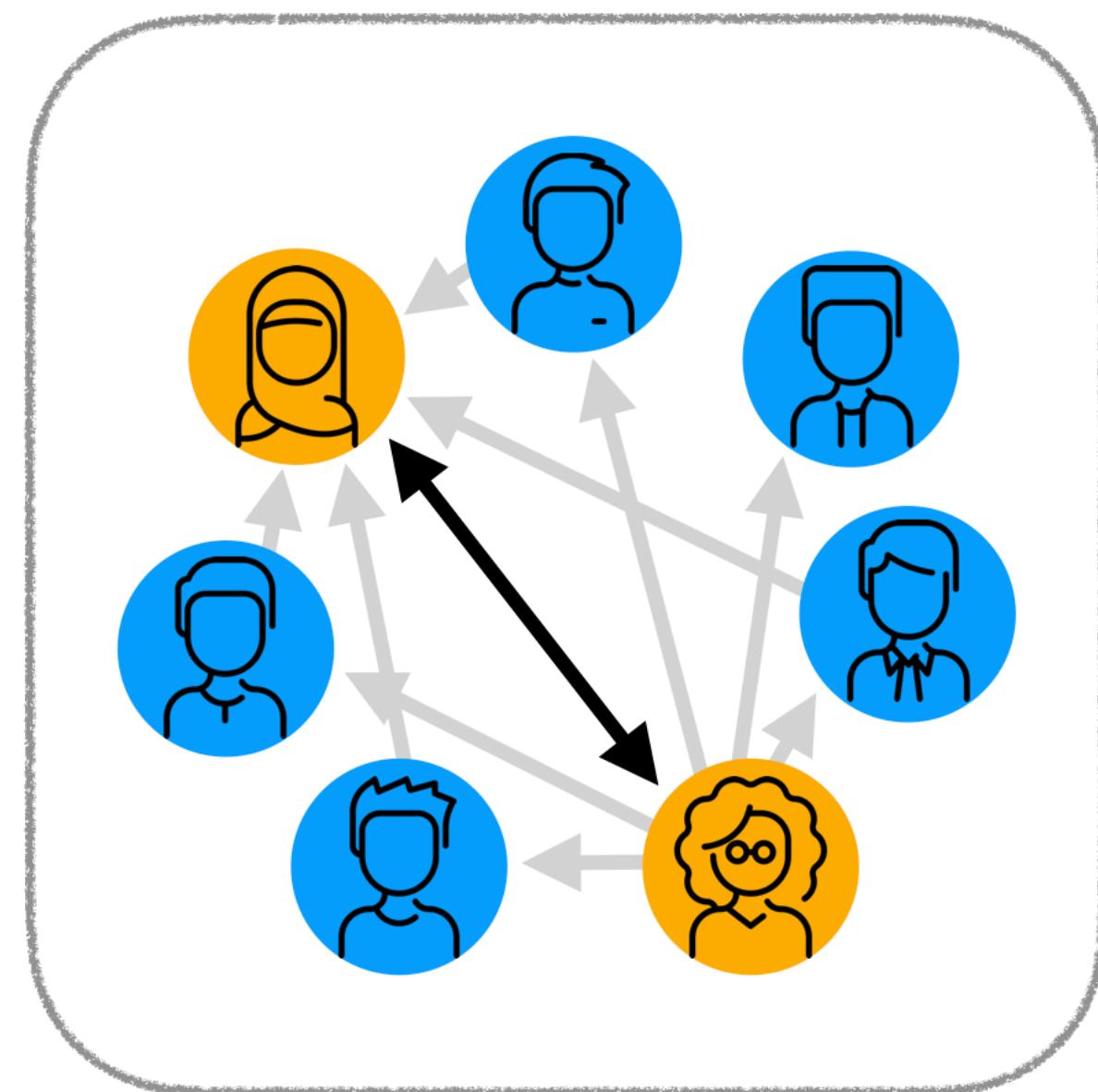
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Homophily

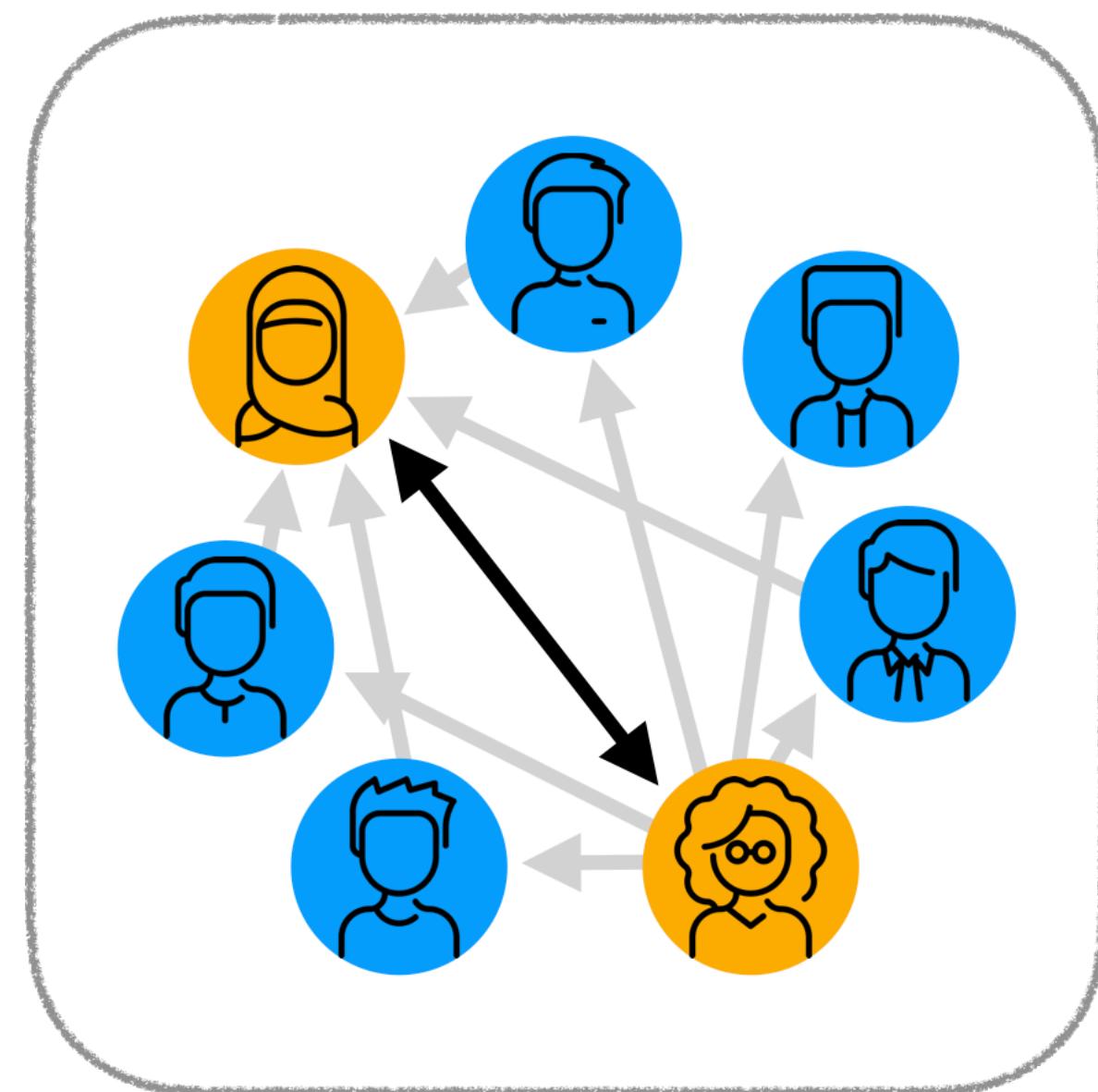
a.k.a. similarity



Homophily

Homophily

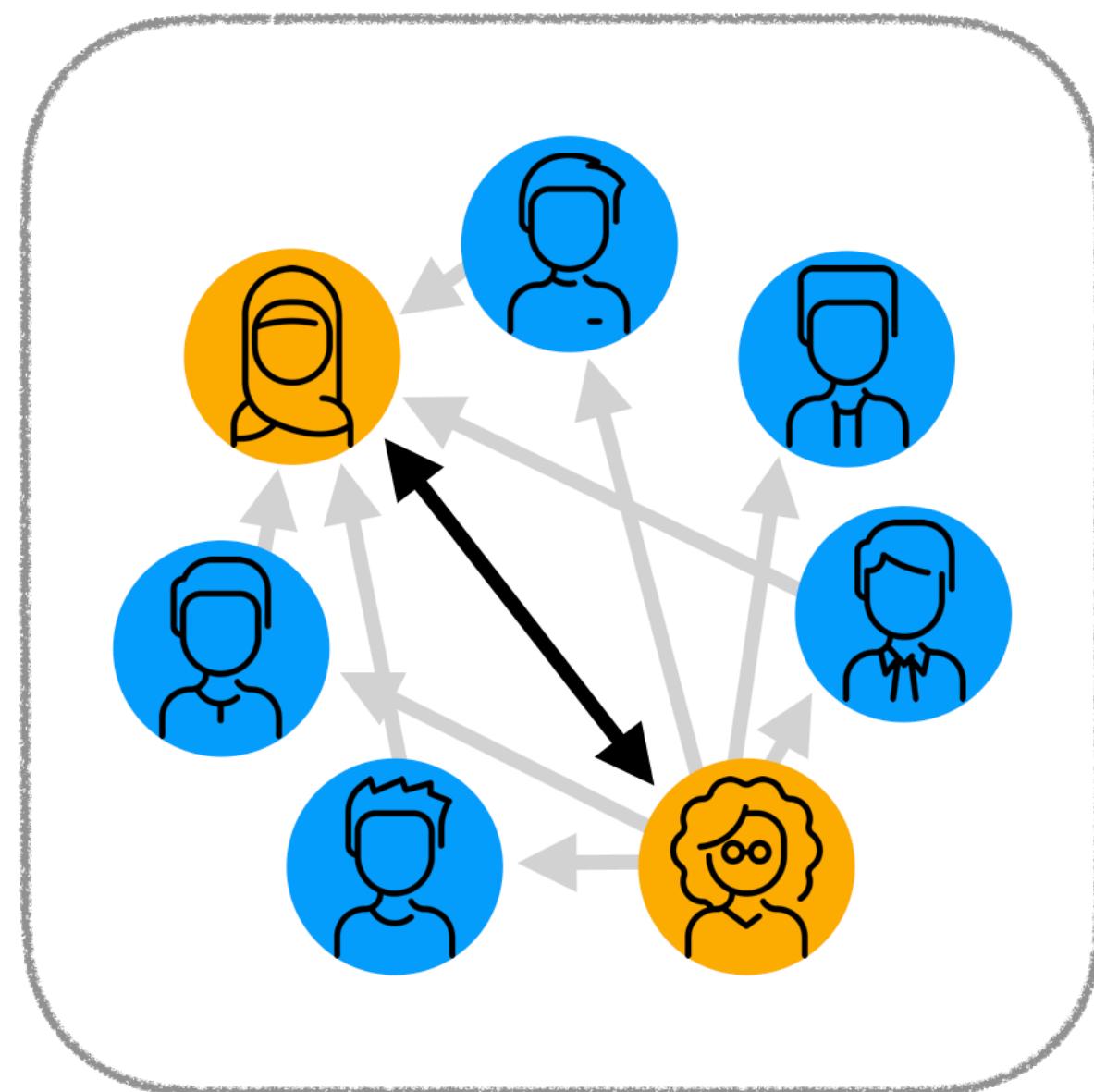
a.k.a. similarity



- The tendency that **similar actors are more likely to connect** (Lazarsfeld, et al. 1954; McPherson et al. 2001). Its structural position is defined by the **attribute similarity** of the sender and receiver of the explained tie.

Homophily

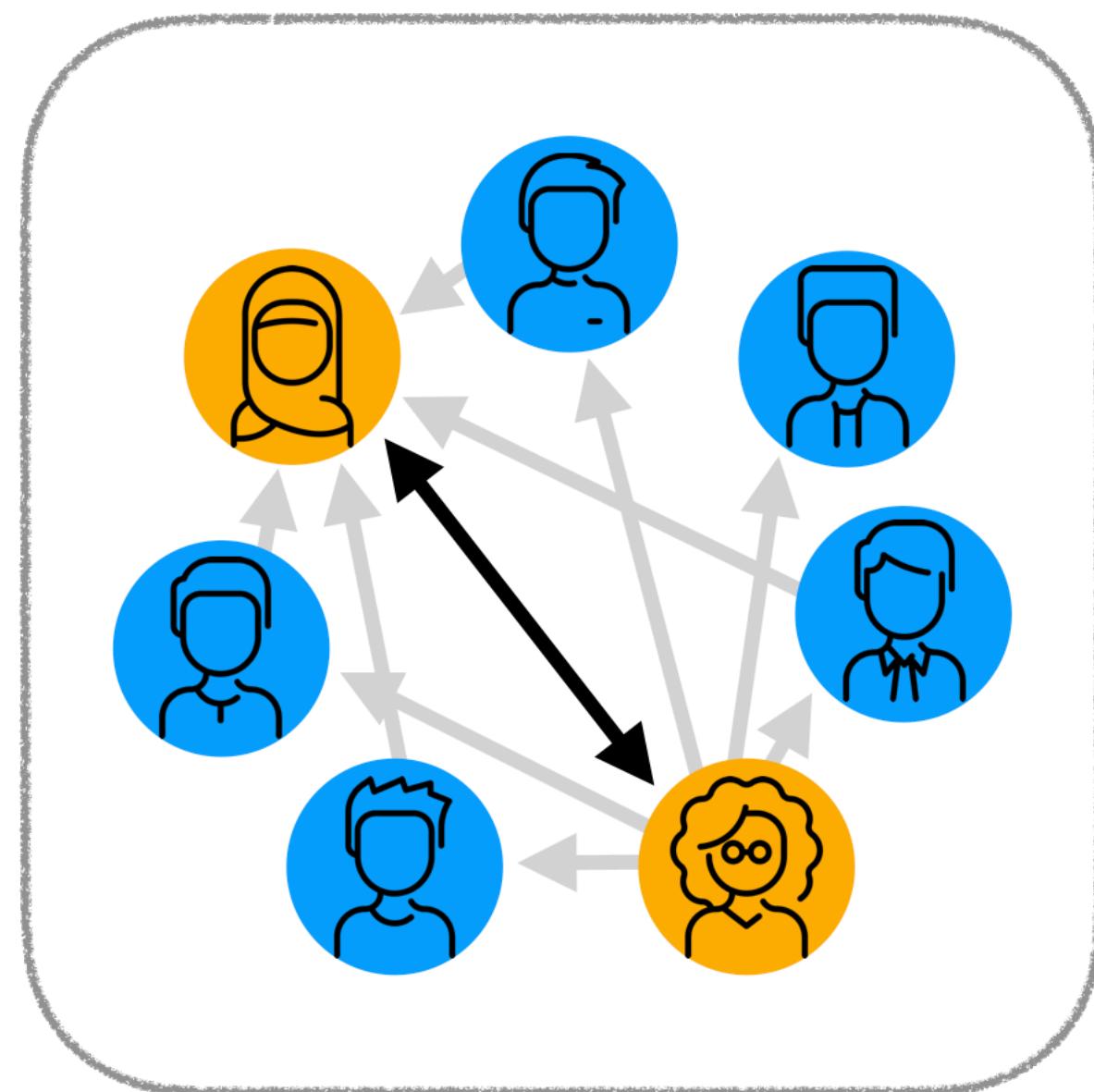
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- Causal explanations:

Homophily

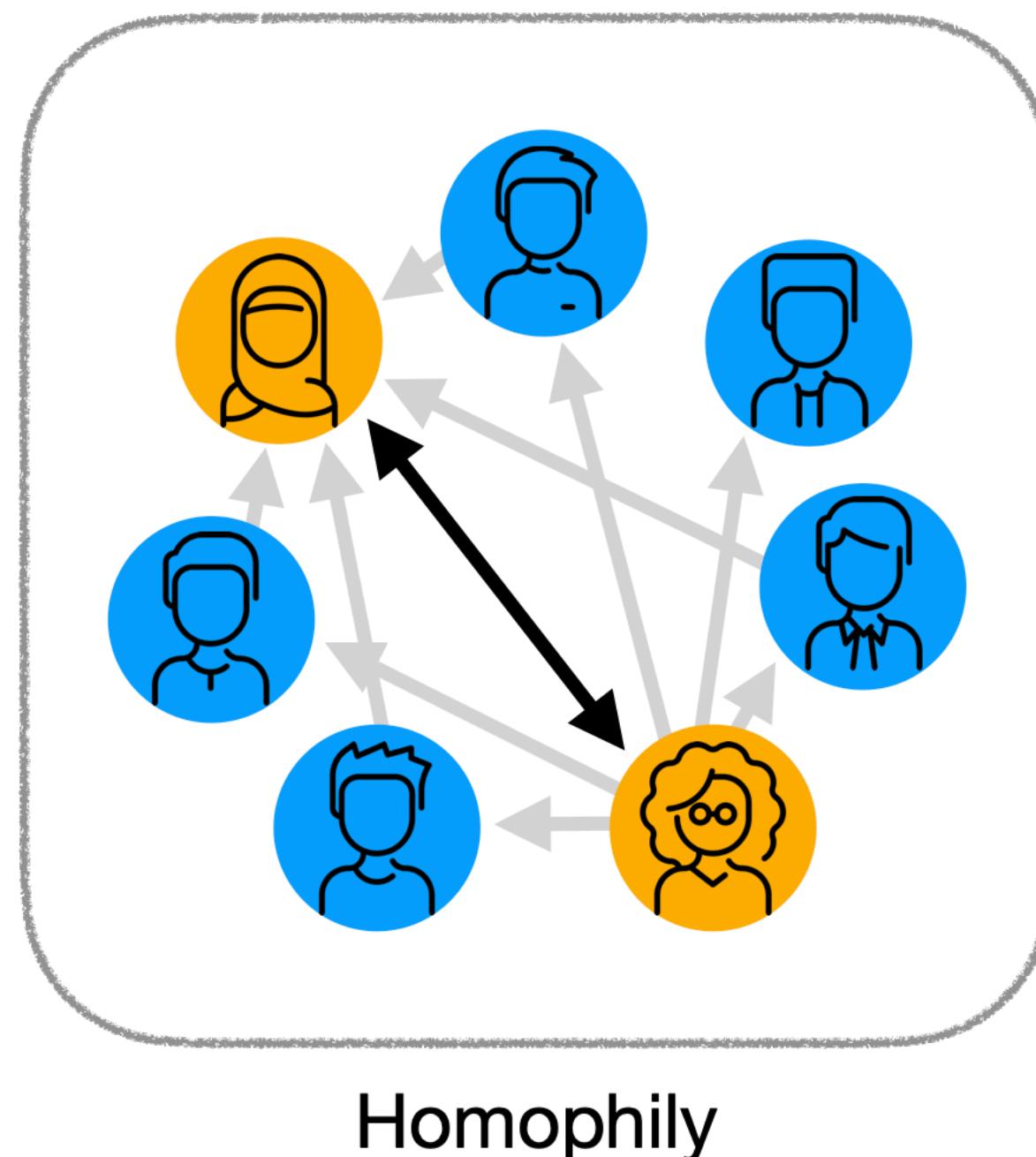
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Homophily

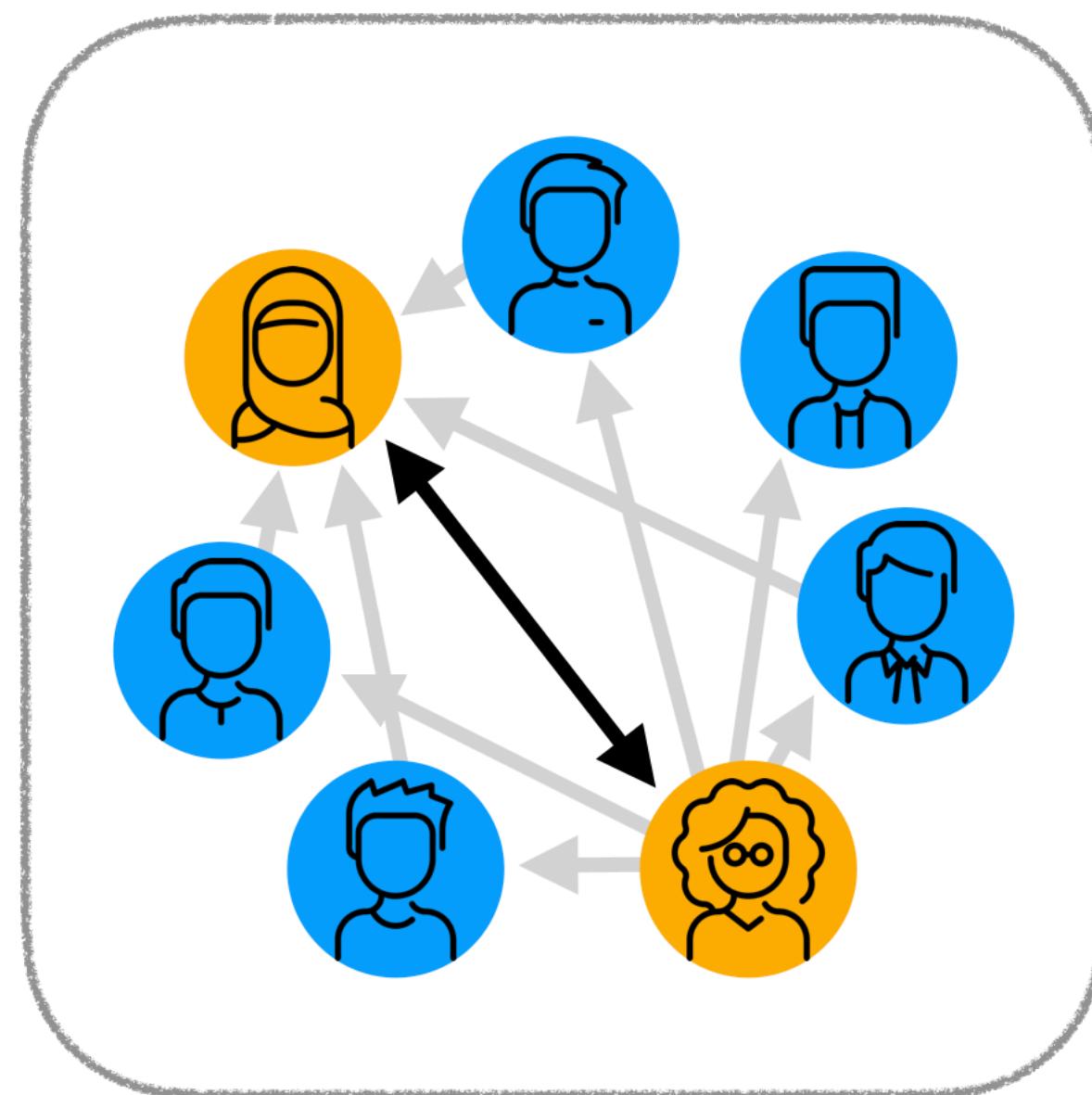
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$$P(a \rightarrow b) = P(b \mid a) = p_{ab} = \text{similarity}(a, b) = h_{a,b}$$

Modeling “homophily” in node-attributed undirected networks



Modeling “homophily” in node-attributed undirected networks



Parameters

n: int

number of nodes (minimum=2)

k: int

minimum degree of nodes (minimum=1)

f_m: float

fraction of minorities (minimum=1/n, maximum=(n-1)/n)

h_MM: float

homophily (similarity) between majority nodes (minimum=0, maximum=1.)

h_mm: float

homophily (similarity) between minority nodes (minimum=0, maximum=1.)

Modeling “homophily” in node-attributed undirected networks



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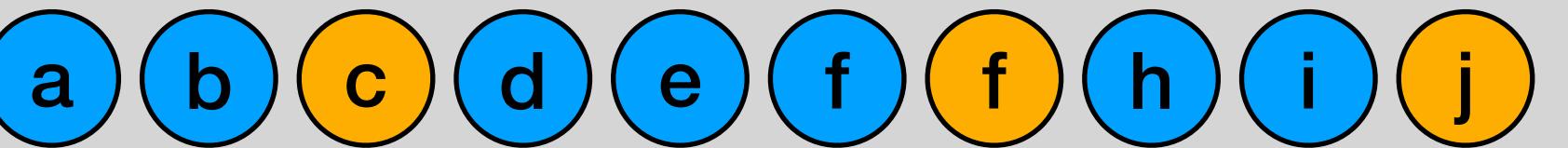
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STEP 1: Initialize nodes $n = 10, f_m = 0.30$



Modeling “homophily”

in node-attributed undirected networks



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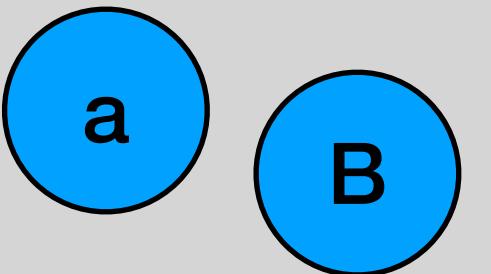
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STEP 1: Initialize nodes $n = 10, f_m = 0.30$



STEP 2: Add k nodes

$k=2$



Modeling “homophily”

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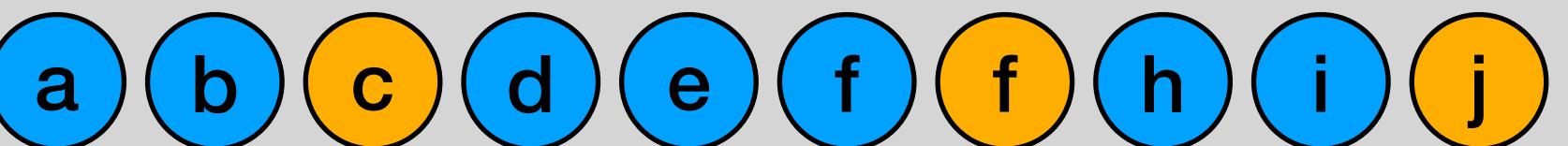
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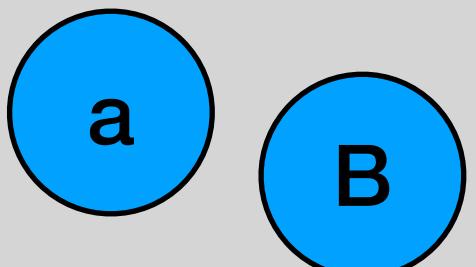
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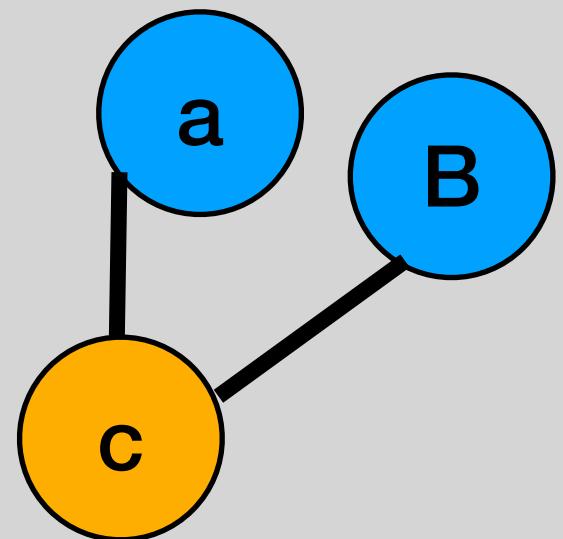


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STEP 3: Add 1 new node and connect to k existing nodes.



Modeling “homophily”

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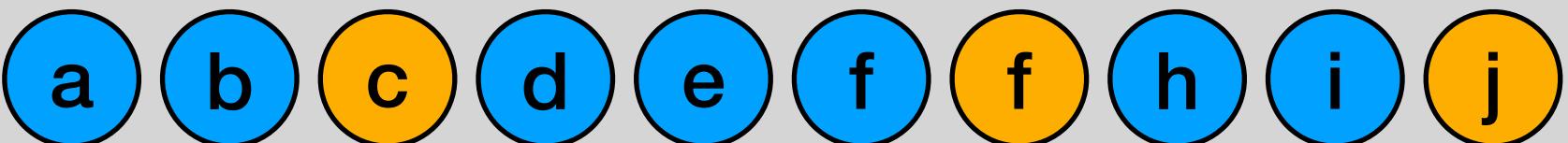
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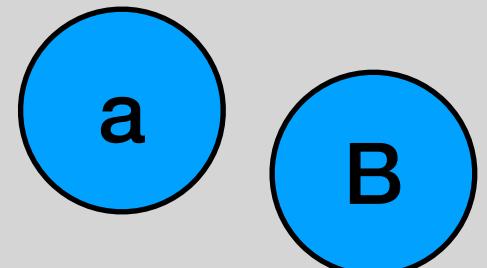
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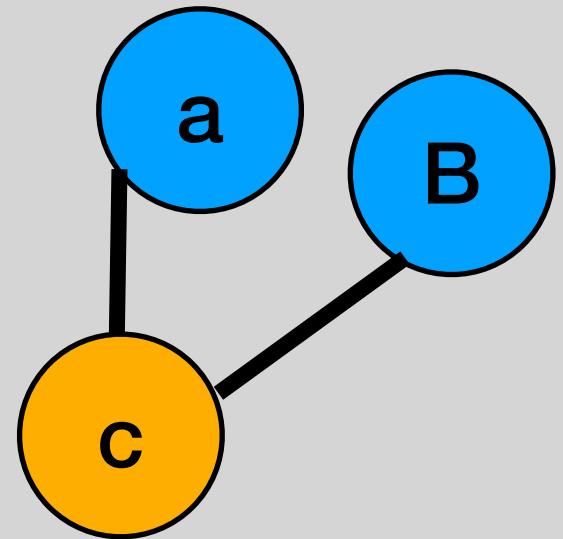


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STEP 4: Repeat step 3 using $P(i \rightarrow j) \propto h_{ij}$
Stop once n nodes have been added.

Modeling “homophily & preferential attachment”

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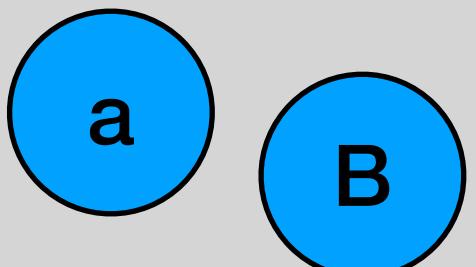
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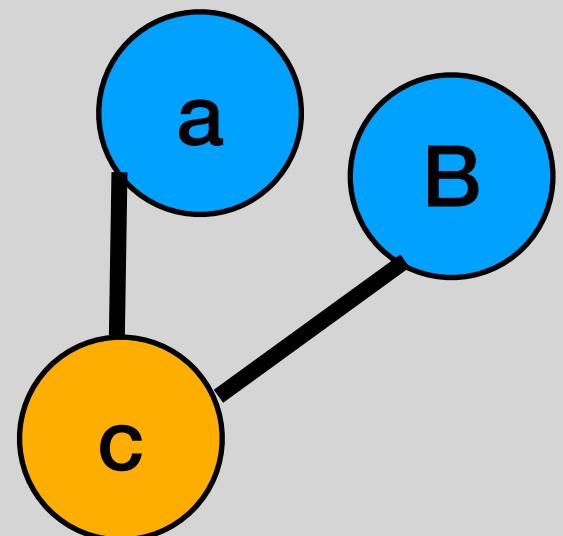


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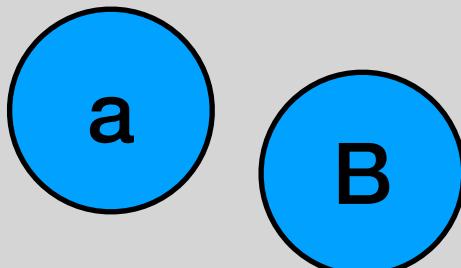
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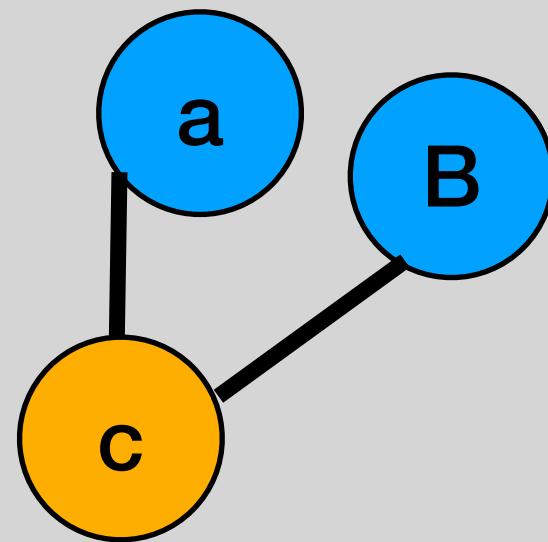


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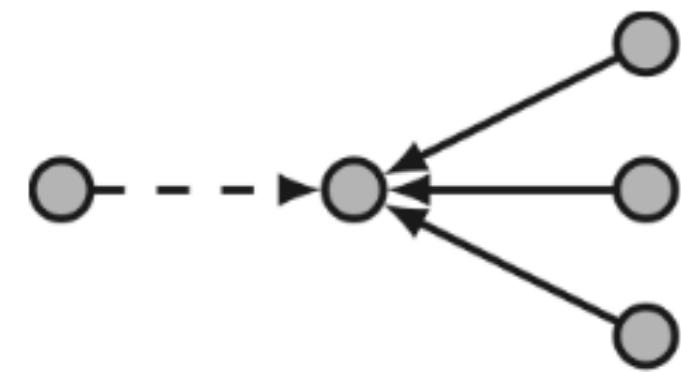
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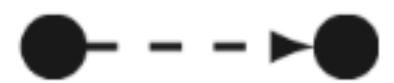
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How can these mechanisms of edge formation help us understand social phenomena?

Popularity



Homophily



Understanding influence maximization

Using synthetic networks

Wang, Xindi, Onur Varol, and Tina Eliassi-Rad. "Information Access Equality on Network Generative Models." Available at SSRN 3880680 (2021).

Understanding influence maximization

Using synthetic networks

Goal: Understand the correlation between network structure and information access (spreading) equality
Who gets more access to information? majority or minority? Both equally?

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 2. PA: Preferential attachment
 3. H: Homophily
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3. Run a contagion simulation and report the “spreading equality” for each network
 1. Simple contagion: a spreading process induced by a single exposure to a contagious entity.
 2. Complex contagion: demands multiple exposures for transmission.

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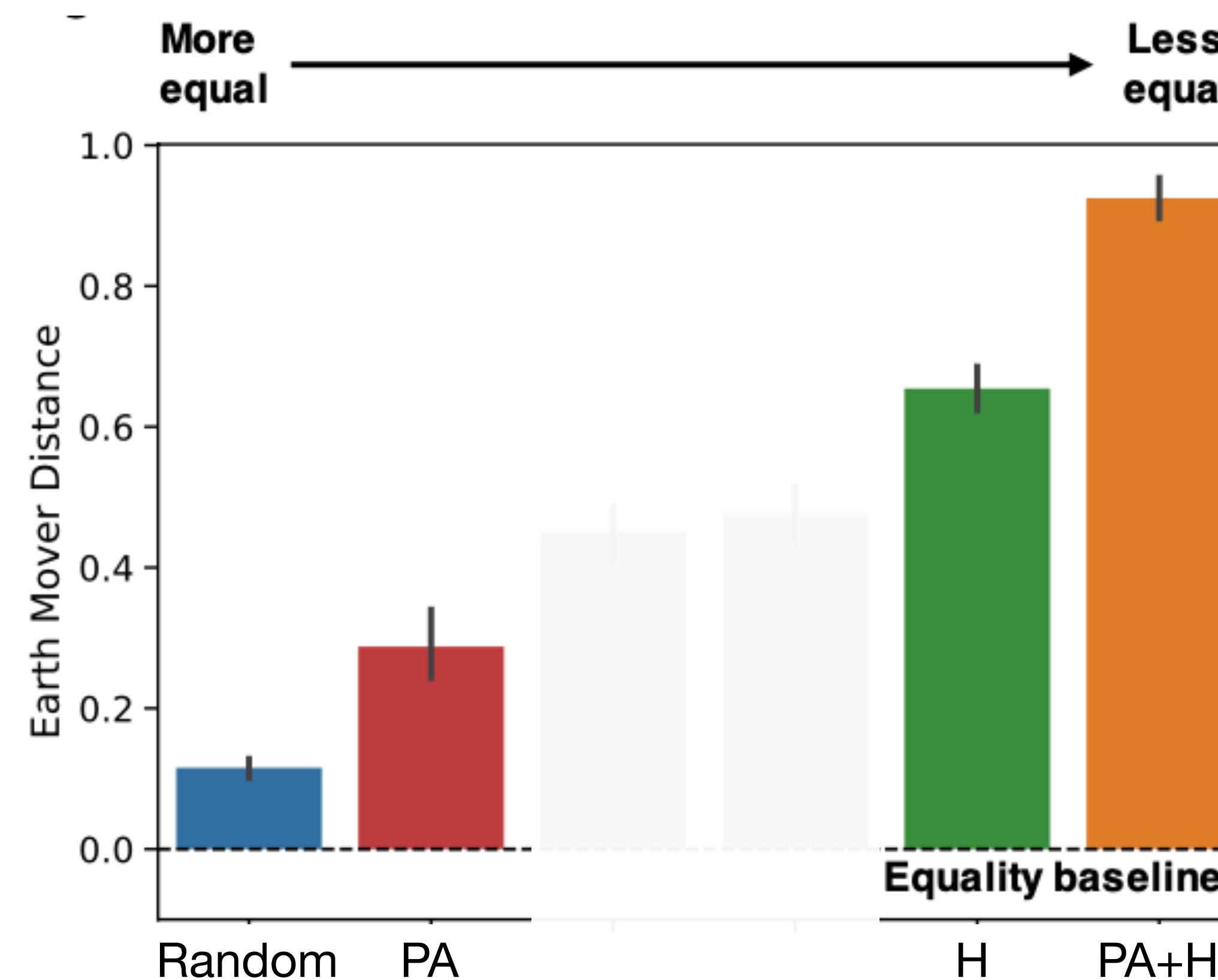
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Task 2. Degree equality (social capital)

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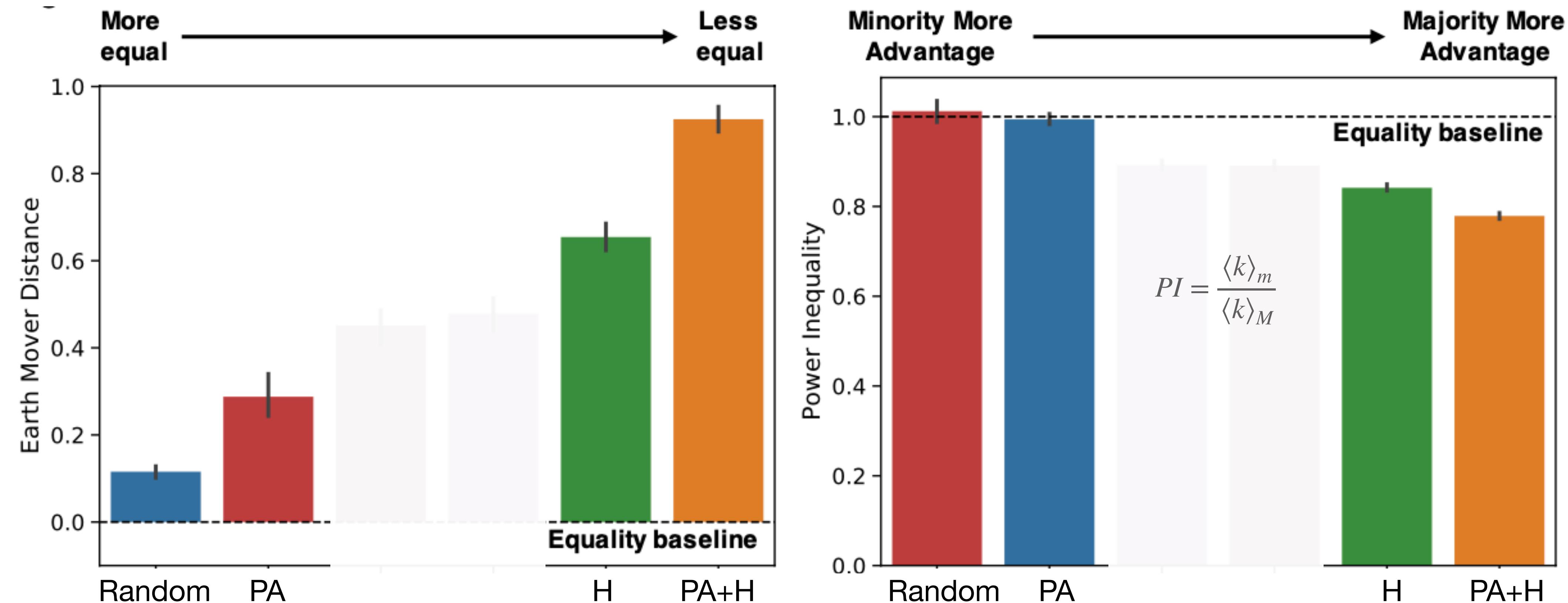
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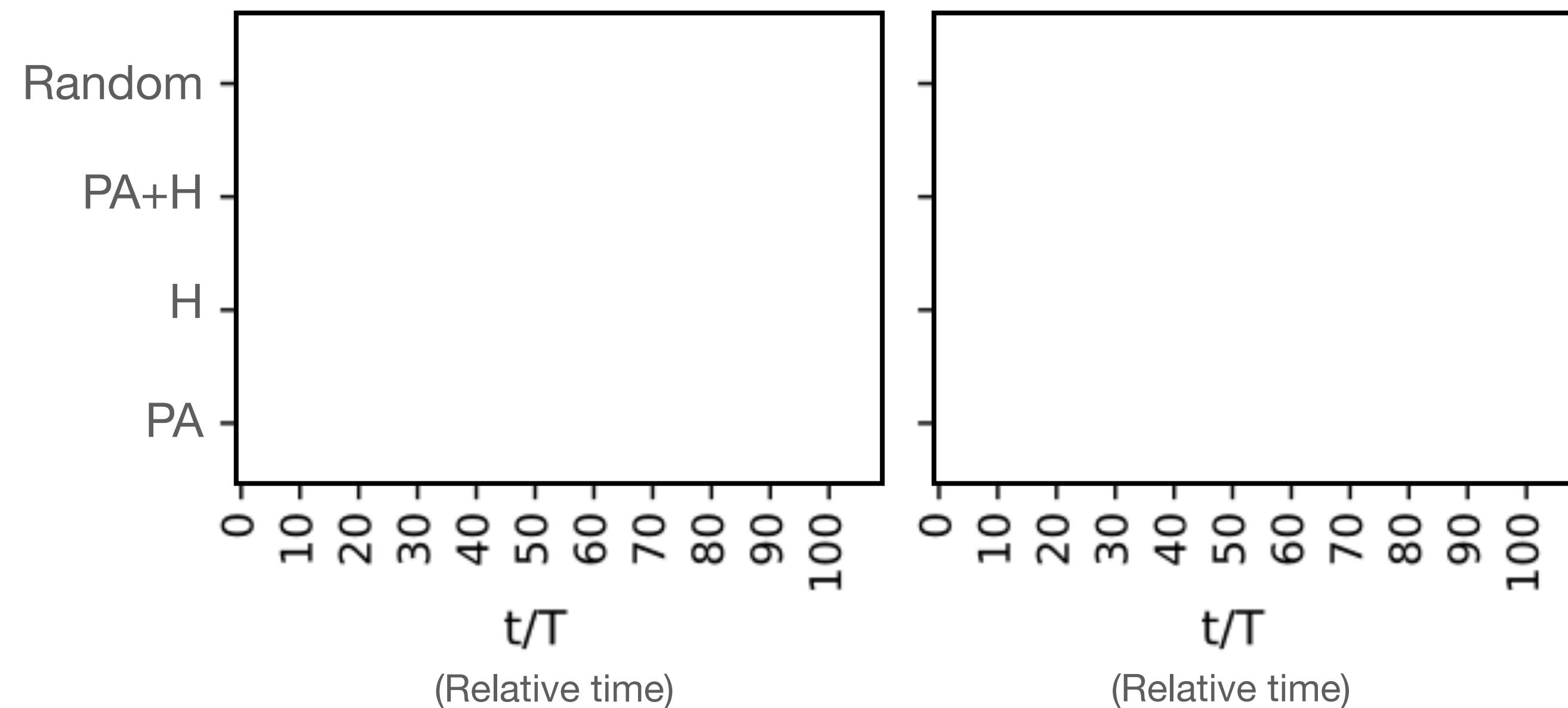
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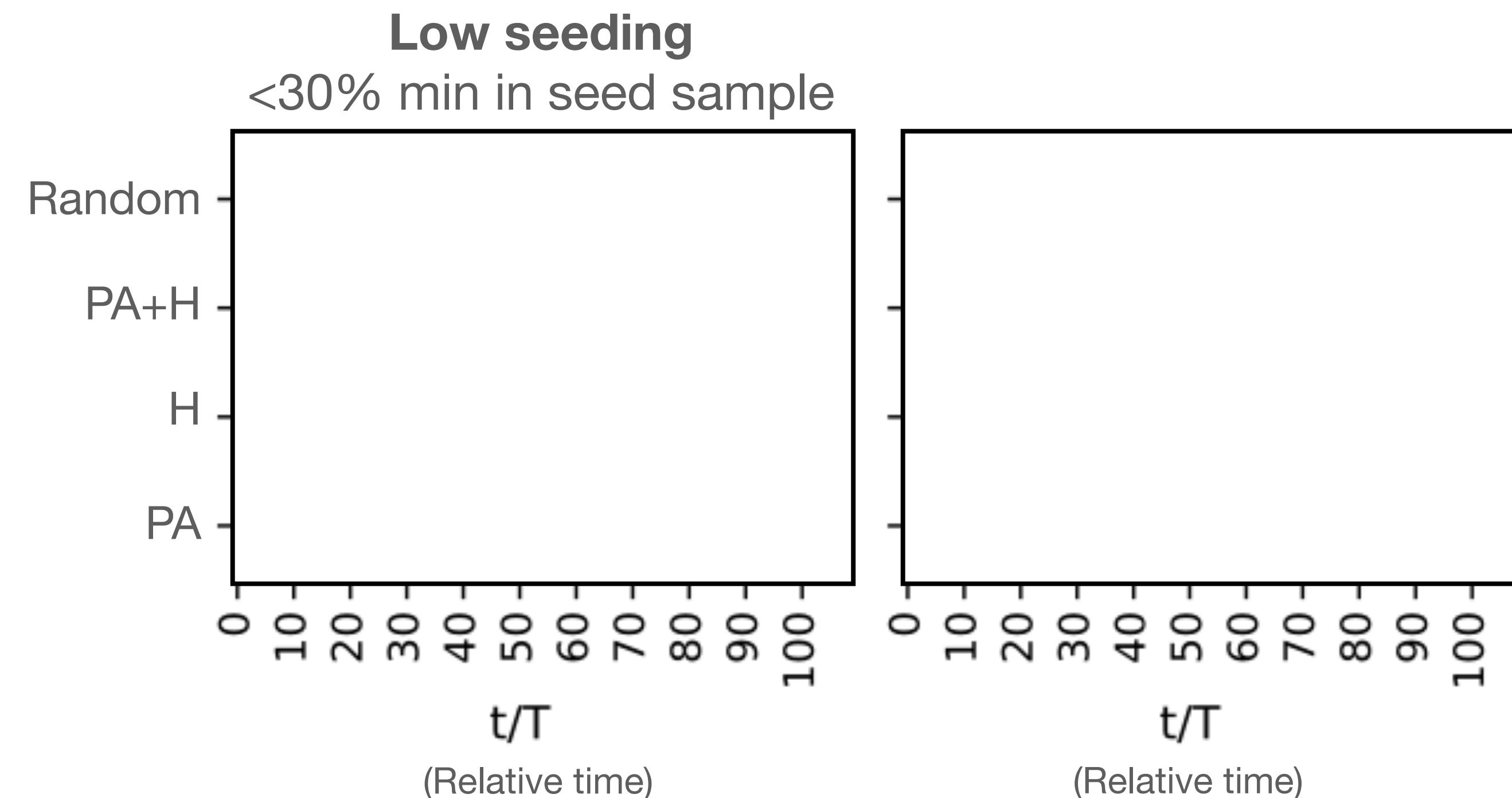
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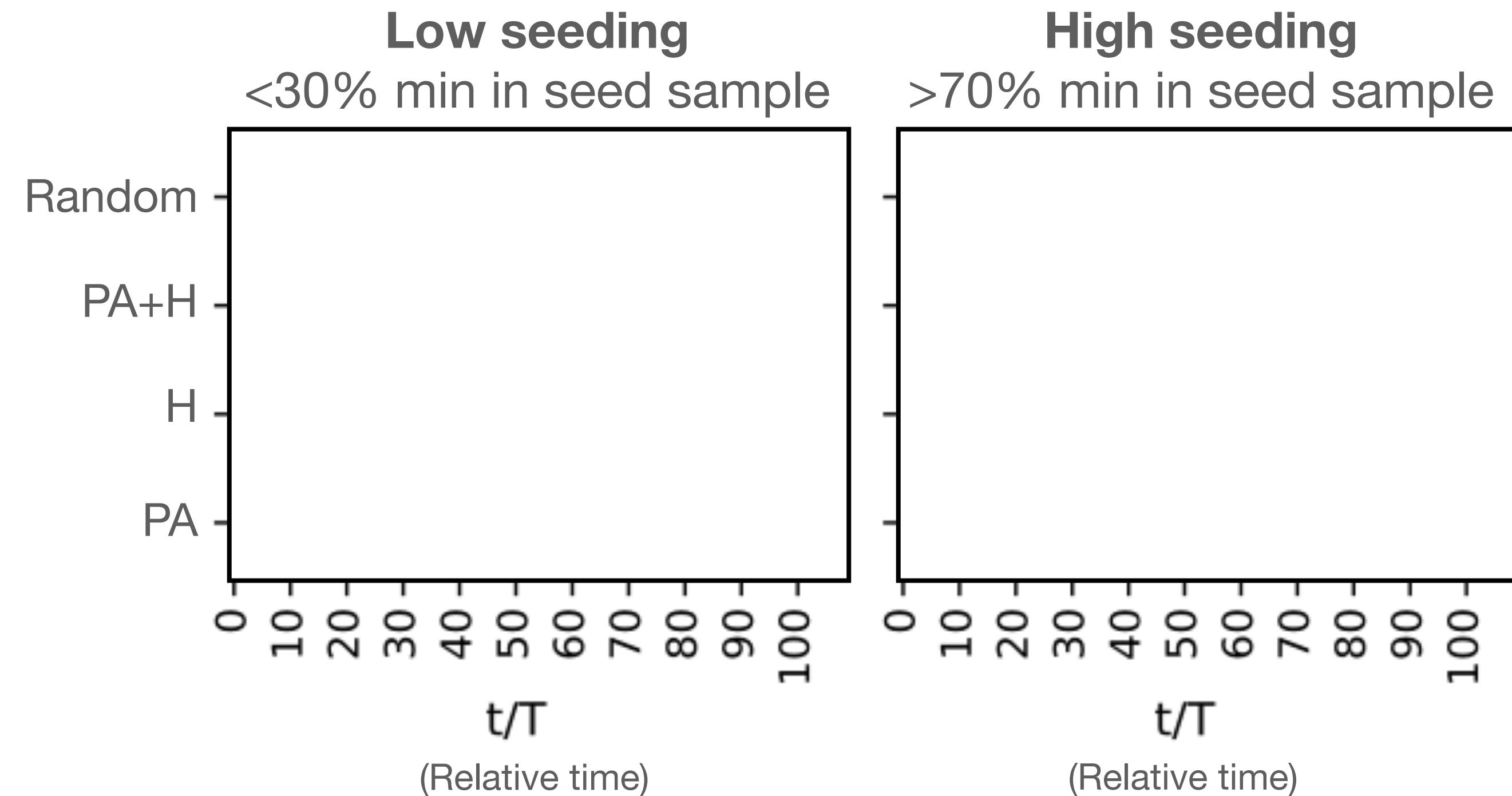
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Understanding influence maximization

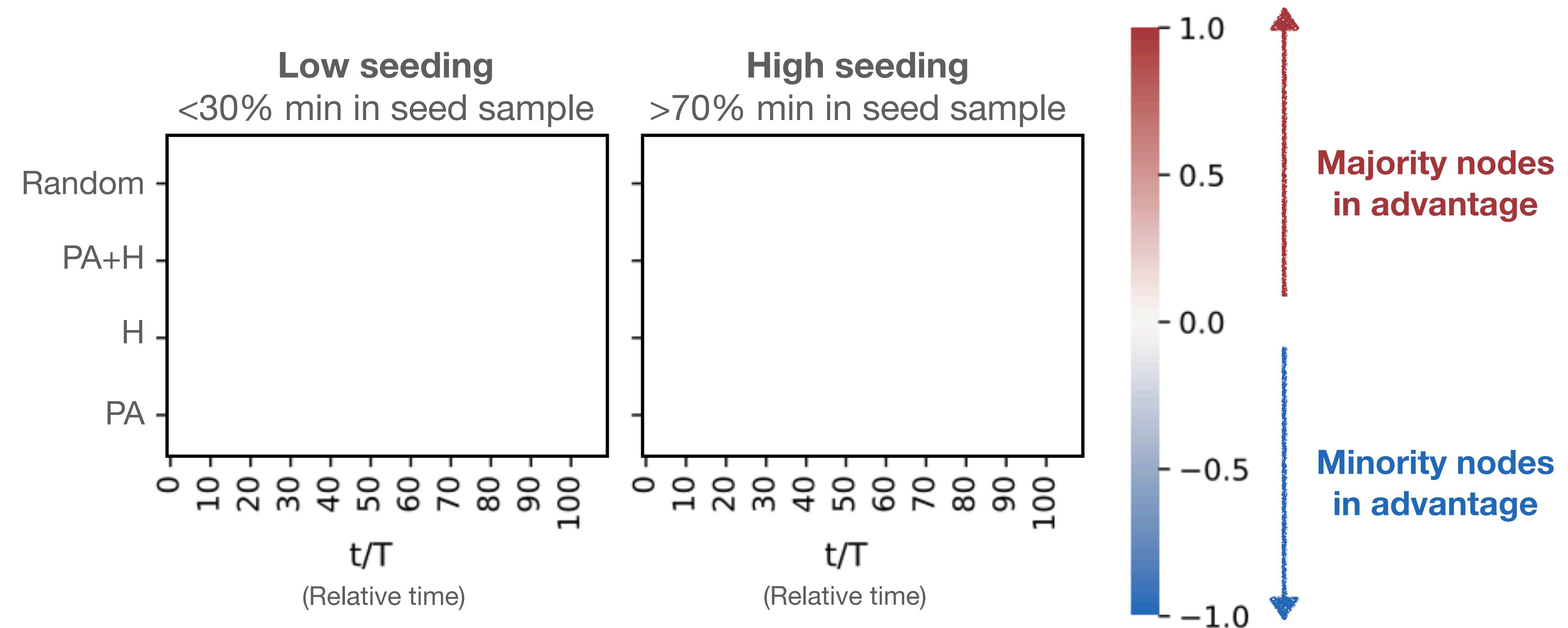
Task 3. Information access equality (simple contagion)



Wang, Xindi, Onur Varol, and Tina Eliassi-Rad. "Information Access Equality on Network Generative Models." Available at SSRN 3880680 (2021).

Understanding influence maximization

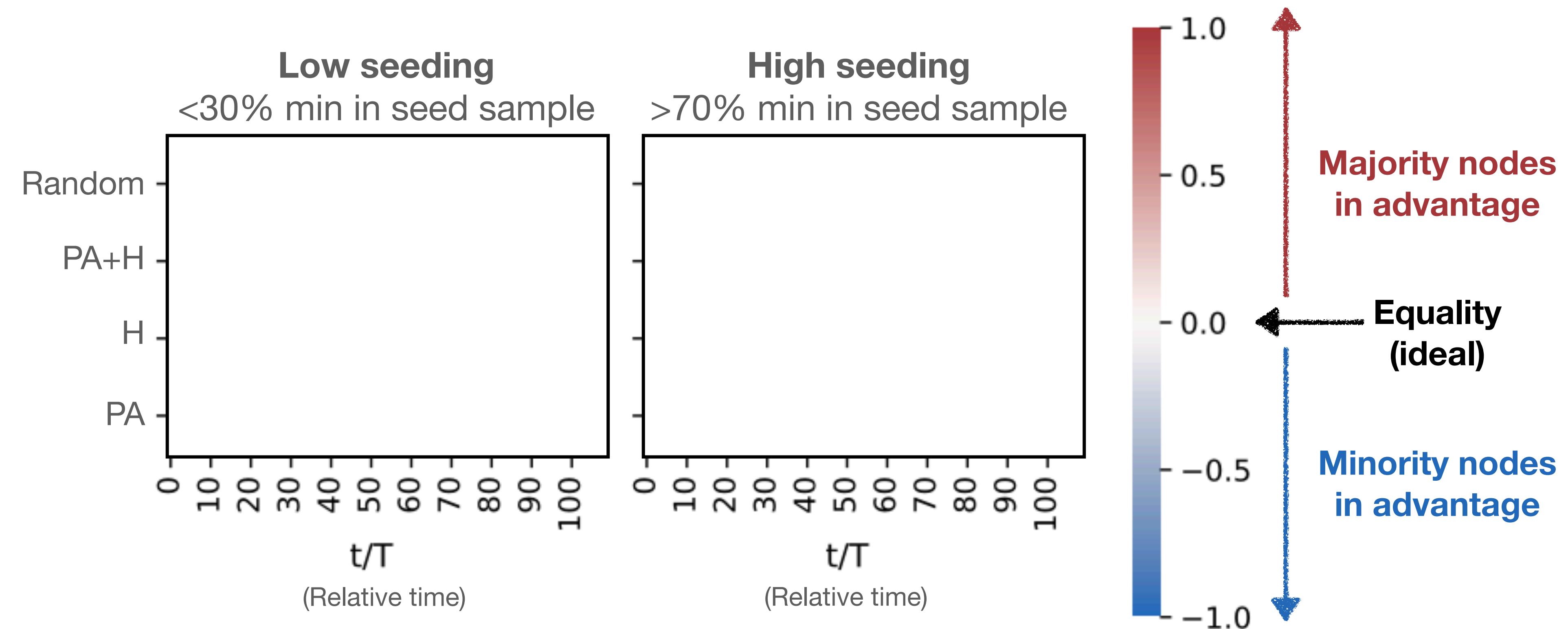
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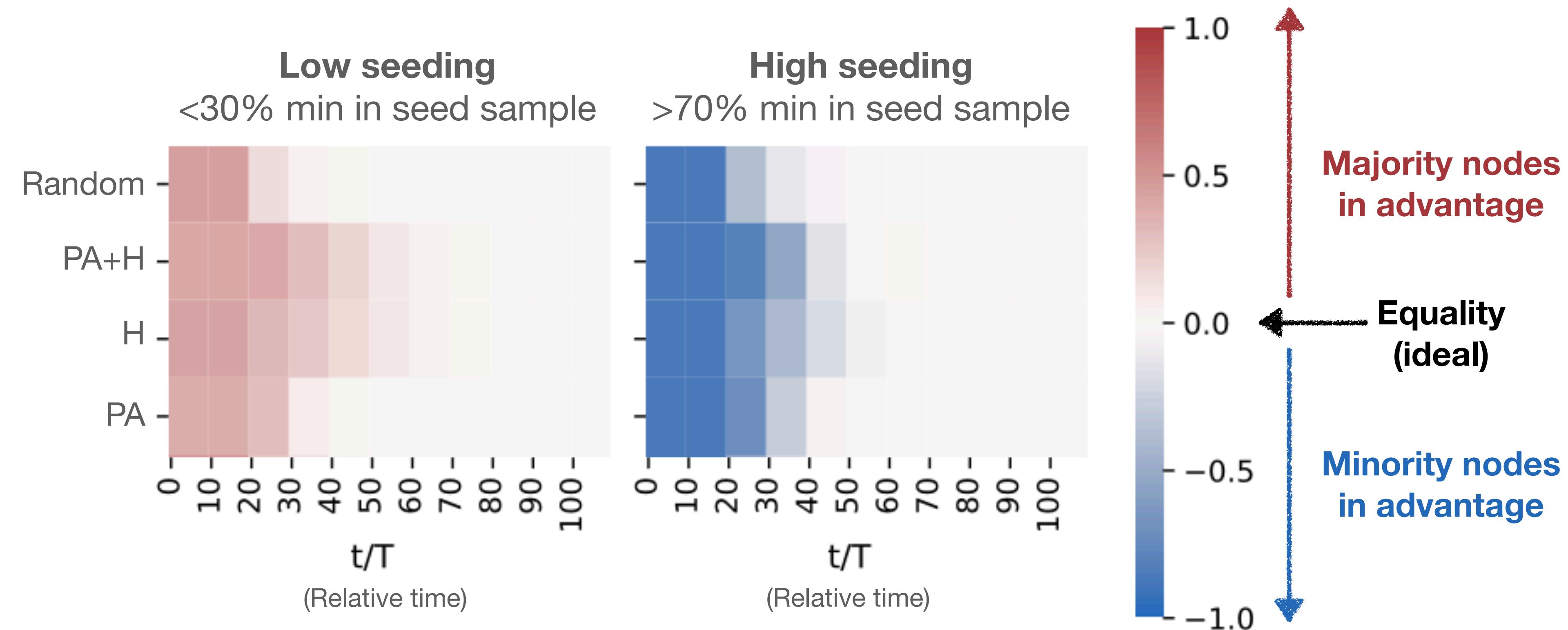
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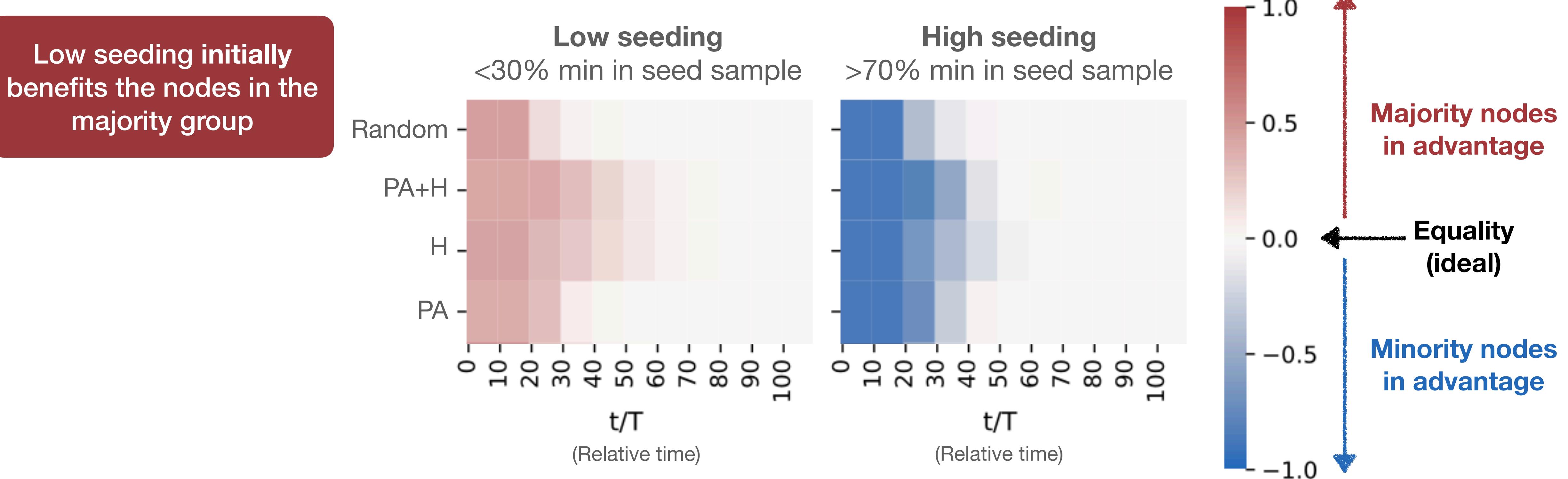
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Understanding influence maximization

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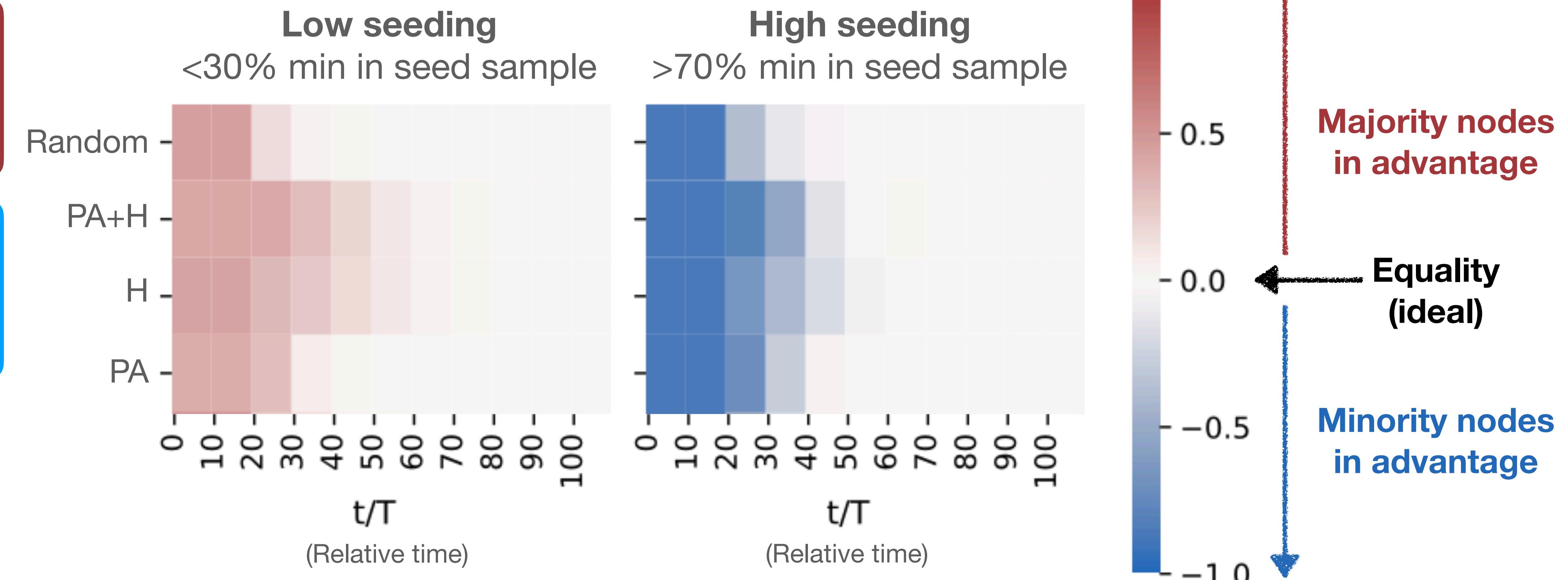
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Understanding influence maximization

Task 3. Information access equality (simple contagion)

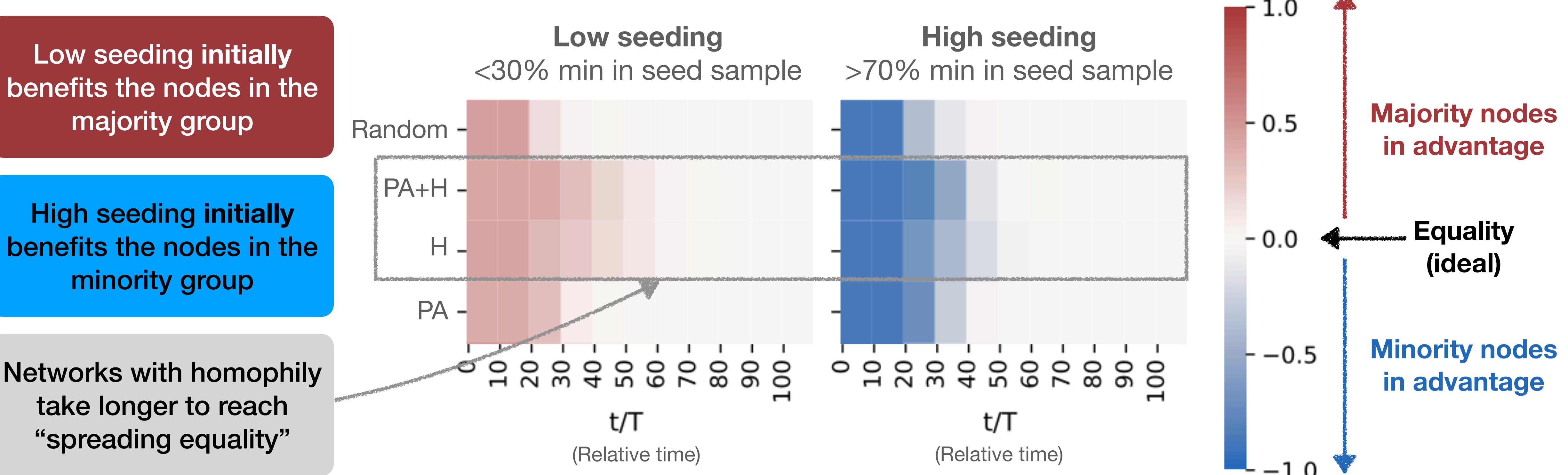
Low seeding initially benefits the nodes in the majority group

High seeding initially benefits the nodes in the minority group



Understanding influence maximization

Task 3. Information access equality (simple contagion)



Wang, Xindi, Onur Varol, and Tina Eliassi-Rad. "Information Access Equality on Network Generative Models." Available at SSRN 3880680 (2021).

Other simulations to understand

Inequalities in network-based algorithms (“algorithmic auditing”)

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- Fairness in Social Influence Maximization (diverse out-reach and seeds)
Stoica et al 2019

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Karimi et al. 2018, Stoica et al. 2018, Fabbri et al. 2020, Espin-Noboa et al. 2022

Other simulations to understand

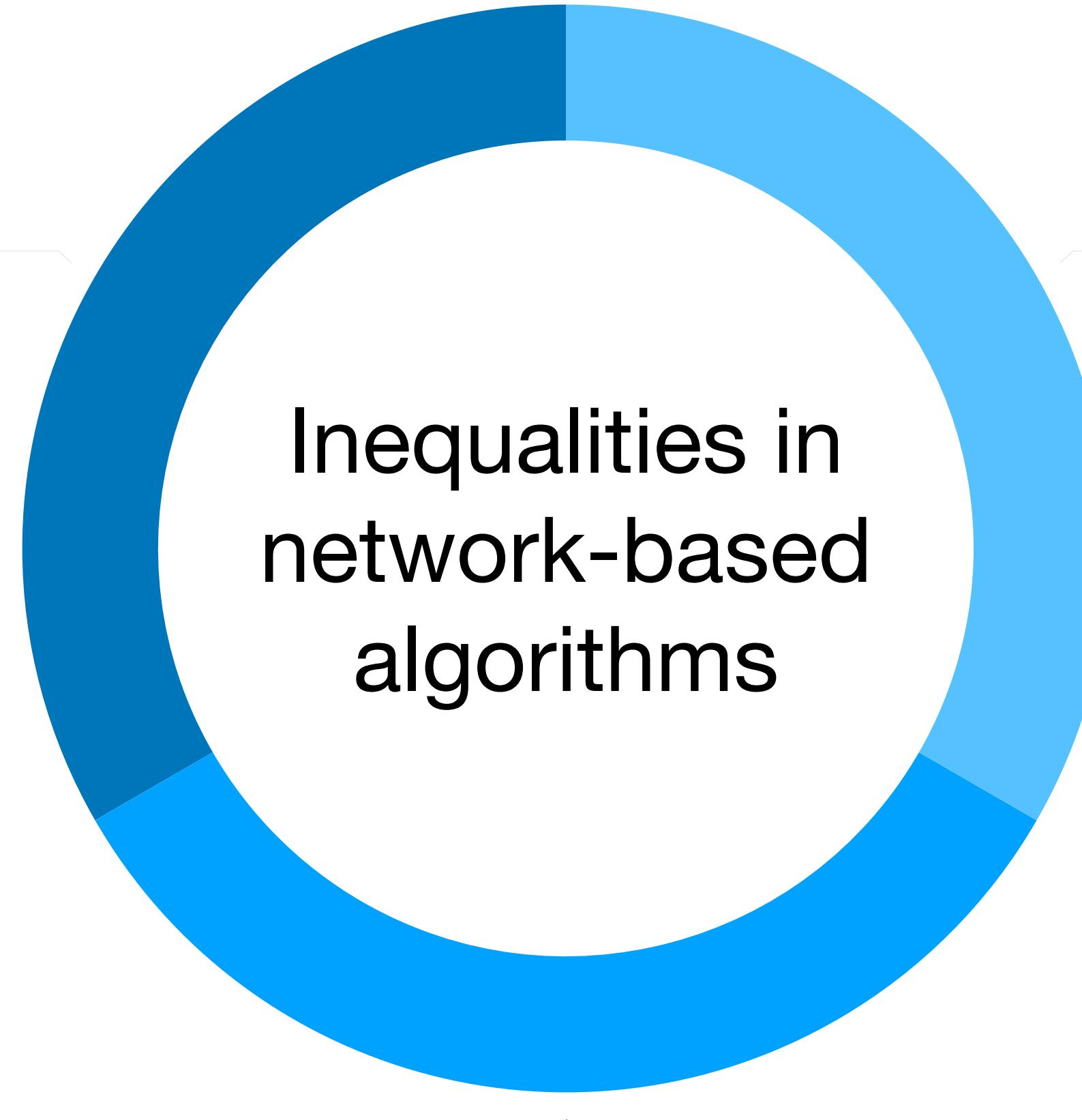
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Other simulations to understand

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- How network structure affects node sampling and relational (node) classification in social networks
Espin-Noboa et al. 2018, Espin-Noboa et al. 2021
- How network structure affects node link prediction algorithms (and vice versa)
Espin-Noboa et al. 2022, Ferrara et al. 2022



Mitigating
inequalities

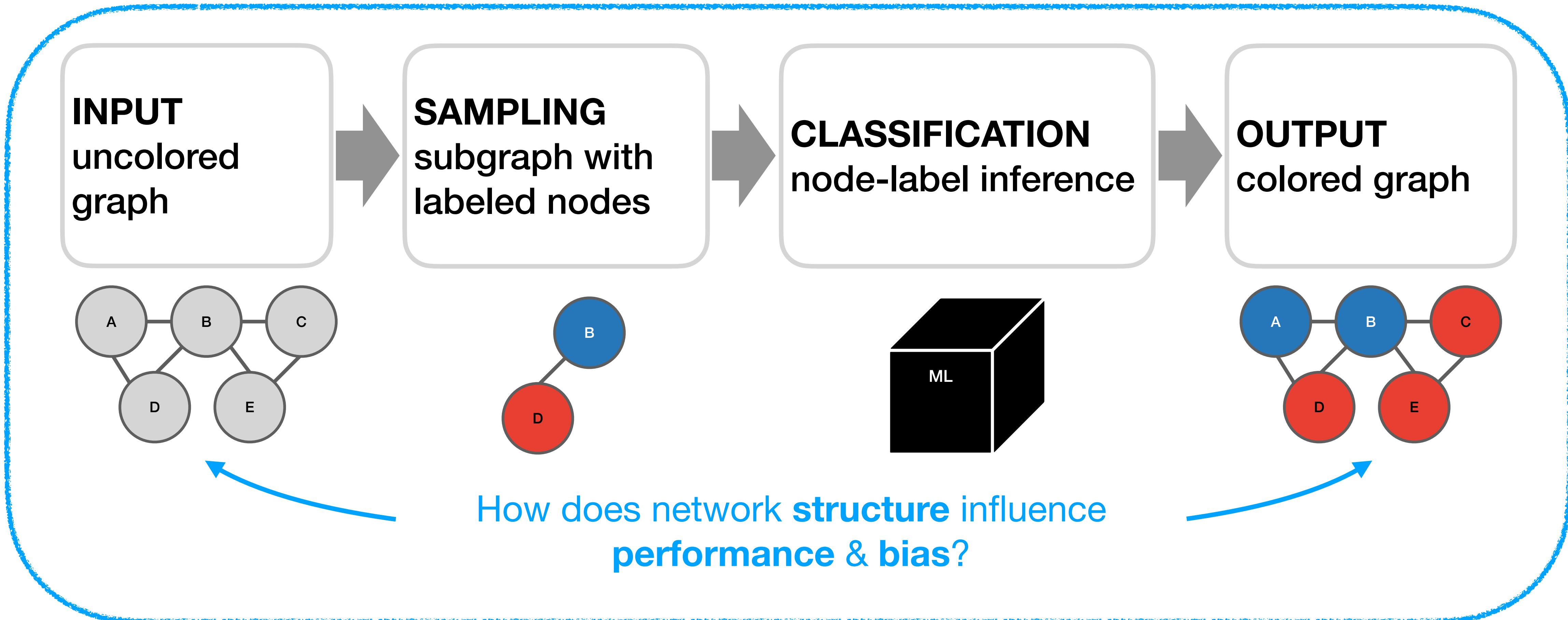
Inequalities in
network-based
algorithms

Understanding
inequalities

2.

**Identifying
inequalities**

Evaluation benchmarks in “Relational classification”



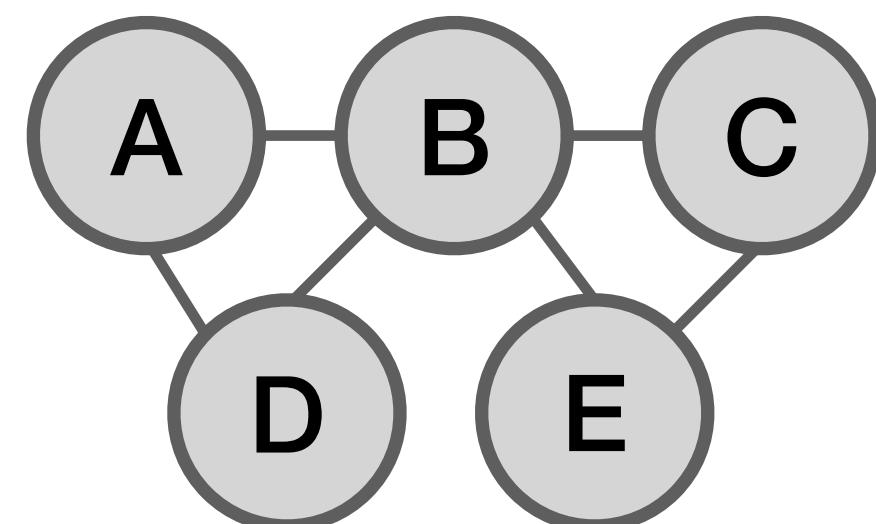
Relational Classification

Machine learning on networked data

Relational Classification

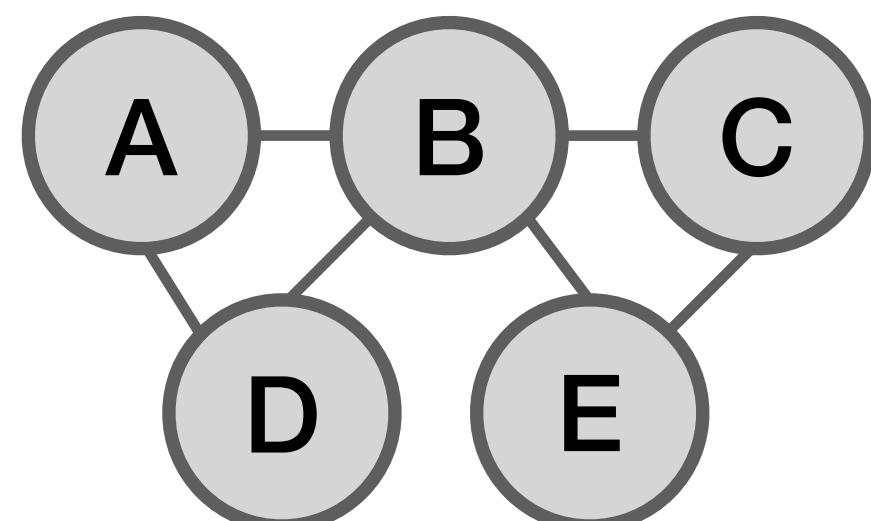
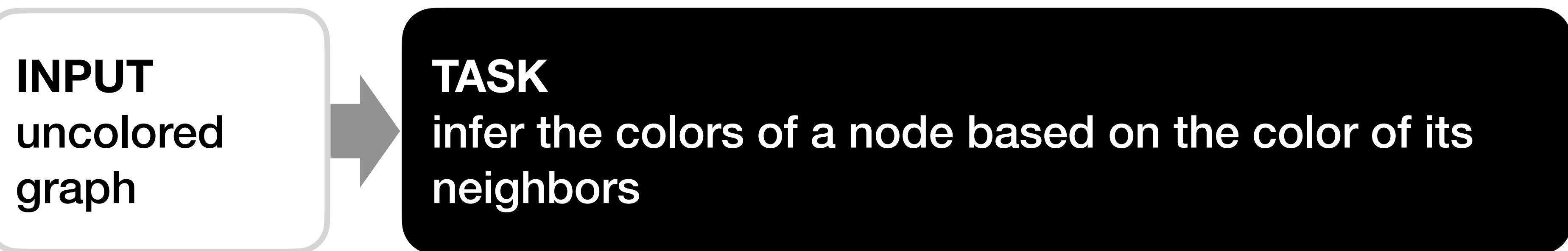
Machine learning on networked data

INPUT
uncolored
graph



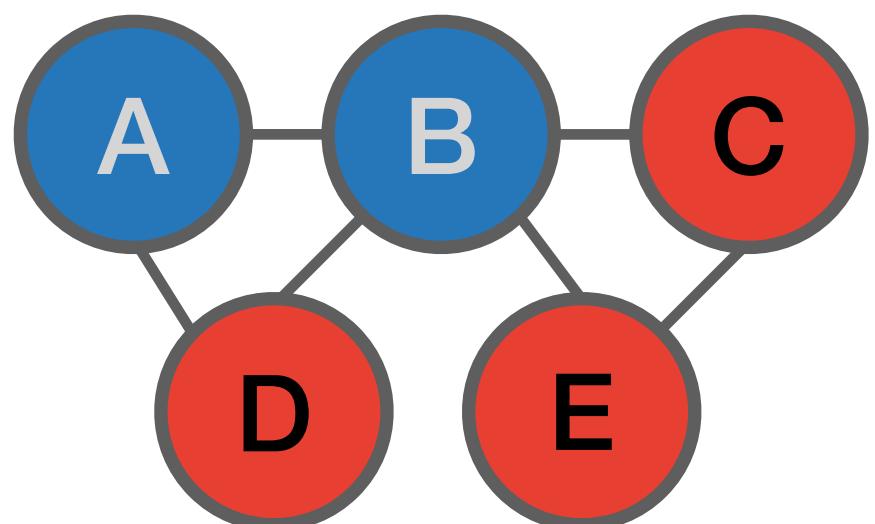
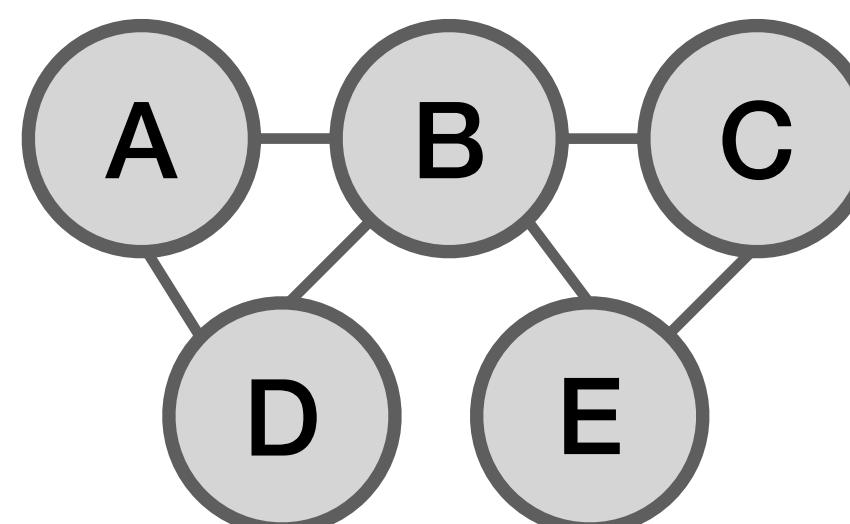
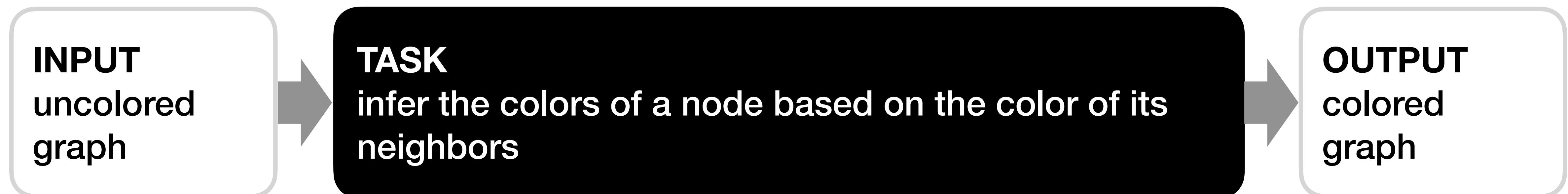
Relational Classification

Machine learning on networked data



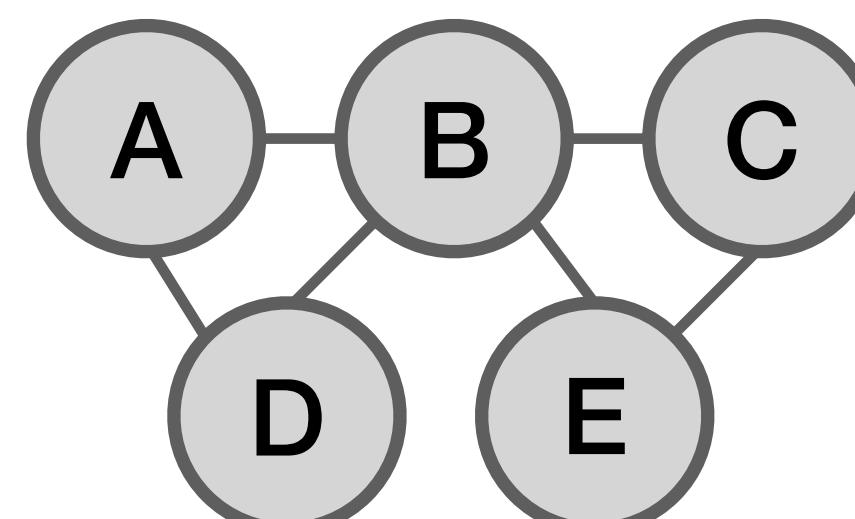
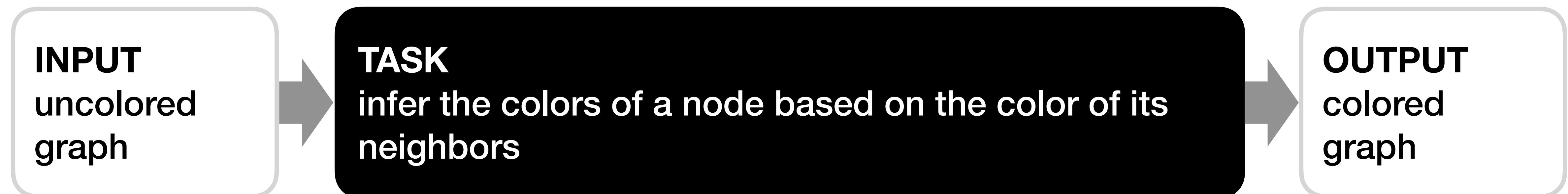
Relational Classification

Machine learning on networked data

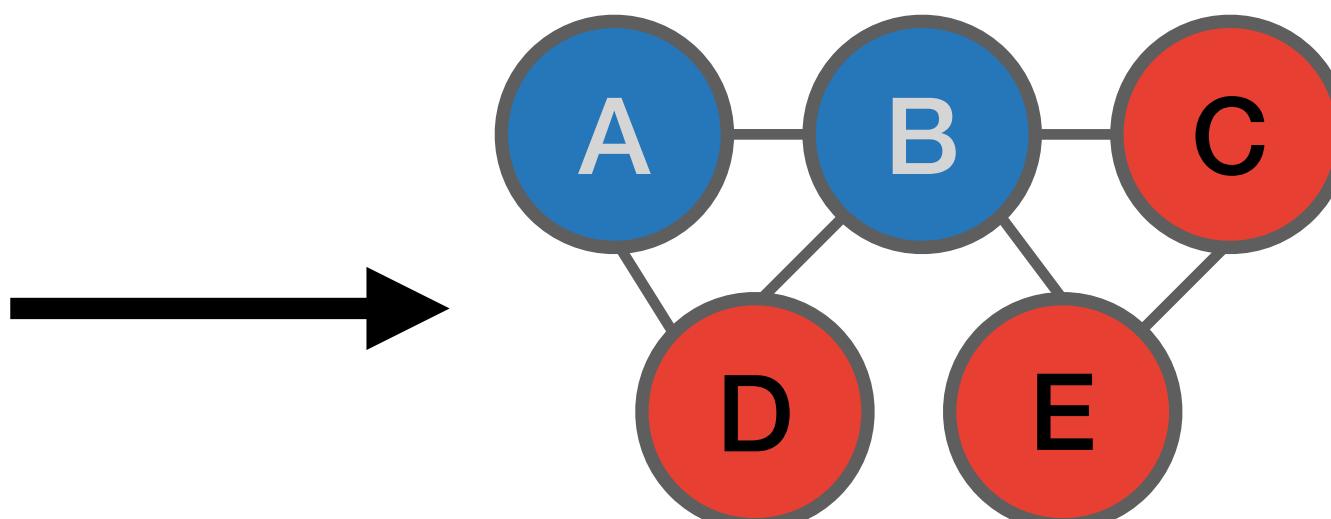


Relational Classification

Machine learning on networked data

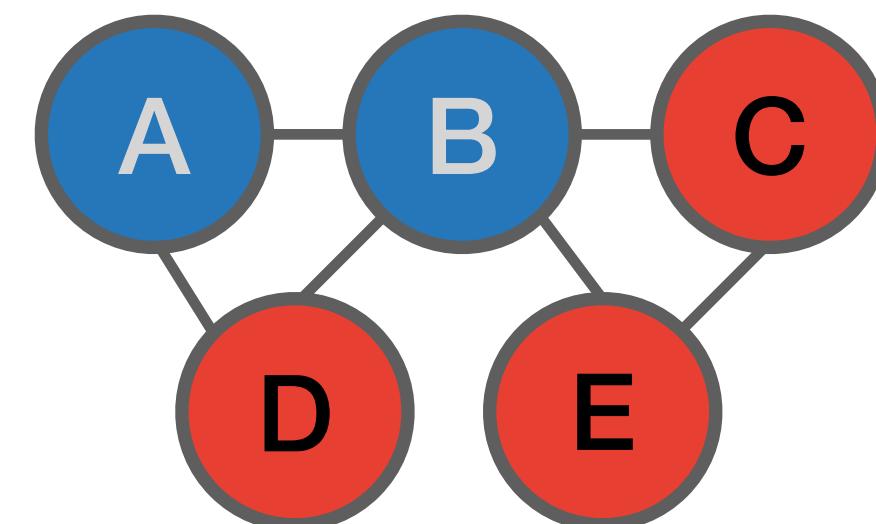
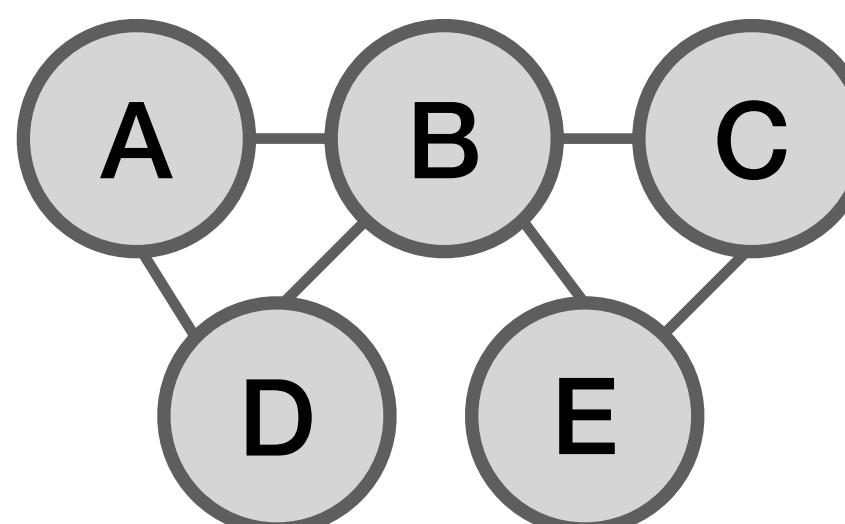
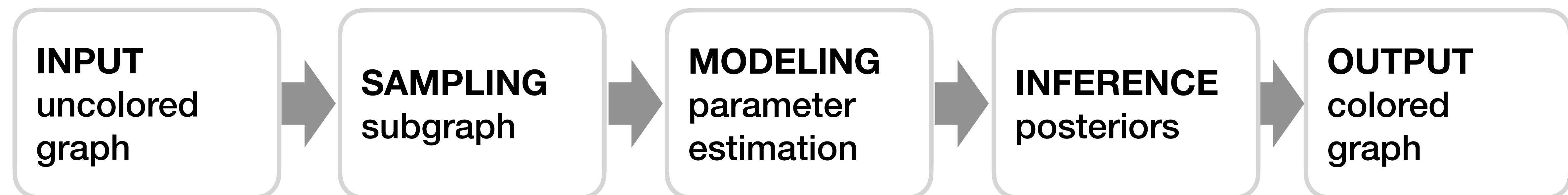


Are these results correct?
Or, are they biased against blue nodes?



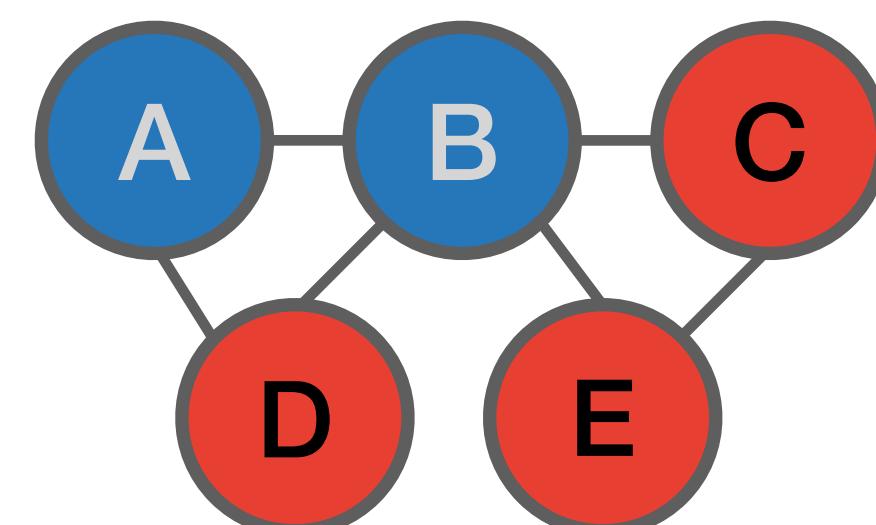
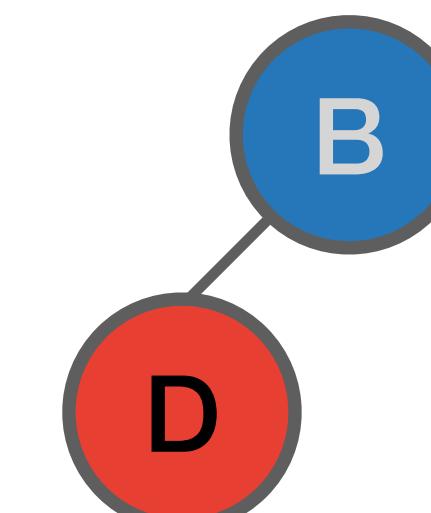
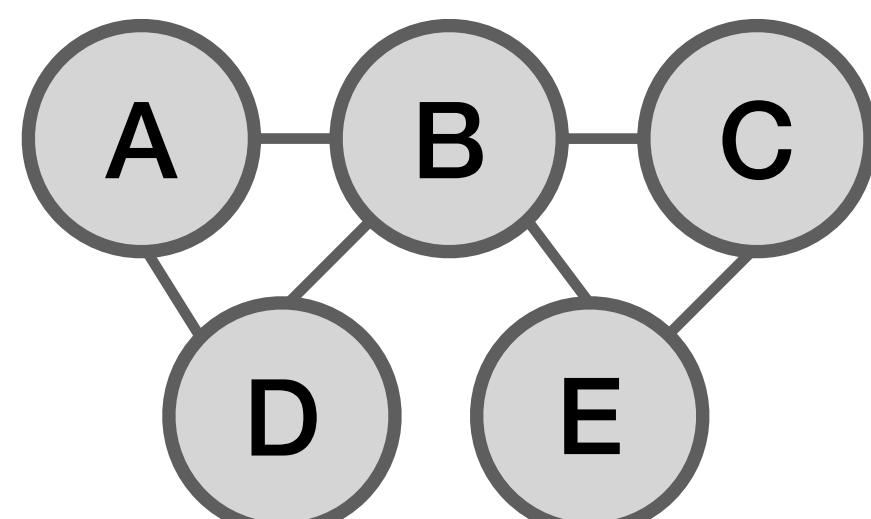
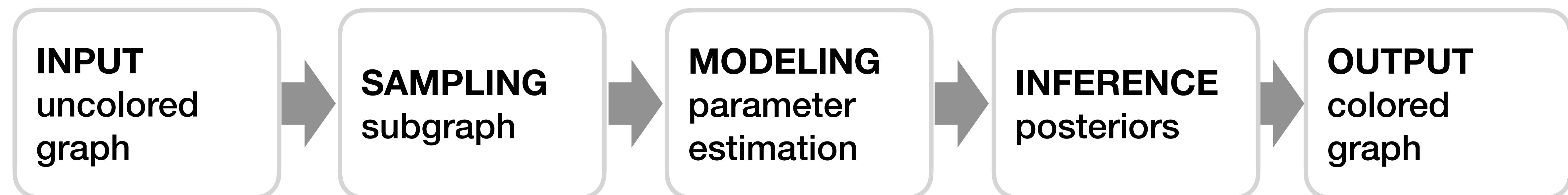
Relational Classification

Machine learning on networked data



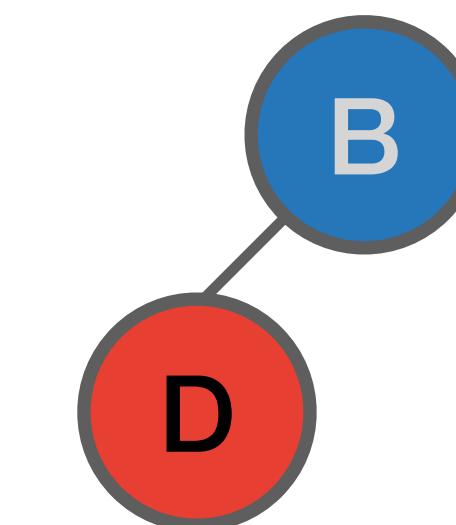
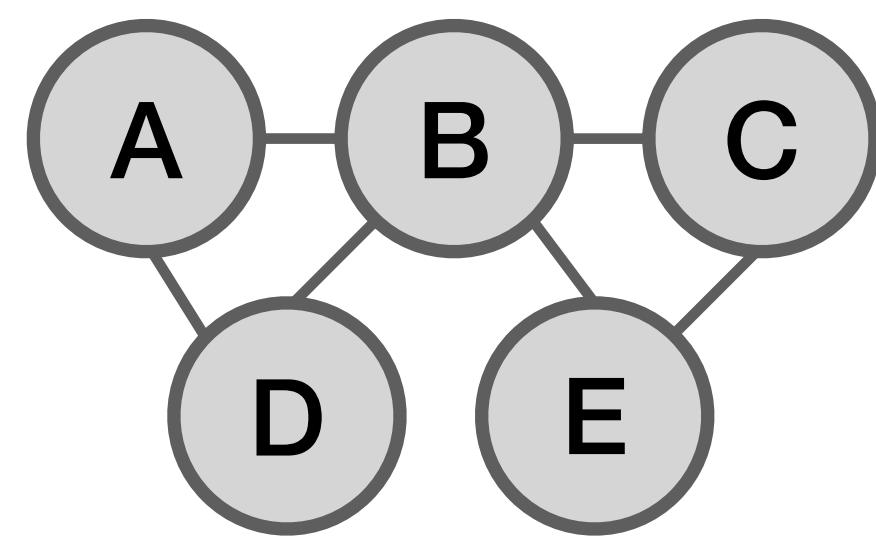
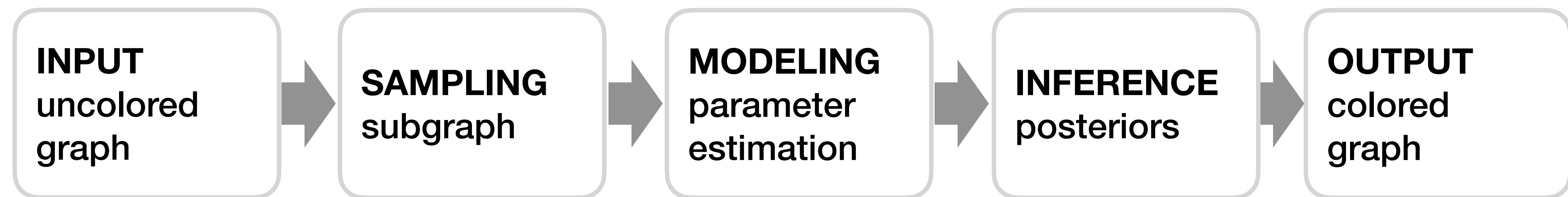
Relational Classification

Machine learning on networked data



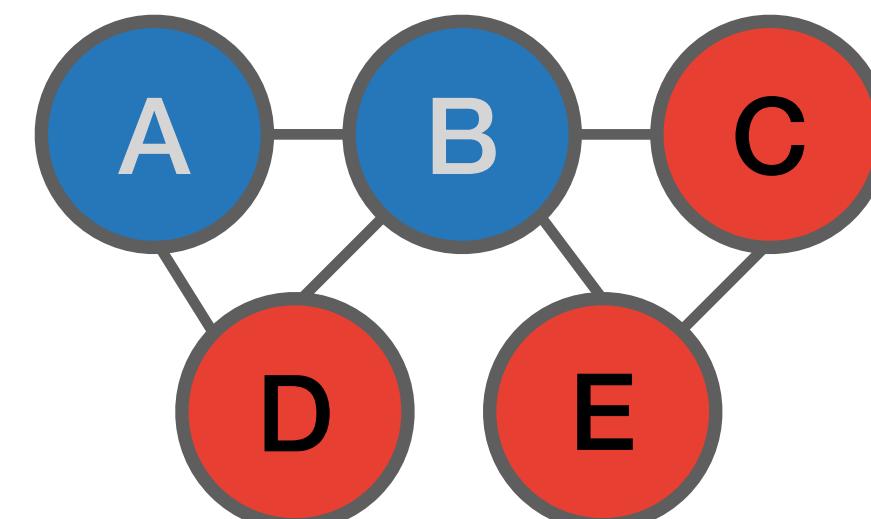
Relational Classification

Machine learning on networked data



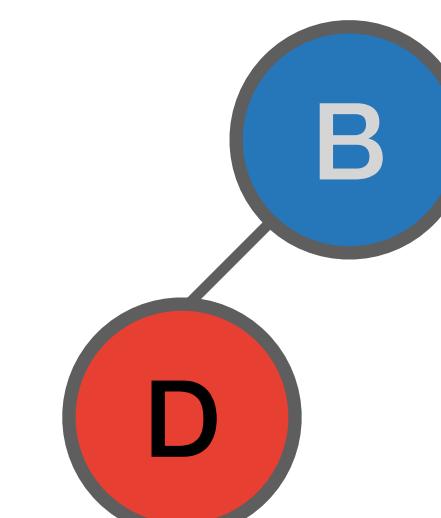
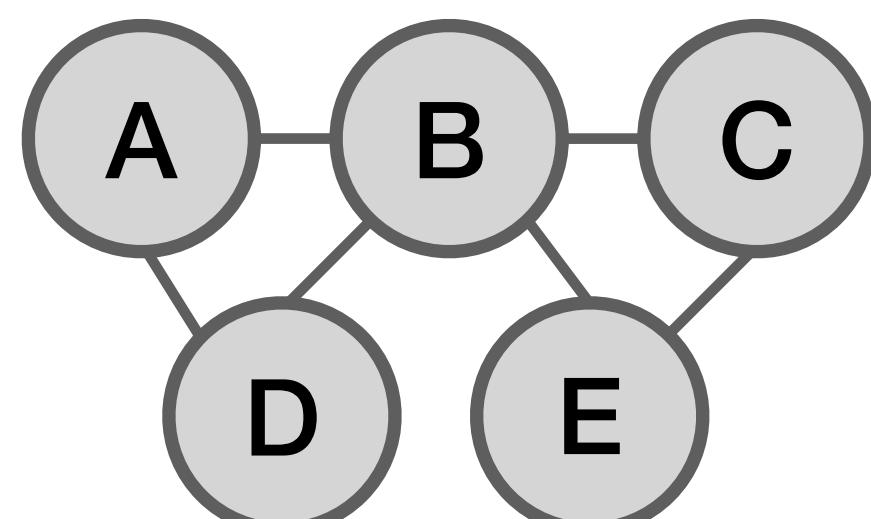
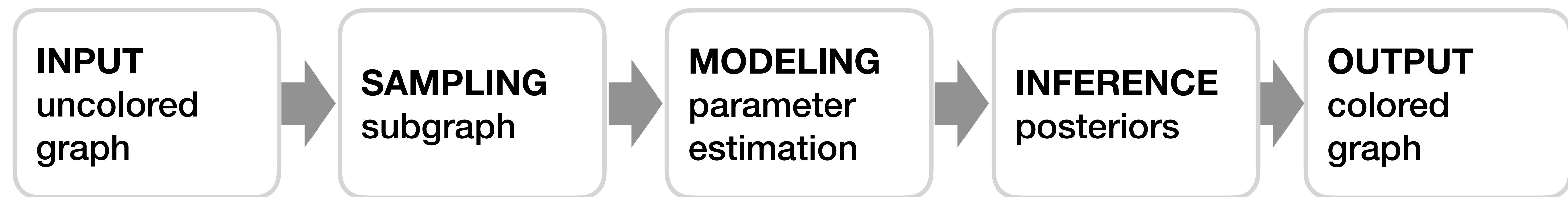
$$P(v_i = \text{red}) = 0.5$$

$$P(v_i = \text{red} \mid v_j = \text{blue}) = 1.0$$



Relational Classification

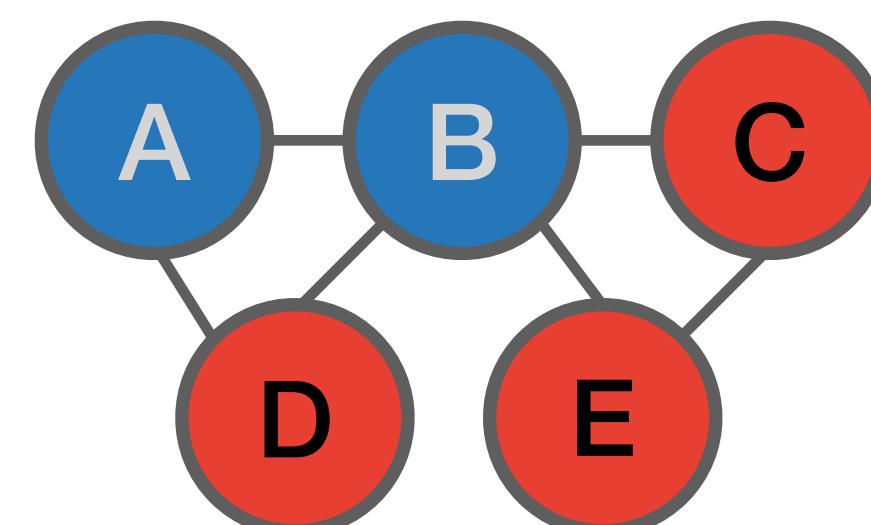
Machine learning on networked data



$$P(v_i = \text{red}) = 0.5$$

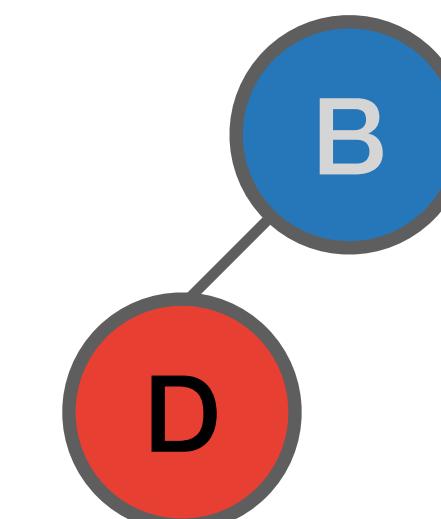
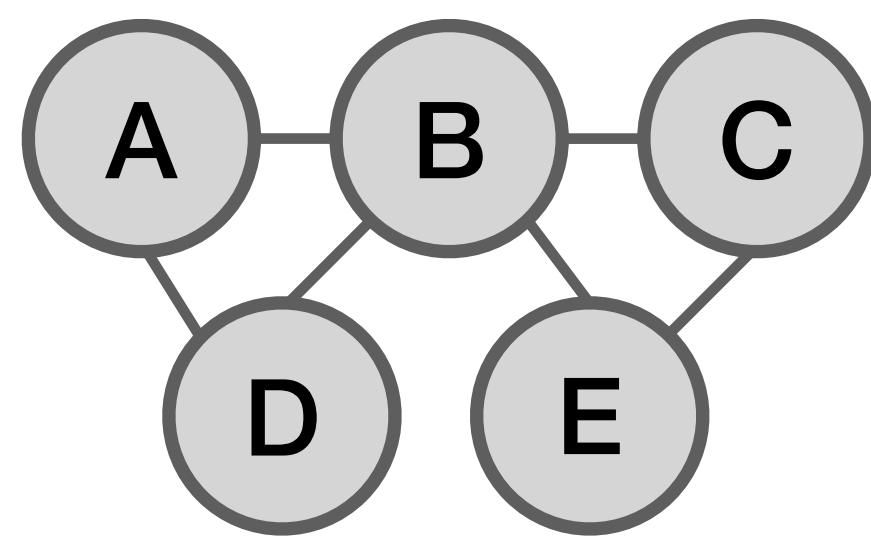
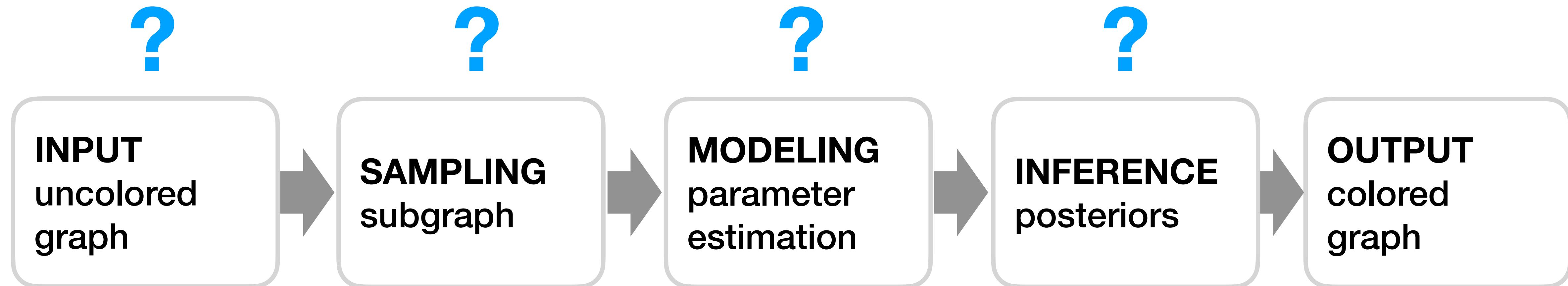
$$P(v_i = \text{red} \mid v_j = \text{blue}) = 1.0$$

$$P(A_b \mid B_b, D_r)$$



Relational Classification

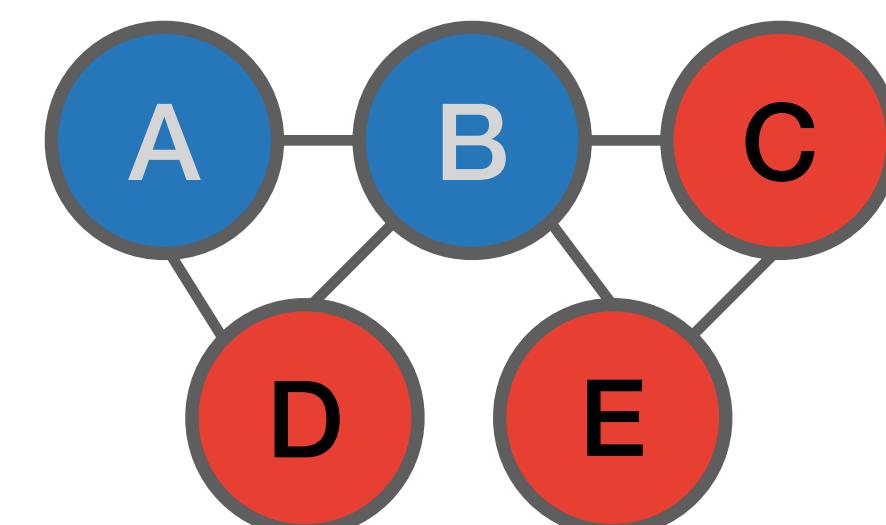
Machine learning on networked data



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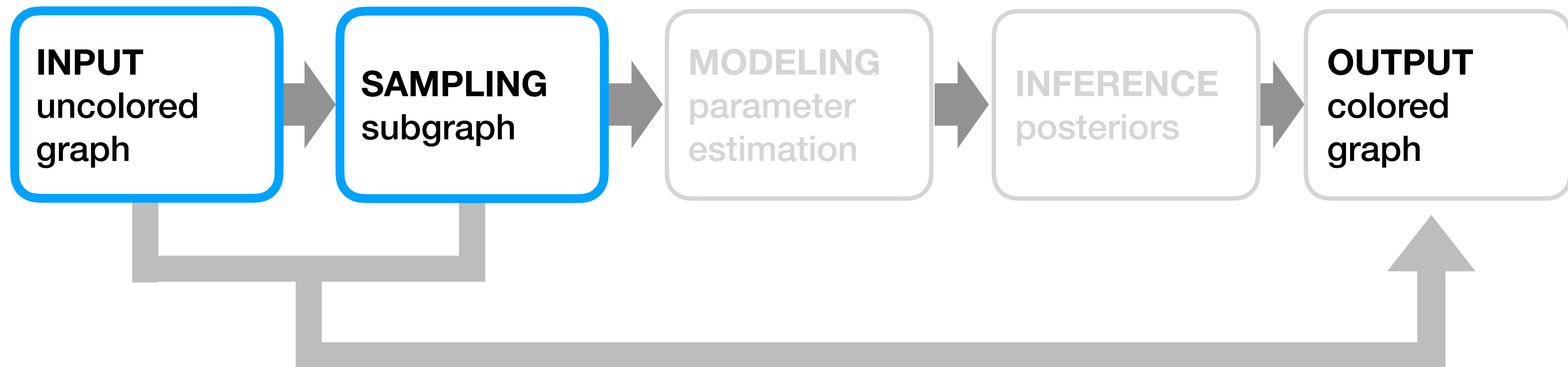
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$$P(A_b \mid B_b, D_r)$$



Relational Classification

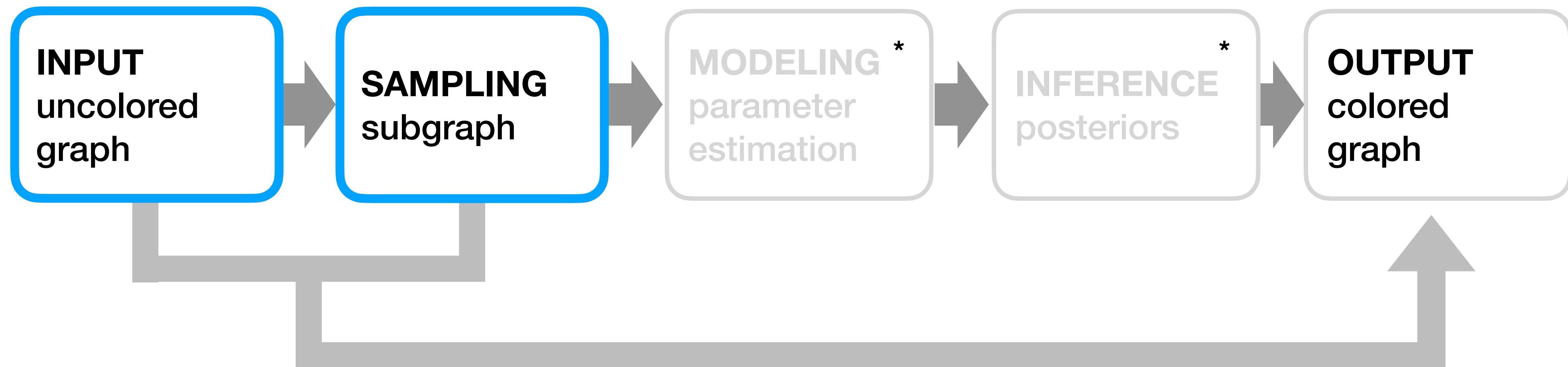
We quantify biases coming from data!



We explain the output performance and bias
with the characteristics of the input and training sample!

Relational Classification

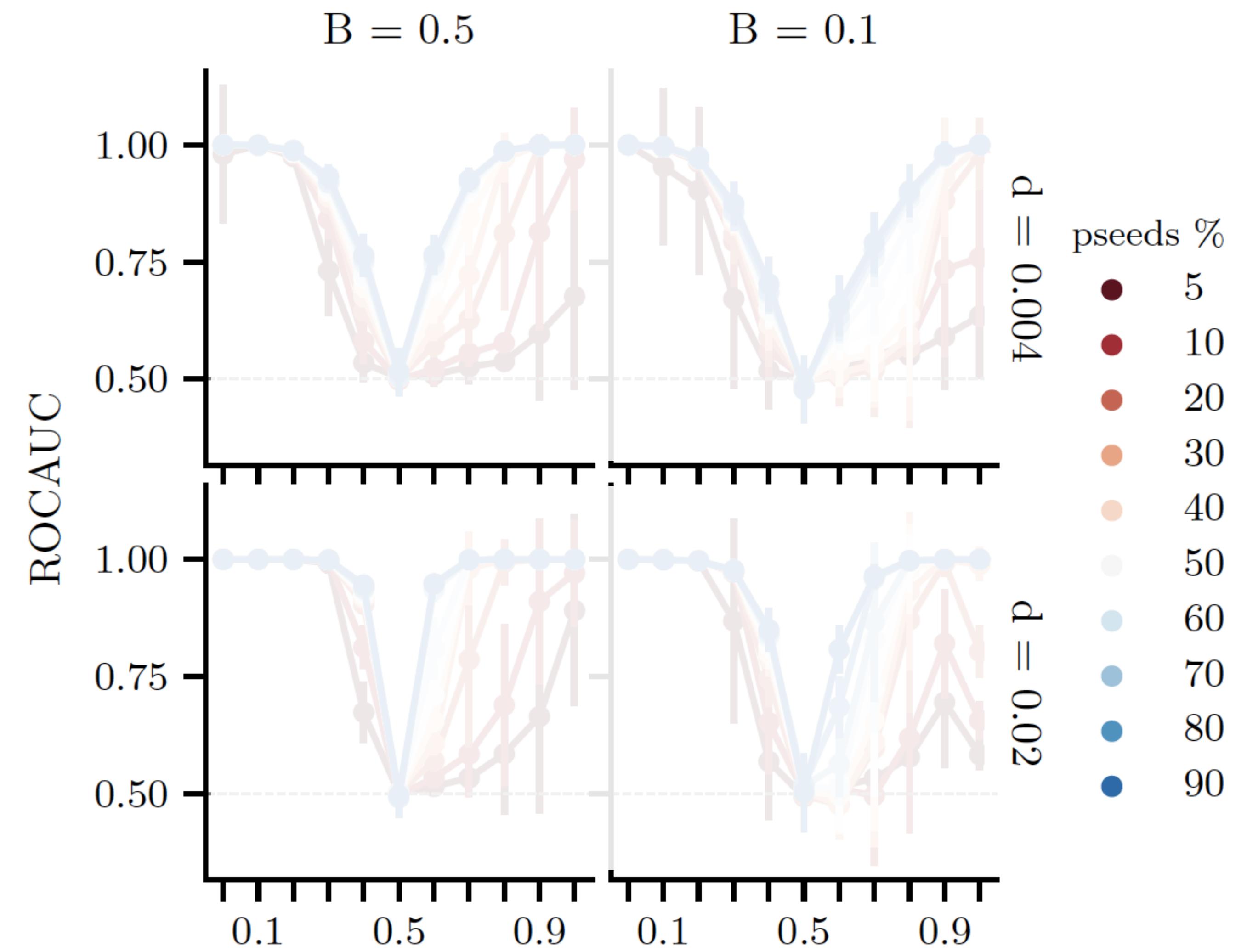
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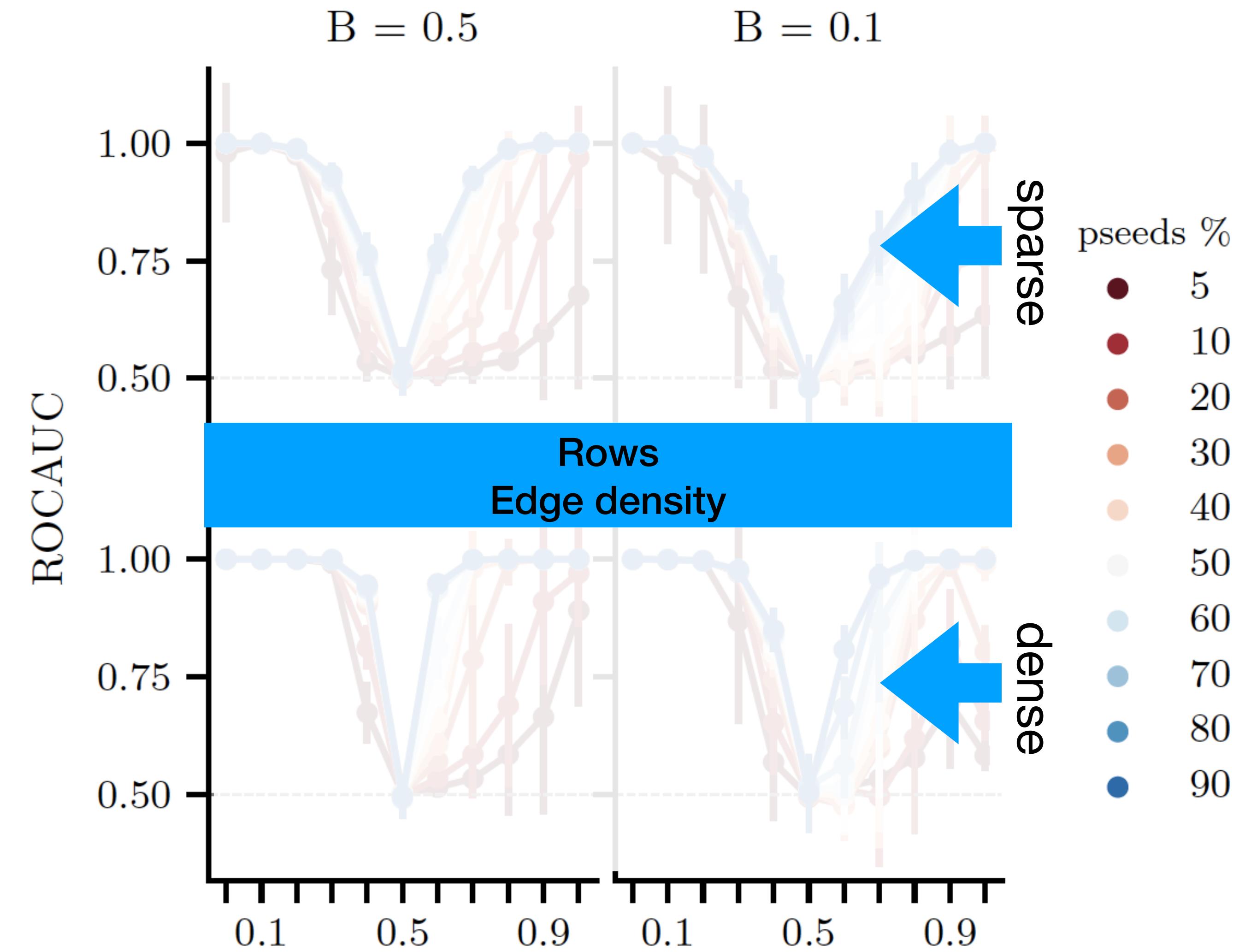
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* Modeling + Inference in [Macskassy and Provost 2007]
(network-only Bayes classifier + relaxation labeling)

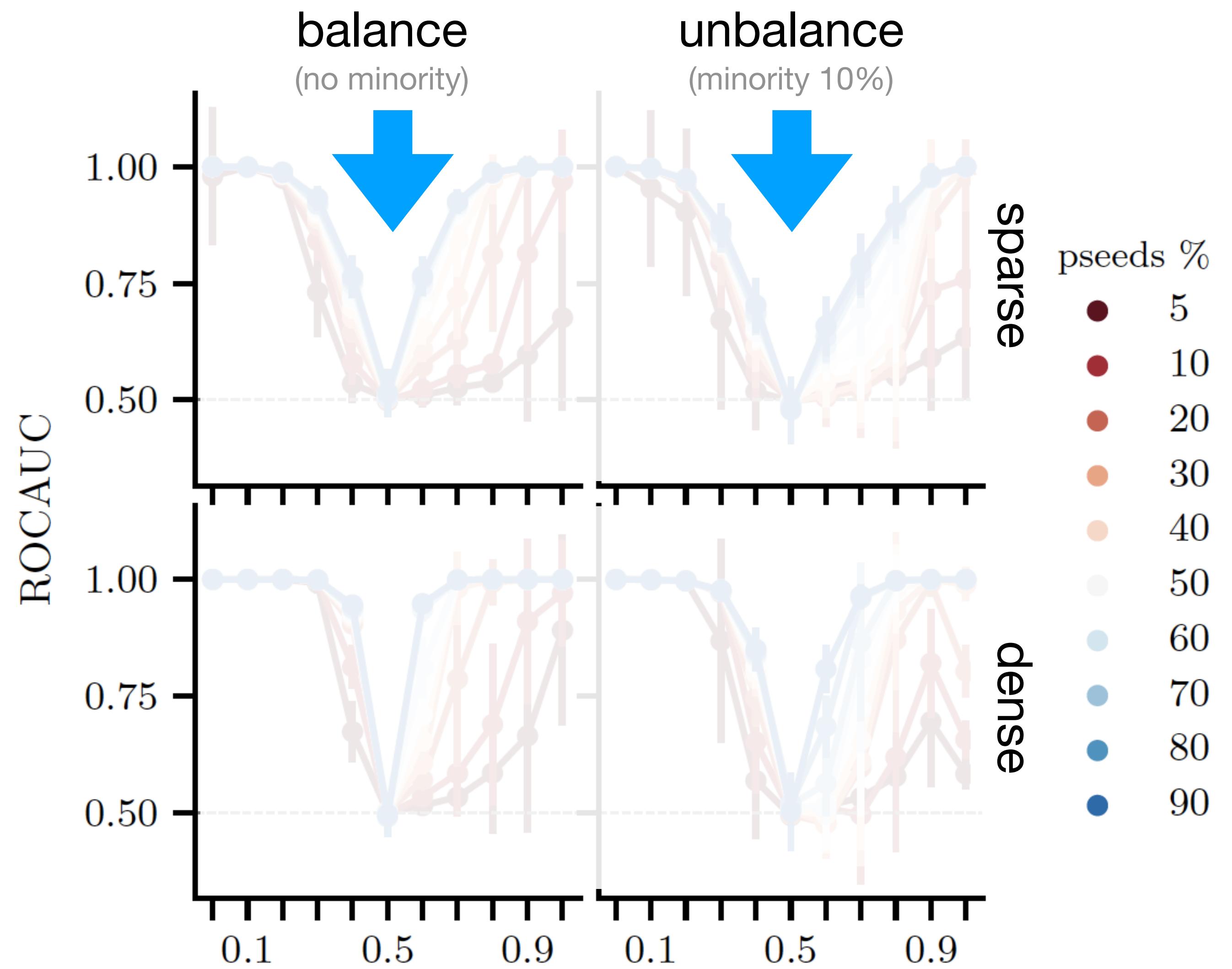
Network structure vs. classification performance



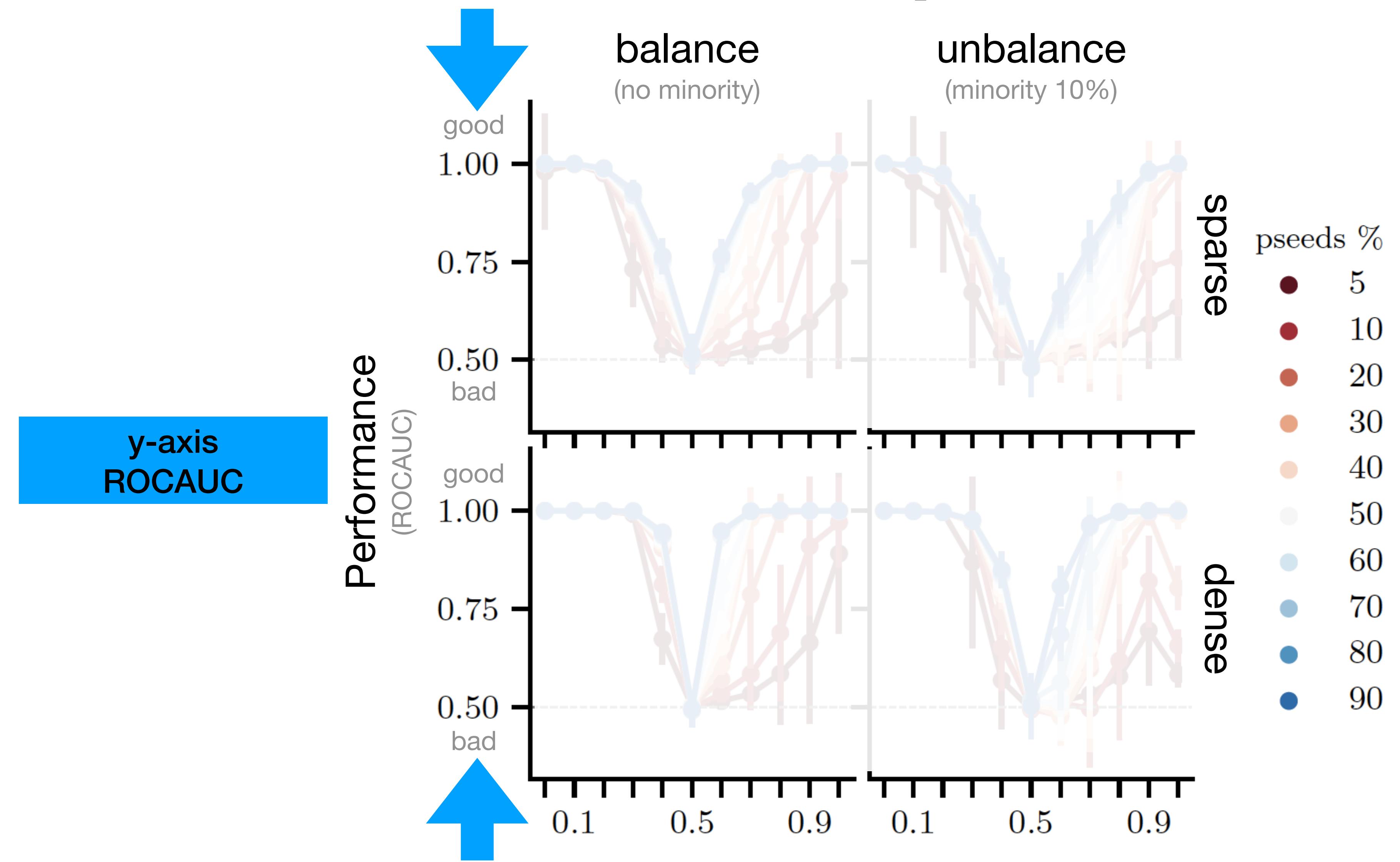
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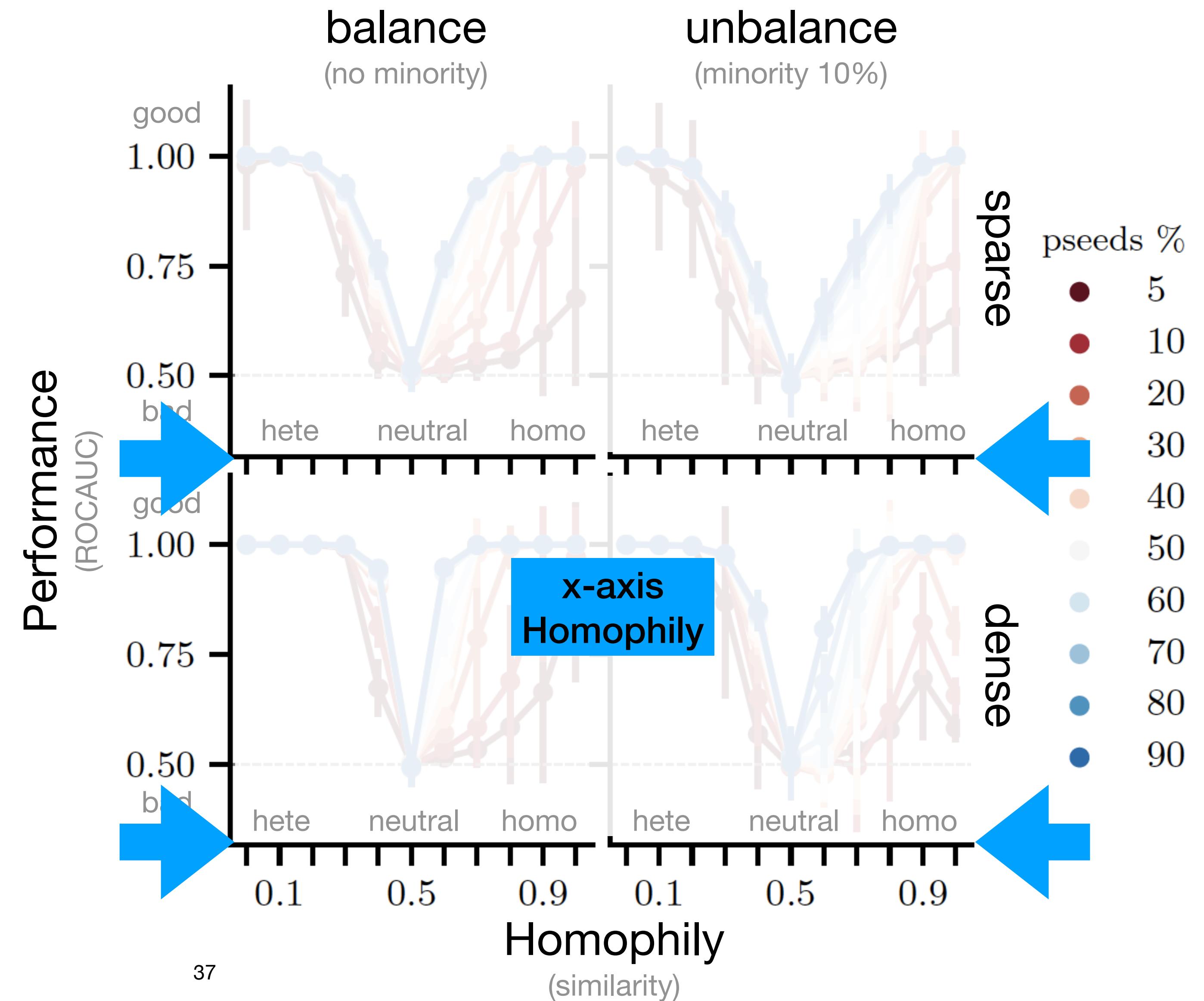
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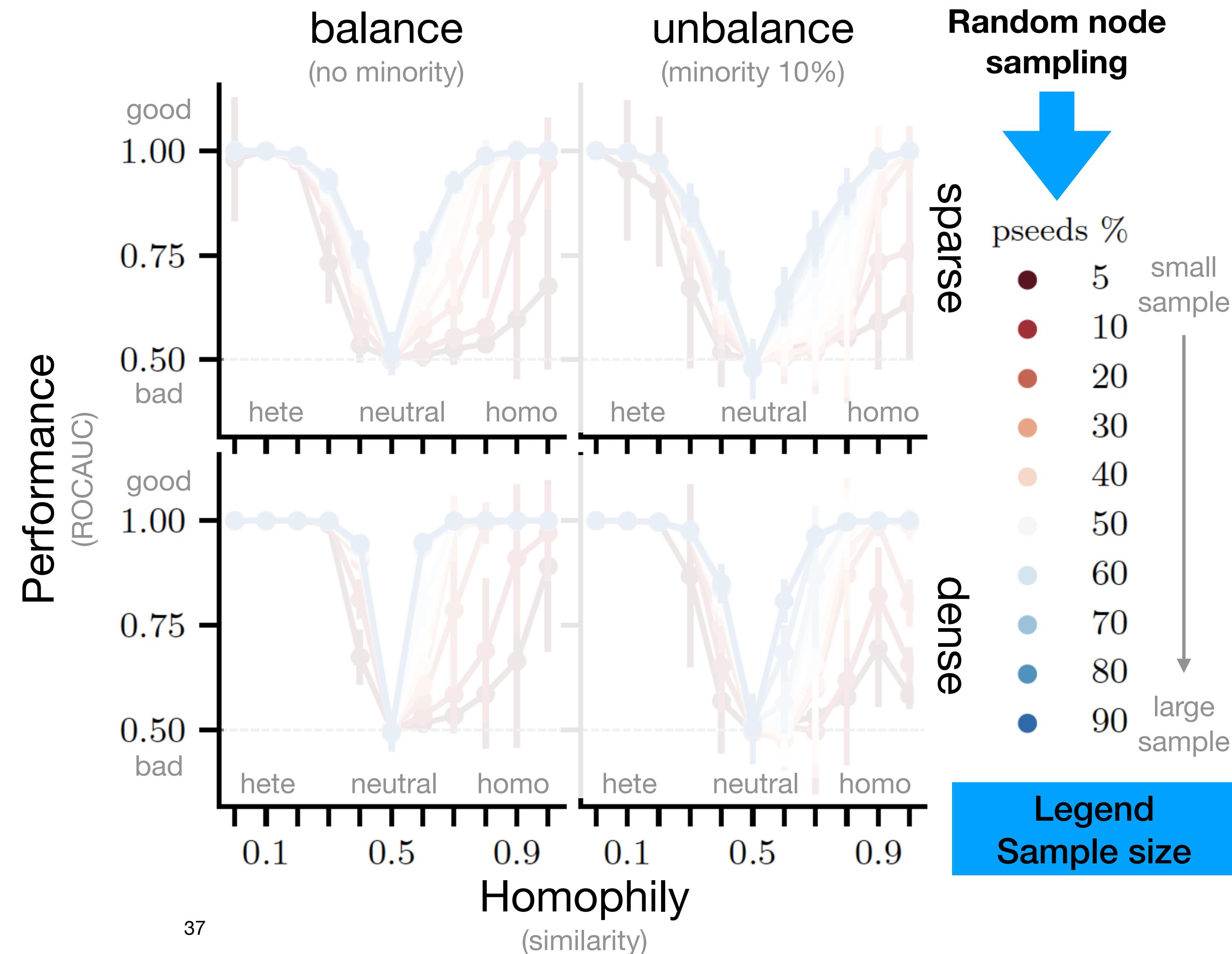
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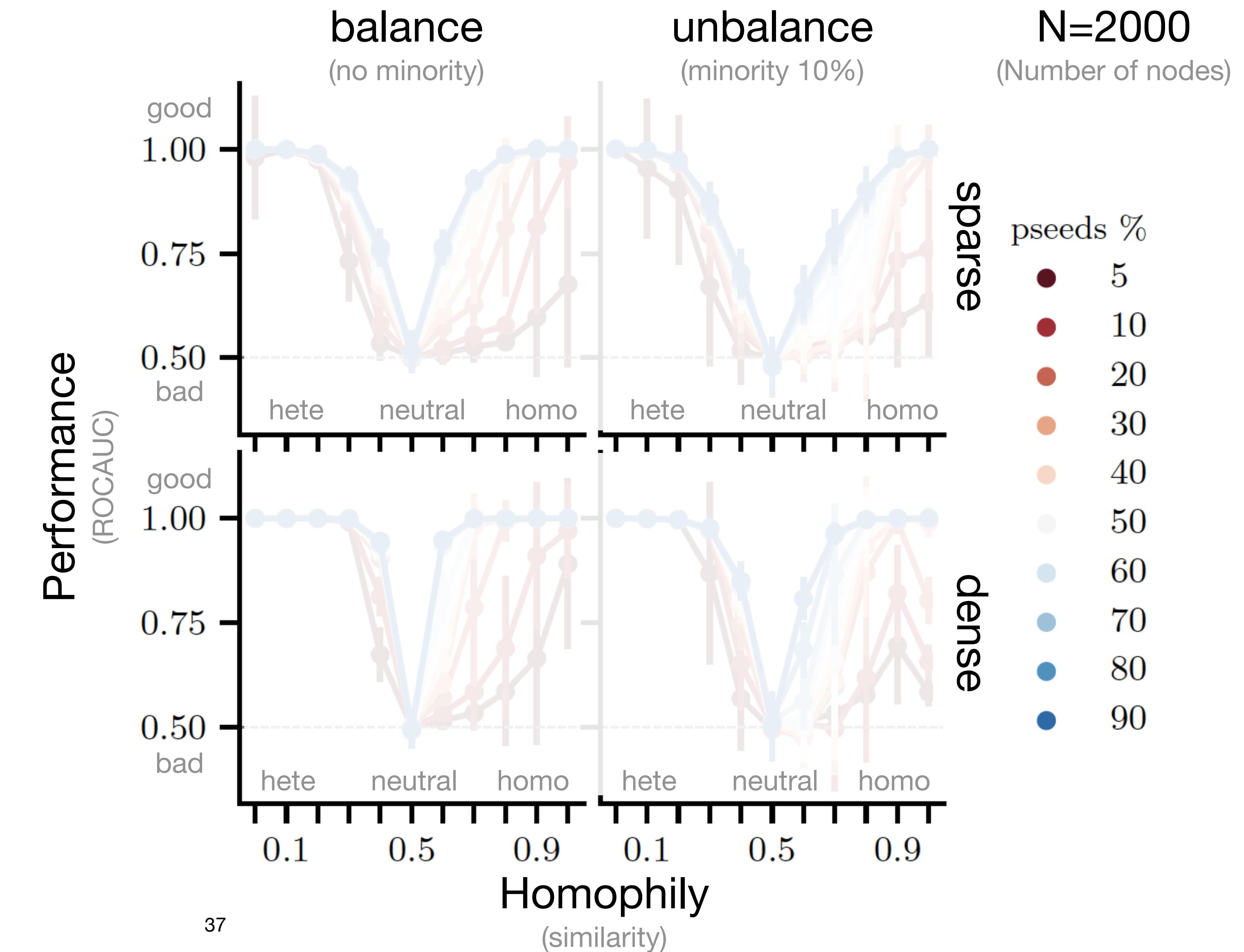
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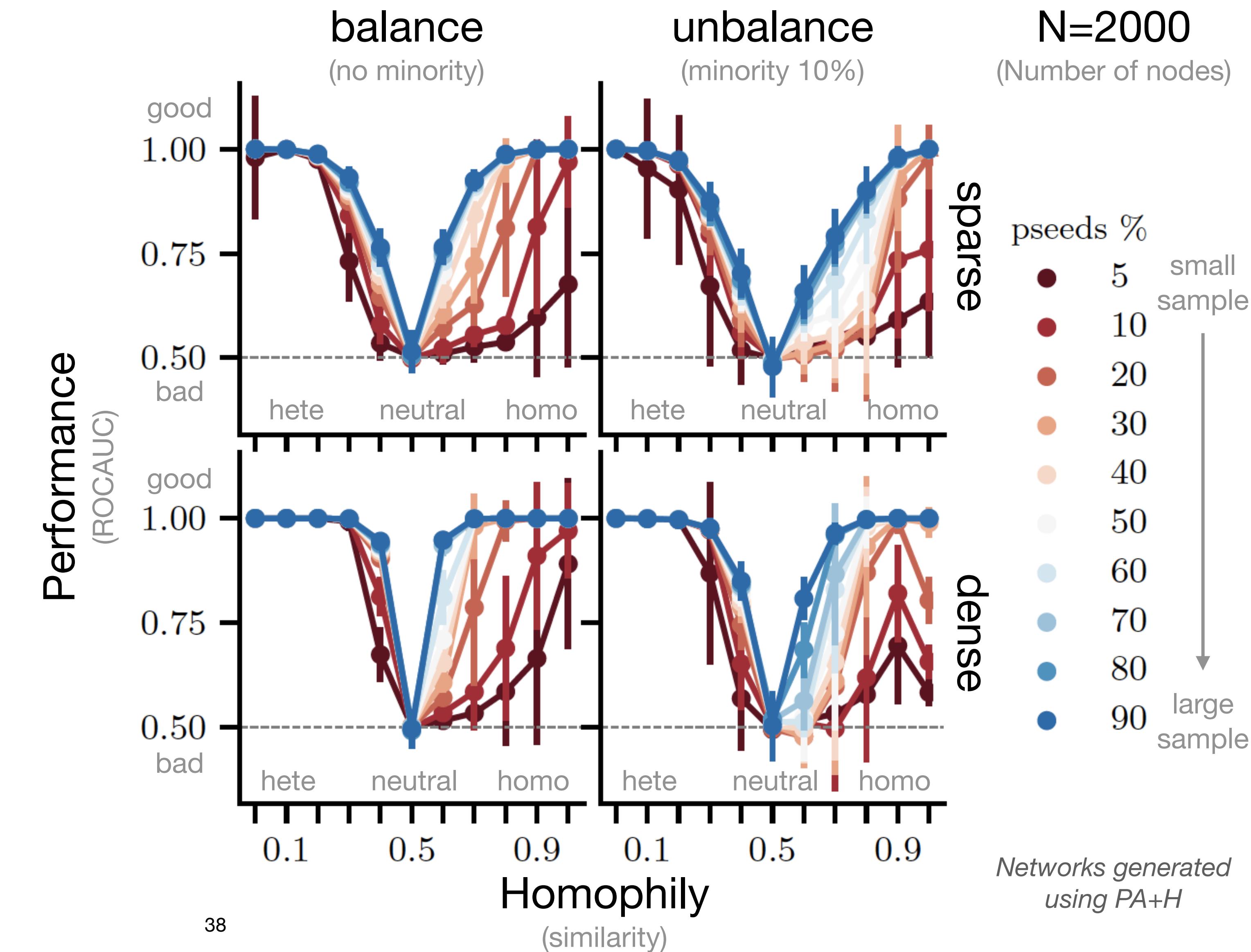
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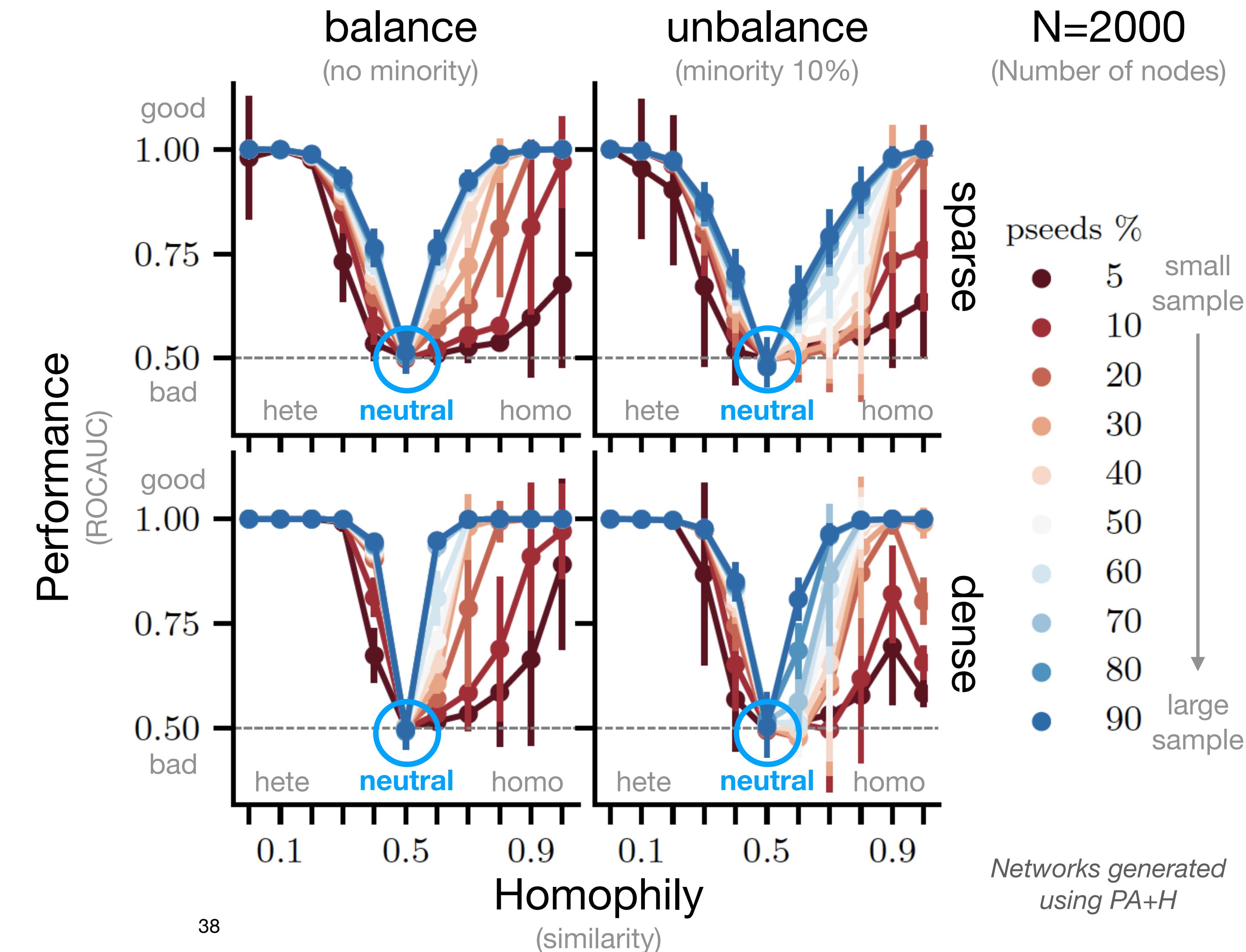


Network structure vs. classification performance



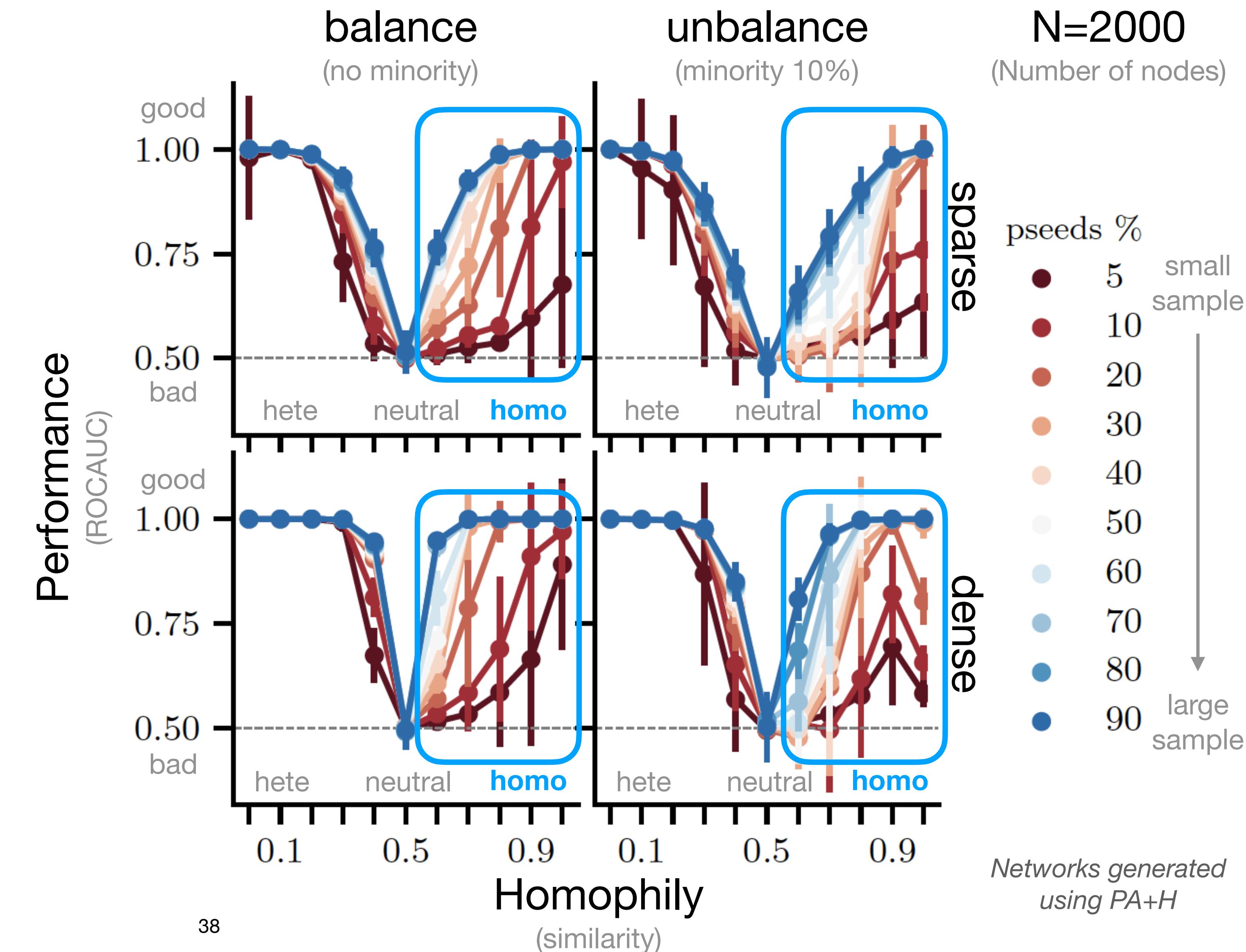
Network structure vs. classification performance

1. Neutral networks ($H=0.5$) cannot be classified better than a random classifier.



Network structure vs. classification performance

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- 2. Homophilic networks ($H>0.5$) achieve lower performance than heterophilic networks when samples are small.**

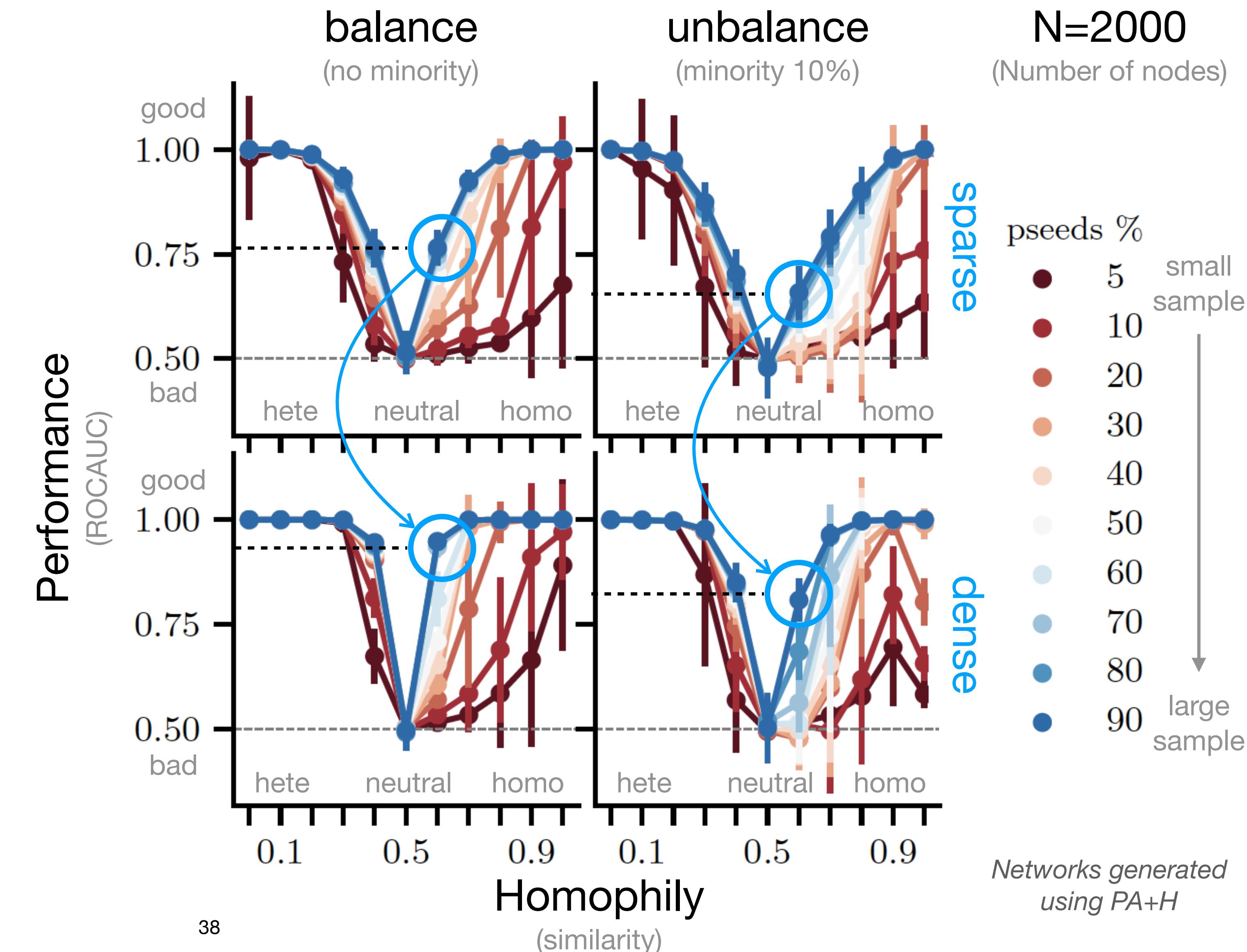


Network structure vs. classification performance

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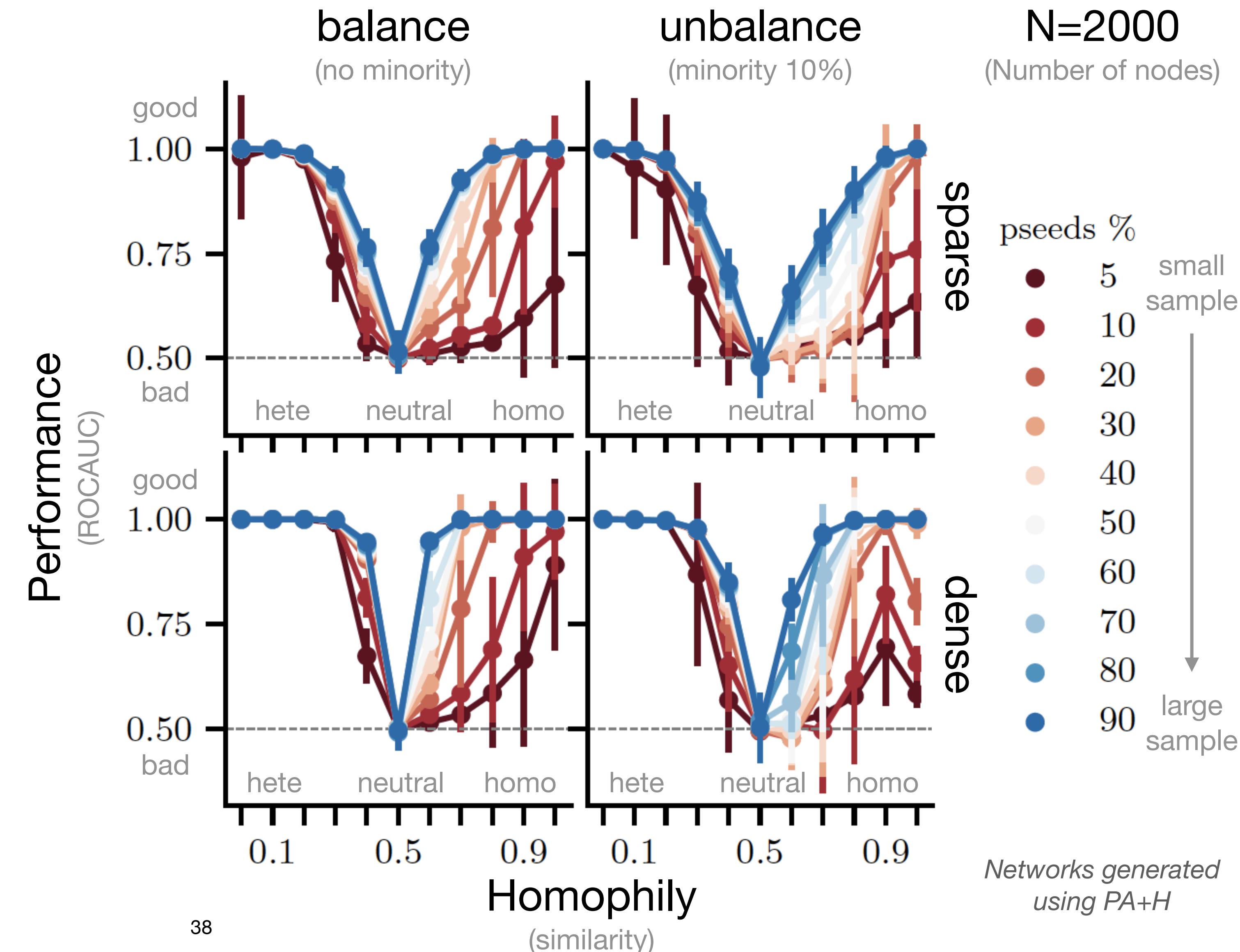
2. Homophilic networks ($H>0.5$) achieve lower performance than heterophilic networks when samples are small.

3. Denser networks achieve higher performance compared to sparse networks.



Network structure vs. classification performance

1. Neutral networks ($H=0.5$) cannot be classified better than a random classifier.
2. Homophilic networks ($H>0.5$) achieve lower performance than heterophilic networks when samples are small.
3. Denser networks achieve higher performance compared to sparse networks.
4. Network size mainly affects ROCAUC variance. Larger networks produce more stable results. (not shown here)



So what?

A real-world scenario

So what?

A real-world scenario



Real-world social network
(people with attributes)

Social Network

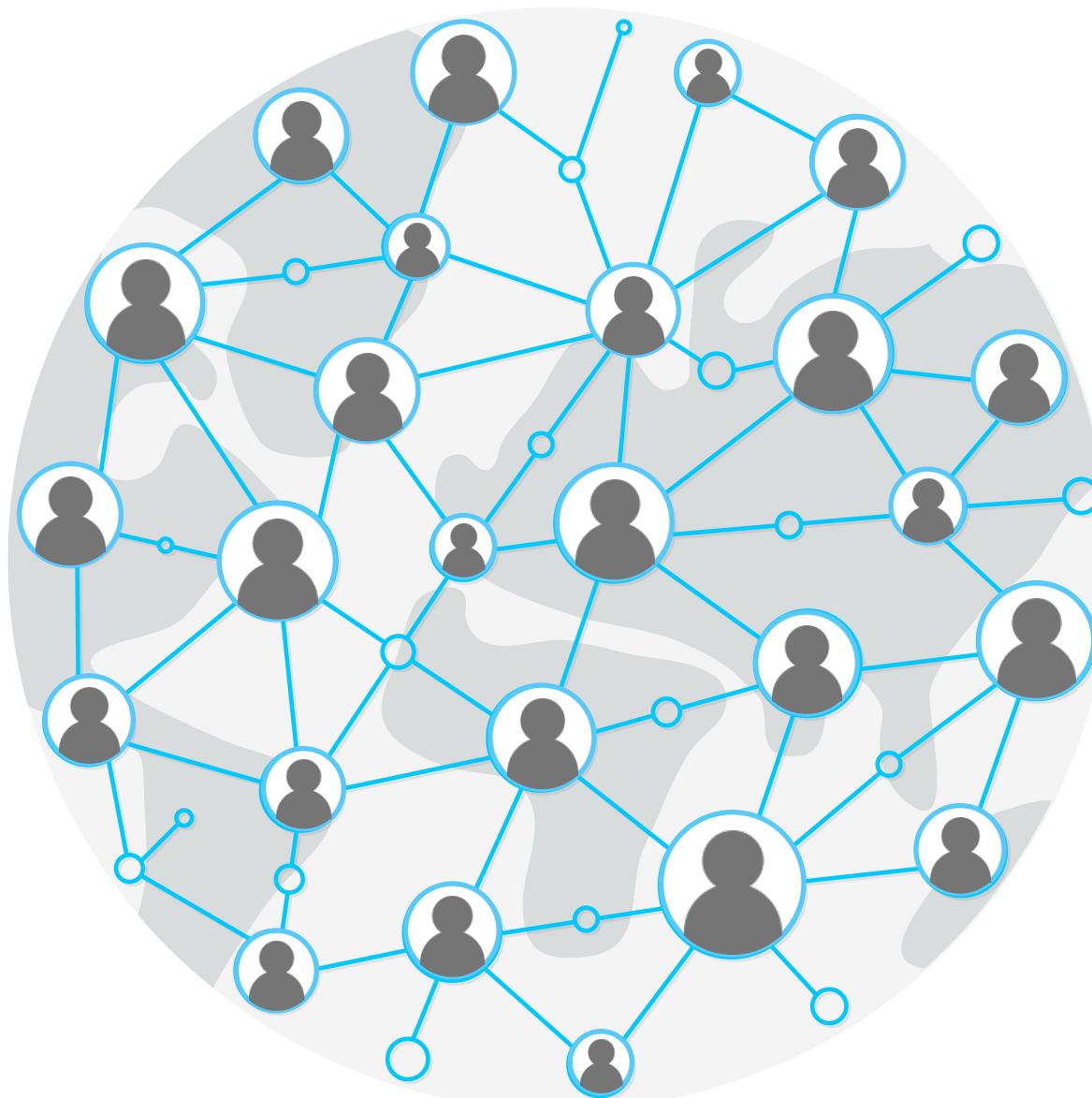
*Mechanism of edge formation:
Homophily & Preferential Attachment*

So what?

A real-world scenario



Real-world social network
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What you get
(people with no attributes)

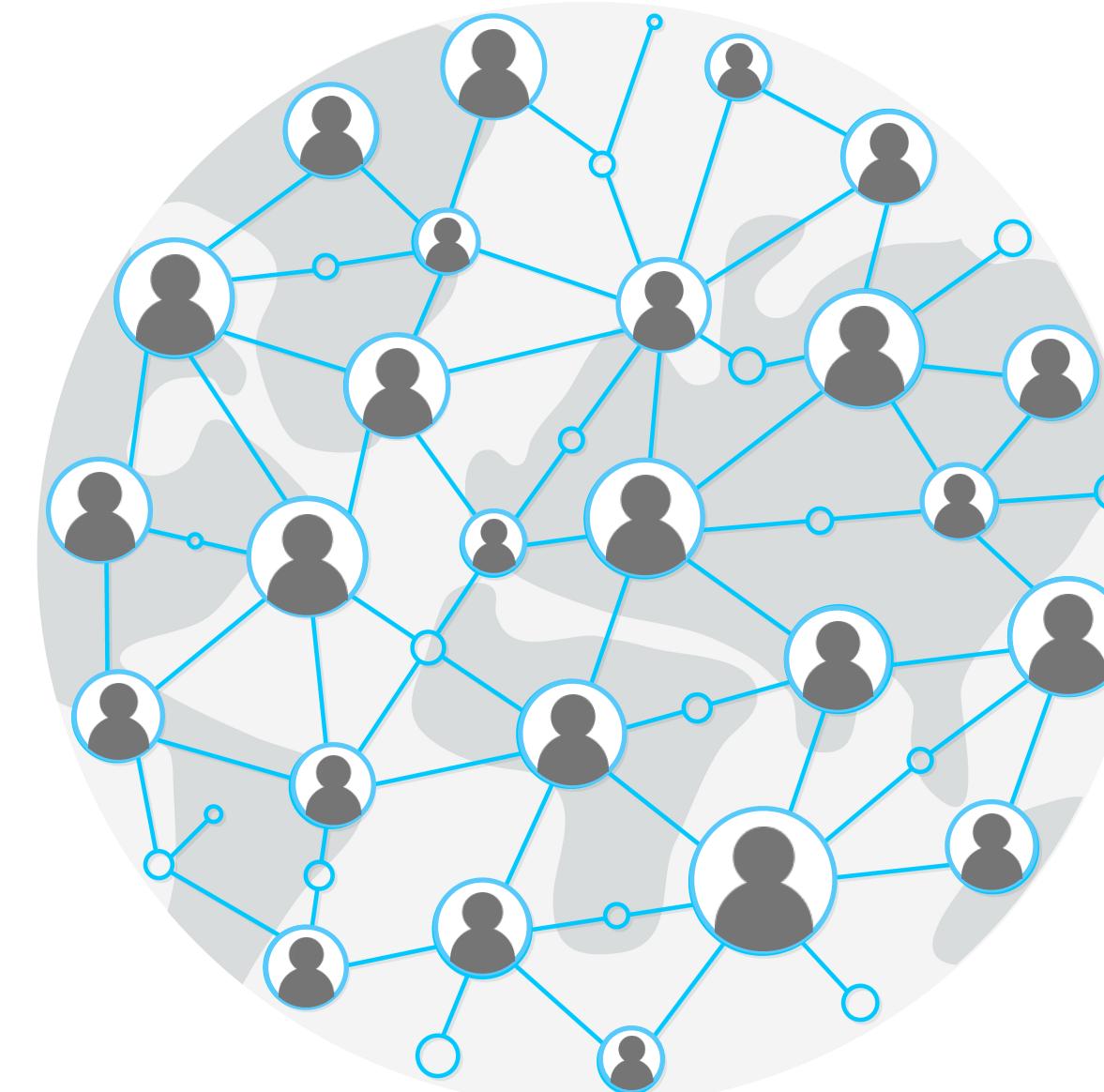
Social Network
Mechanism of edge formation:
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So what?

A real-world scenario



Real-world social network
(people with attributes)



What you get
(people with no attributes)

1. Identify network structure

Inference in OSNs via Lightweight Partial Crawls

Konstantin Avrachenkov
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Bruno Ribeiro
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Purdue University
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INRIA
Sophia Antipolis, France
jithin.sreedharan@inria.fr

Class balance
 $B=0.3$

Homophily
 $H=0.8$

Social Network
Mechanism of edge formation:
Homophily & Preferential Attachment

So what?

A real-world scenario

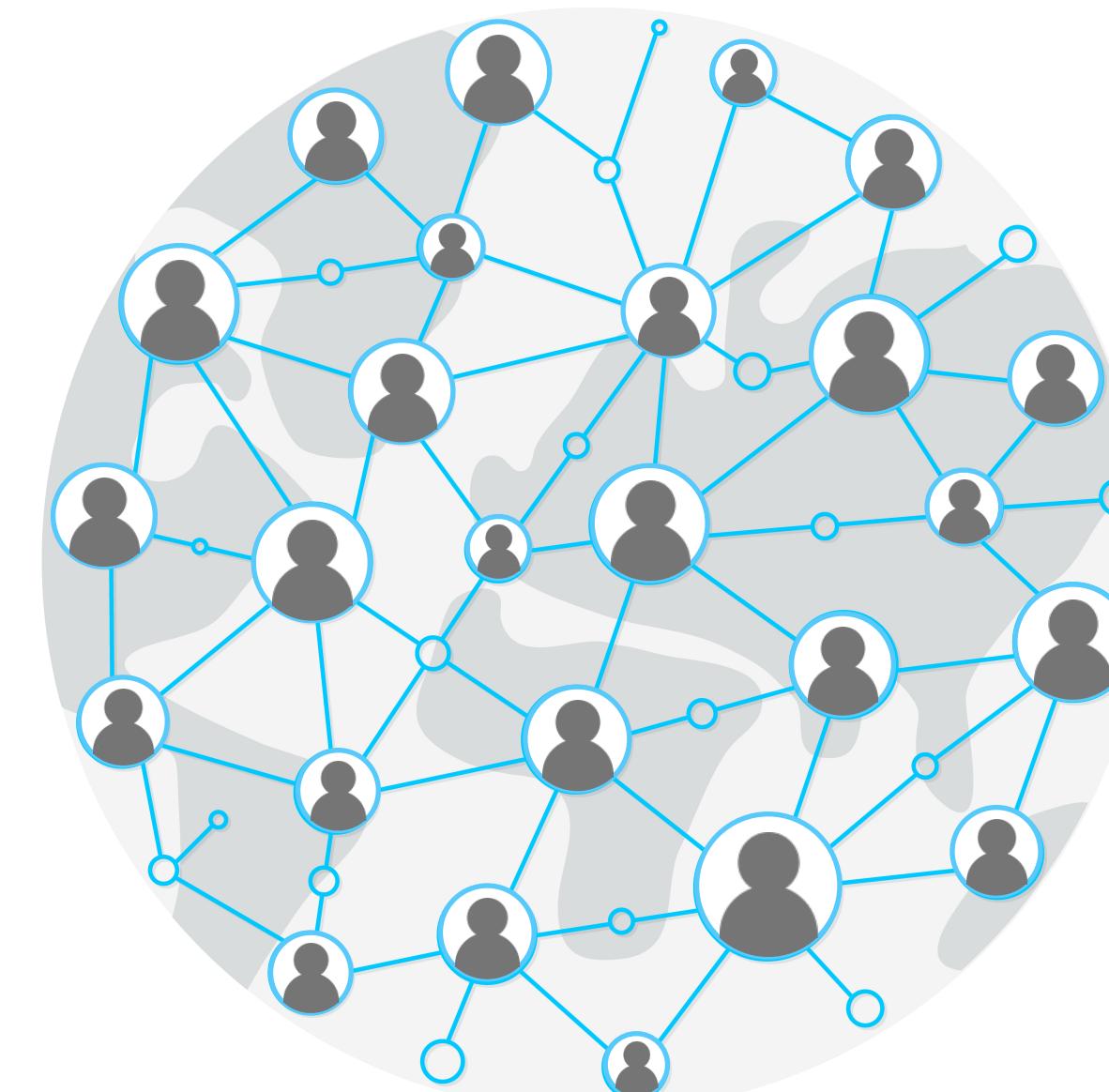


Real-world social network

(people with attributes)

Social Network

Mechanism of edge formation:
Homophily & Preferential Attachment



What you get

(people with no attributes)

1. Identify network structure

Inference in OSNs via Lightweight Partial Crawls

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Class balance
 $B=0.3$

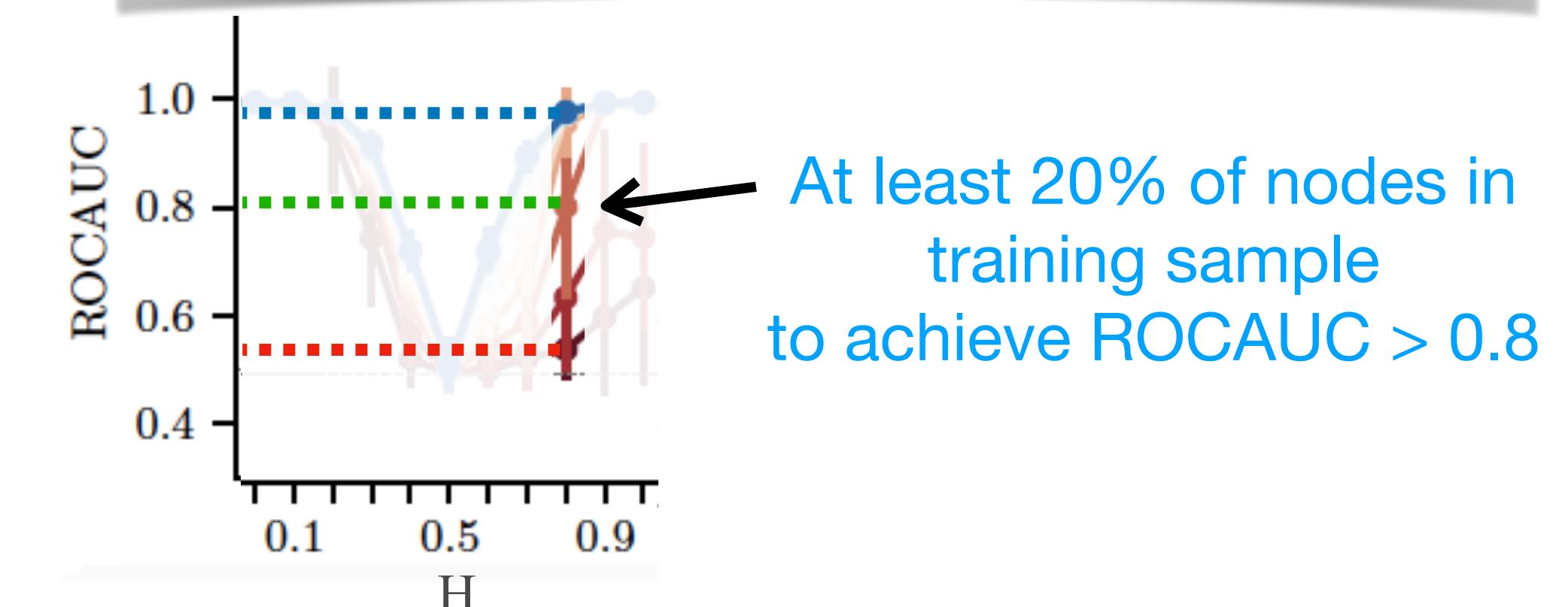
Homophily
 $H=0.8$

2. Identify ROCAUC range for that network

RESEARCH

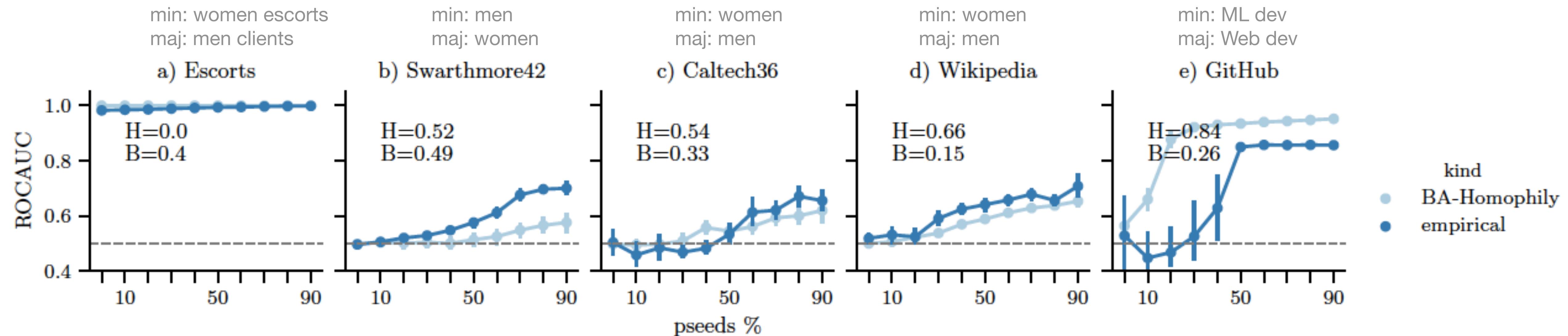
Explaining Classification Performance and Bias via Network Structure and Sampling Technique

Lisette Espin-Noboa, Fariba Karimi, Bruno Ribeiro, Kristina Lerman and Claudia Wagner



Real-world (empirical) networks

Model fitting

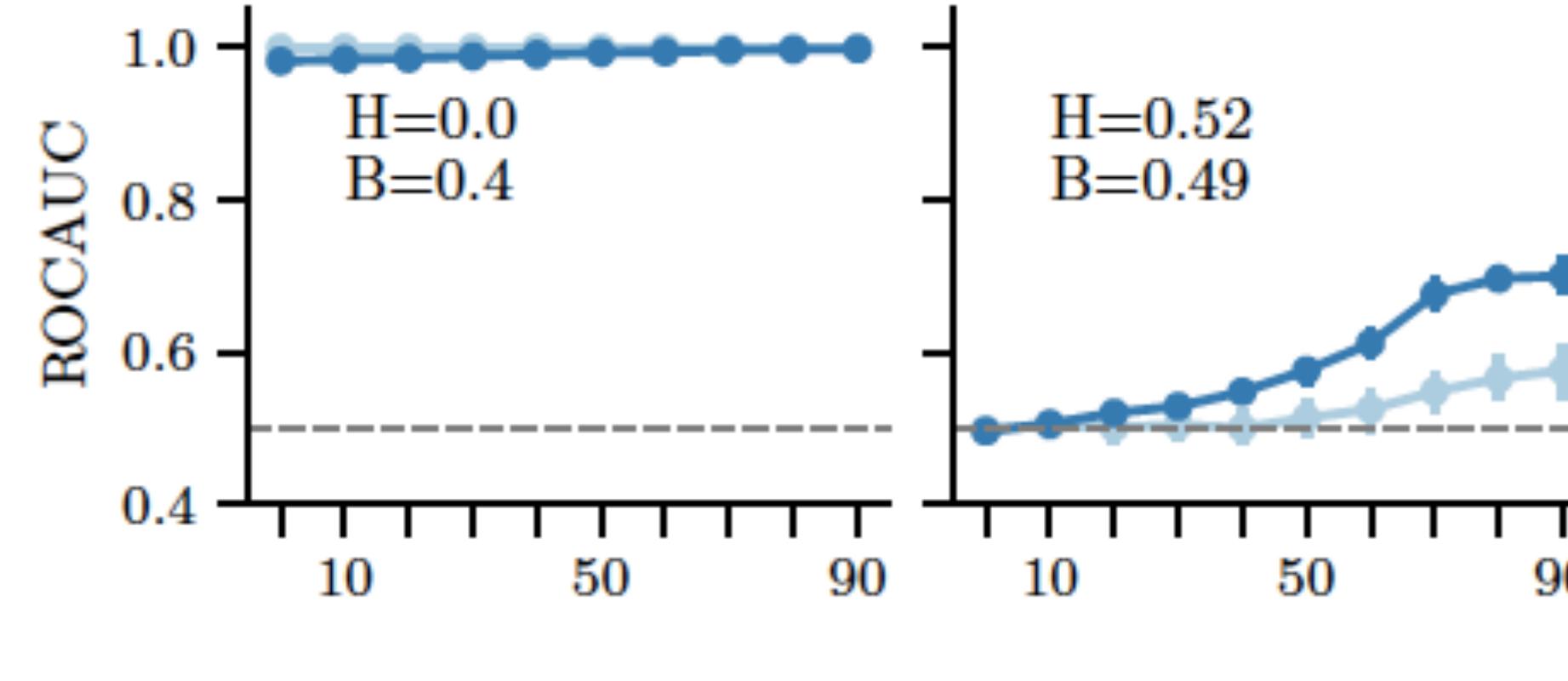


Real-world (empirical) networks

Model fitting

min: women escorts
maj: men clients

a) Escorts



min: men
maj: women

b) Swarthmore42

min: women
maj: men

c) Caltech36

min: women
maj: men

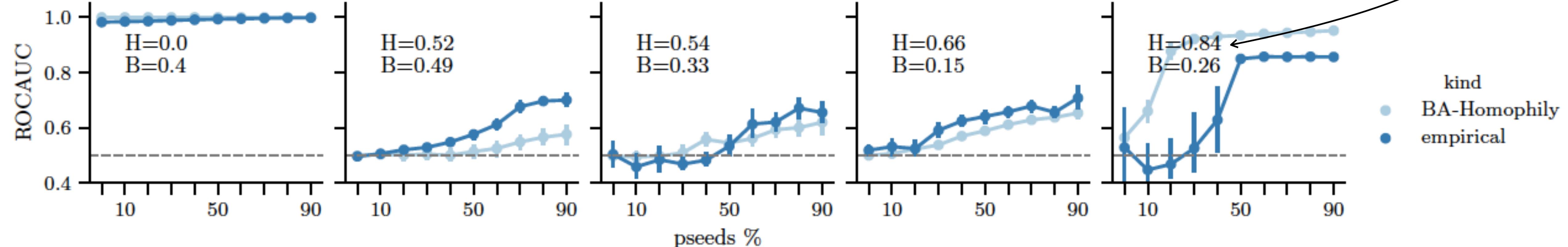
d) Wikipedia

min: ML dev
maj: Web dev

e) GitHub

With symmetric homophily
 $H_{mm} = H_{MM}$

kind
BA-Homophily
empirical

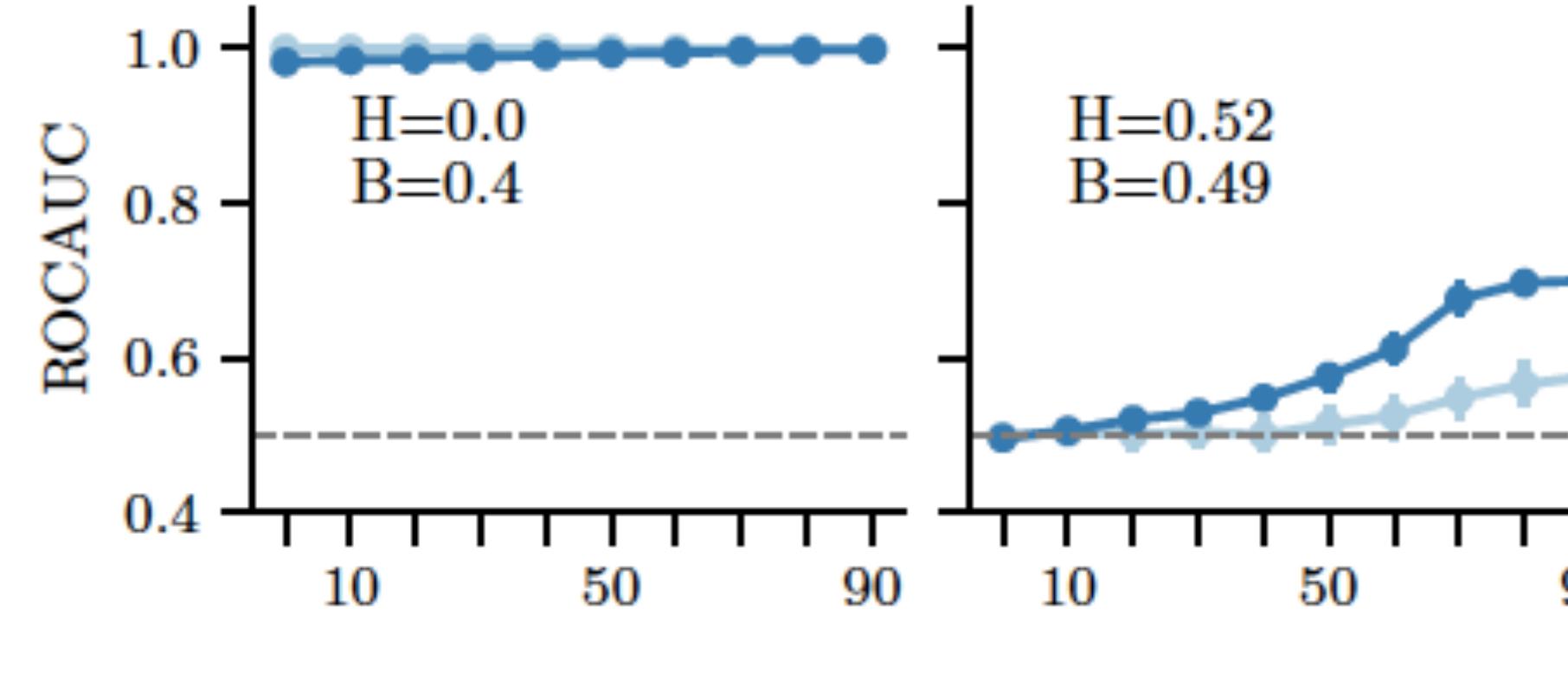


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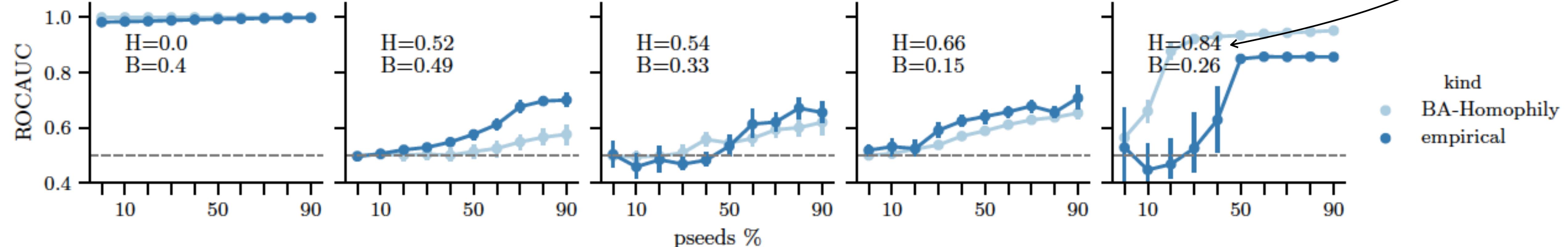
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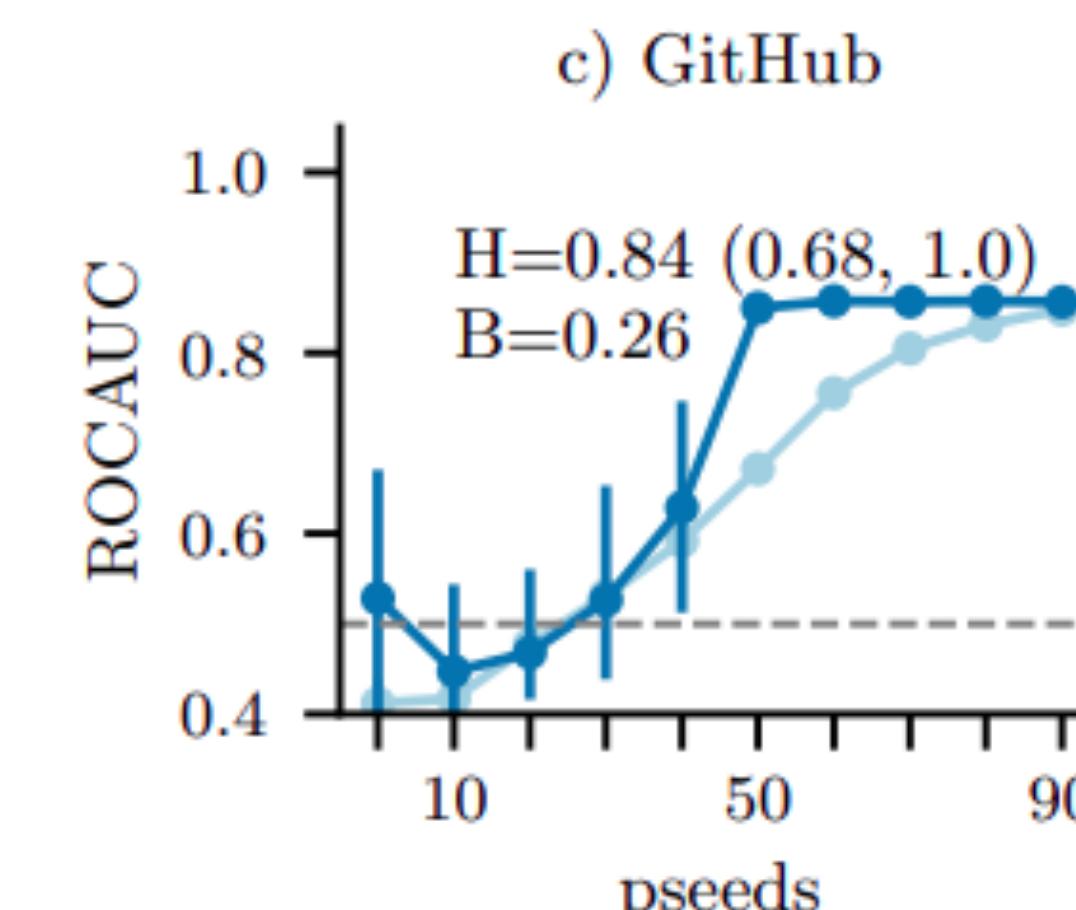
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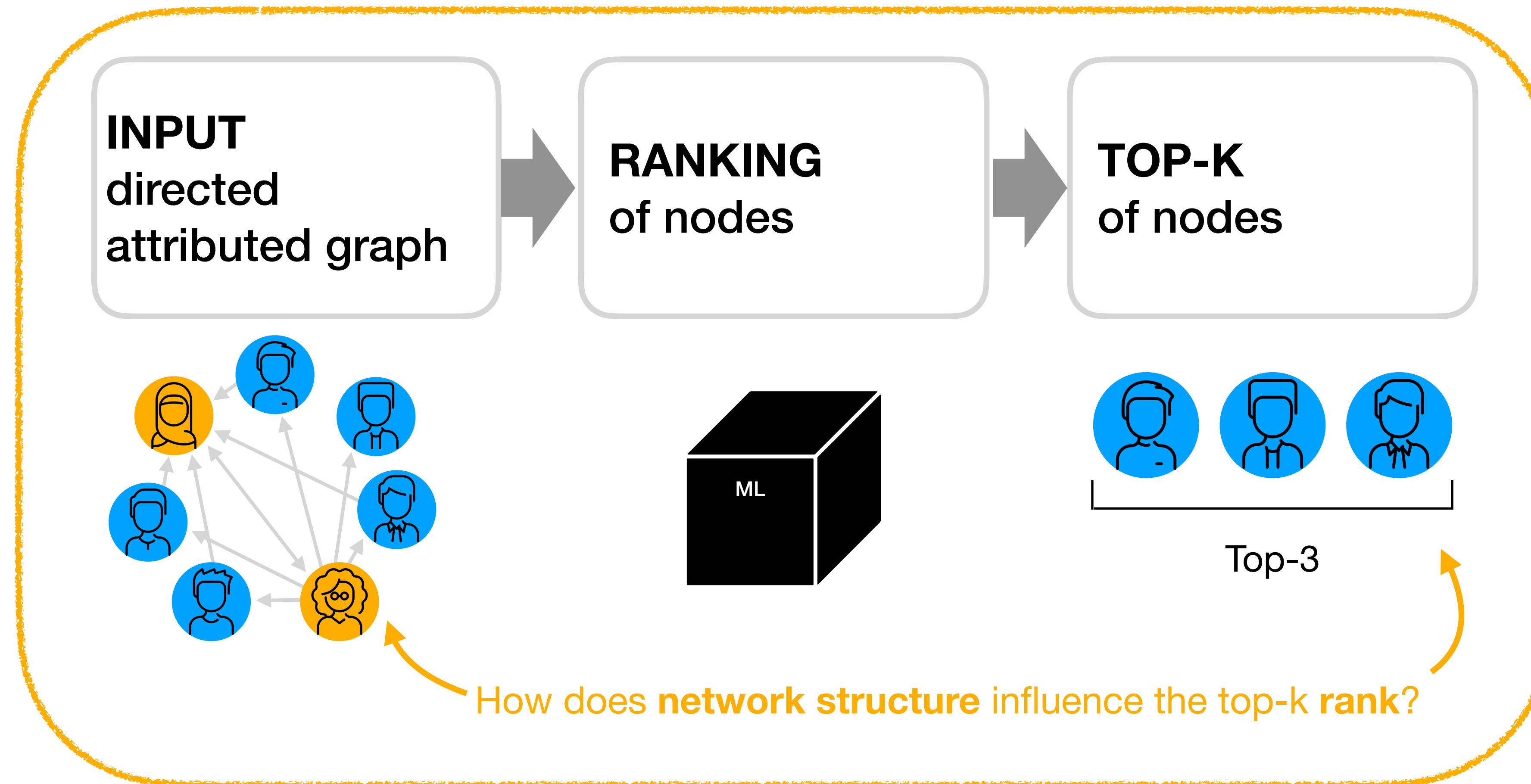


With asymmetric homophily

$H_{mm} \neq H_{MM}$



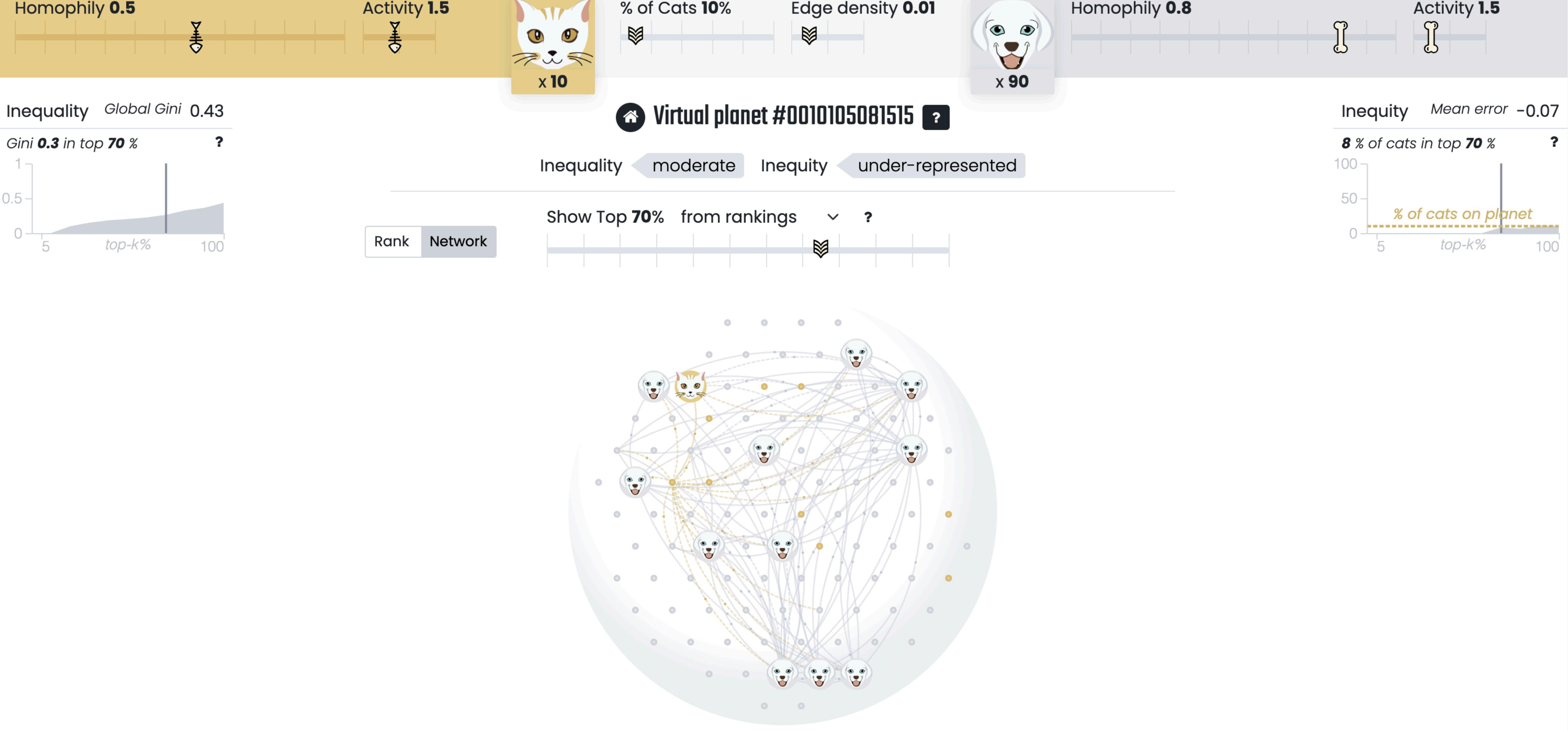
Evaluation benchmarks in “ranking inequalities”

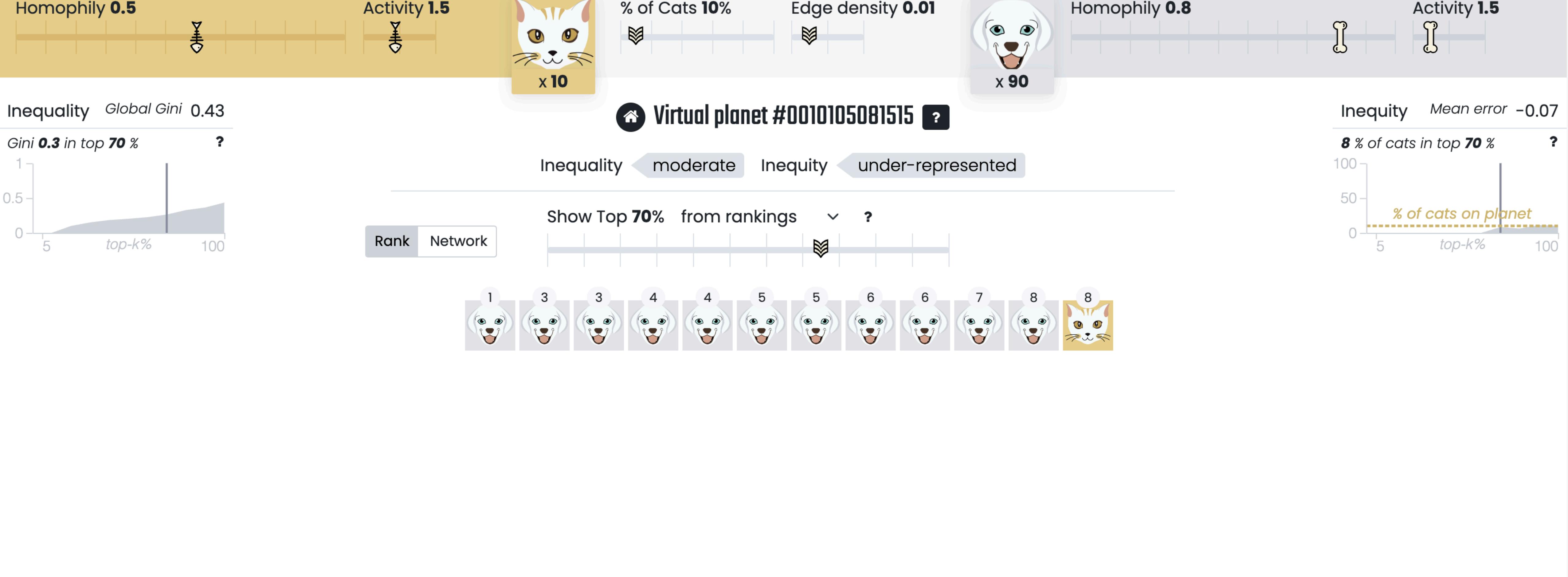


Planets of disparity

vis.csh.ac.at/planets-of-disparity

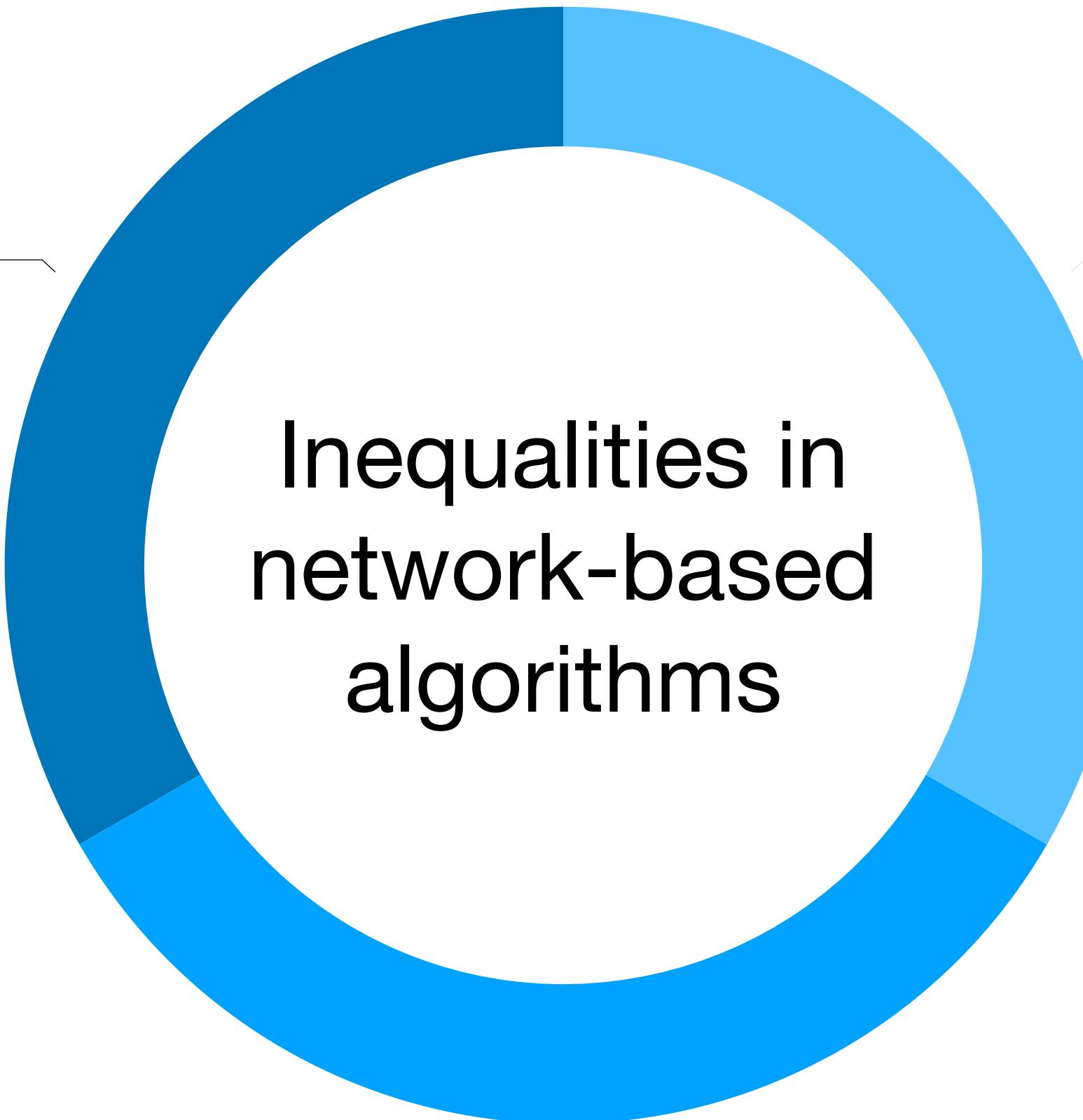






3.

Mitigating inequalities on networks



Understanding
inequalities
on networks

Identifying
inequalities
on networks

We should leverage the benchmarks

By identifying the conditions that lead to good outcomes

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- **With algorithmic interventions**

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 - Recommend new connections to shape the structure of the network

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- **Without algorithmic interventions**

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- **Without algorithmic interventions**
 - Changing the structure of networks strategically

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 - Control for data biases and adjust / calibrate the outputs of algorithms
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- **Without algorithmic interventions**
 - Changing the structure of networks strategically
 - It can be dangerous in the presence of bad actors!

PHASE 1

Network growth under PA+H

Homophily h1

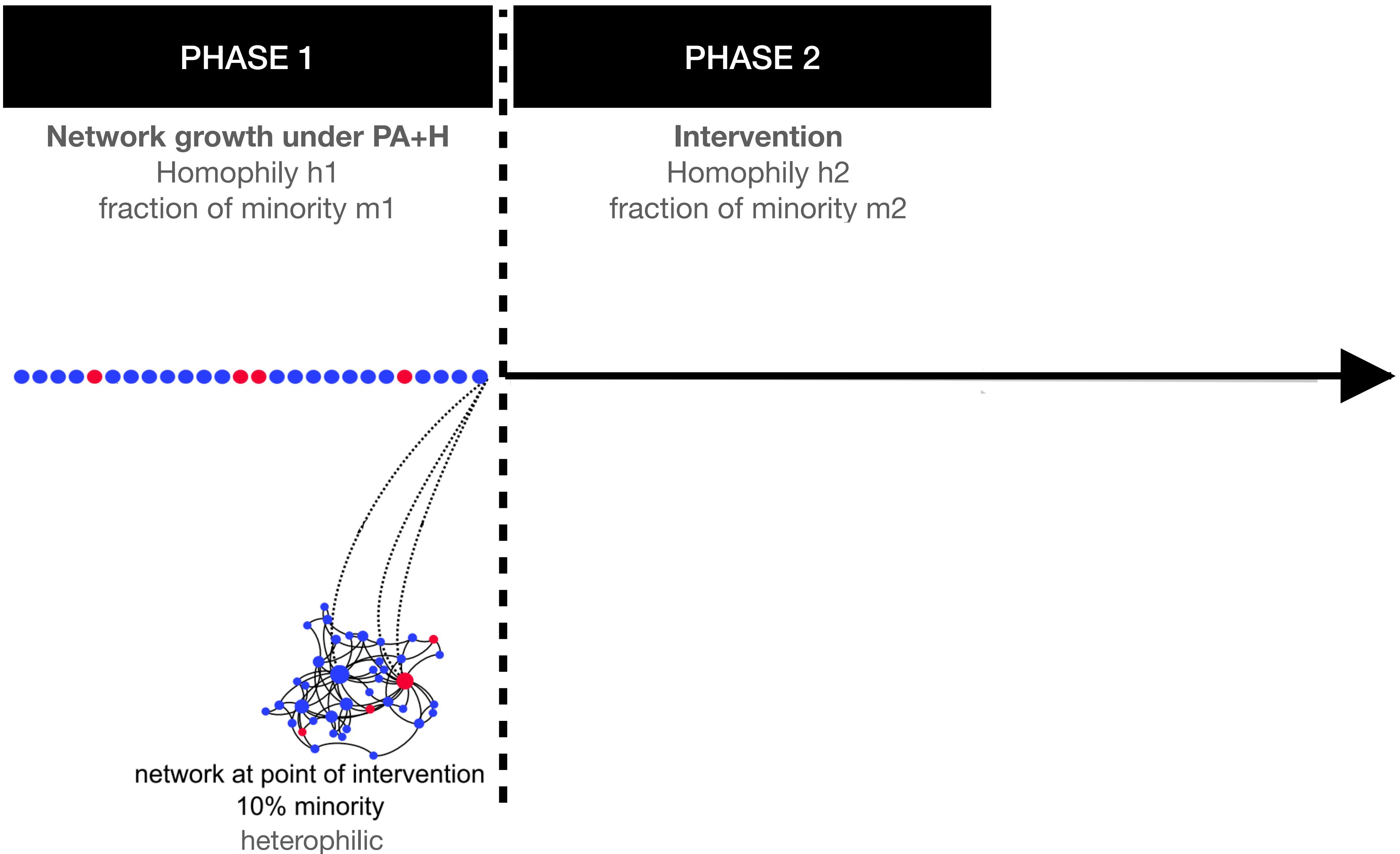
fraction of minority m1

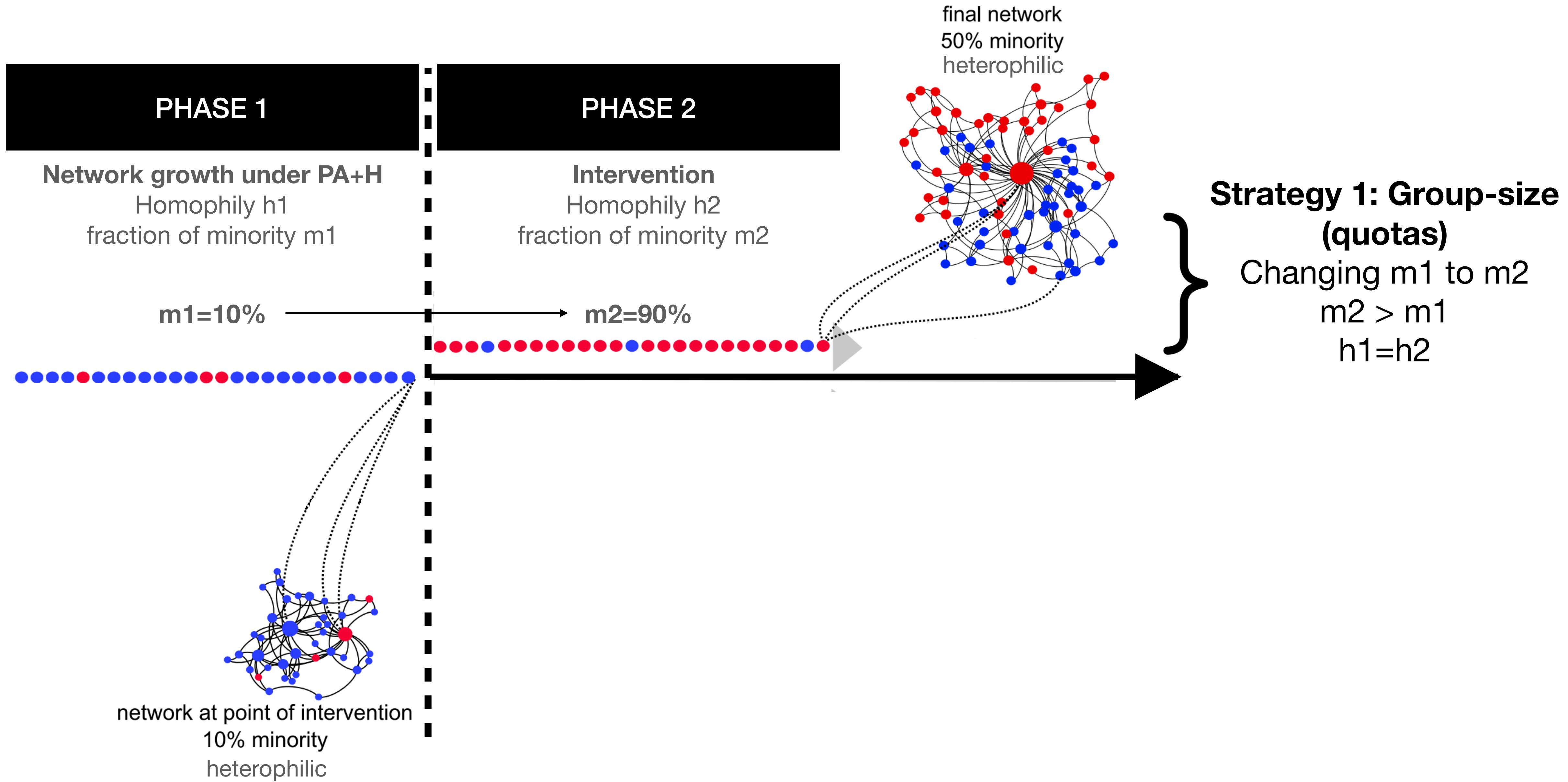


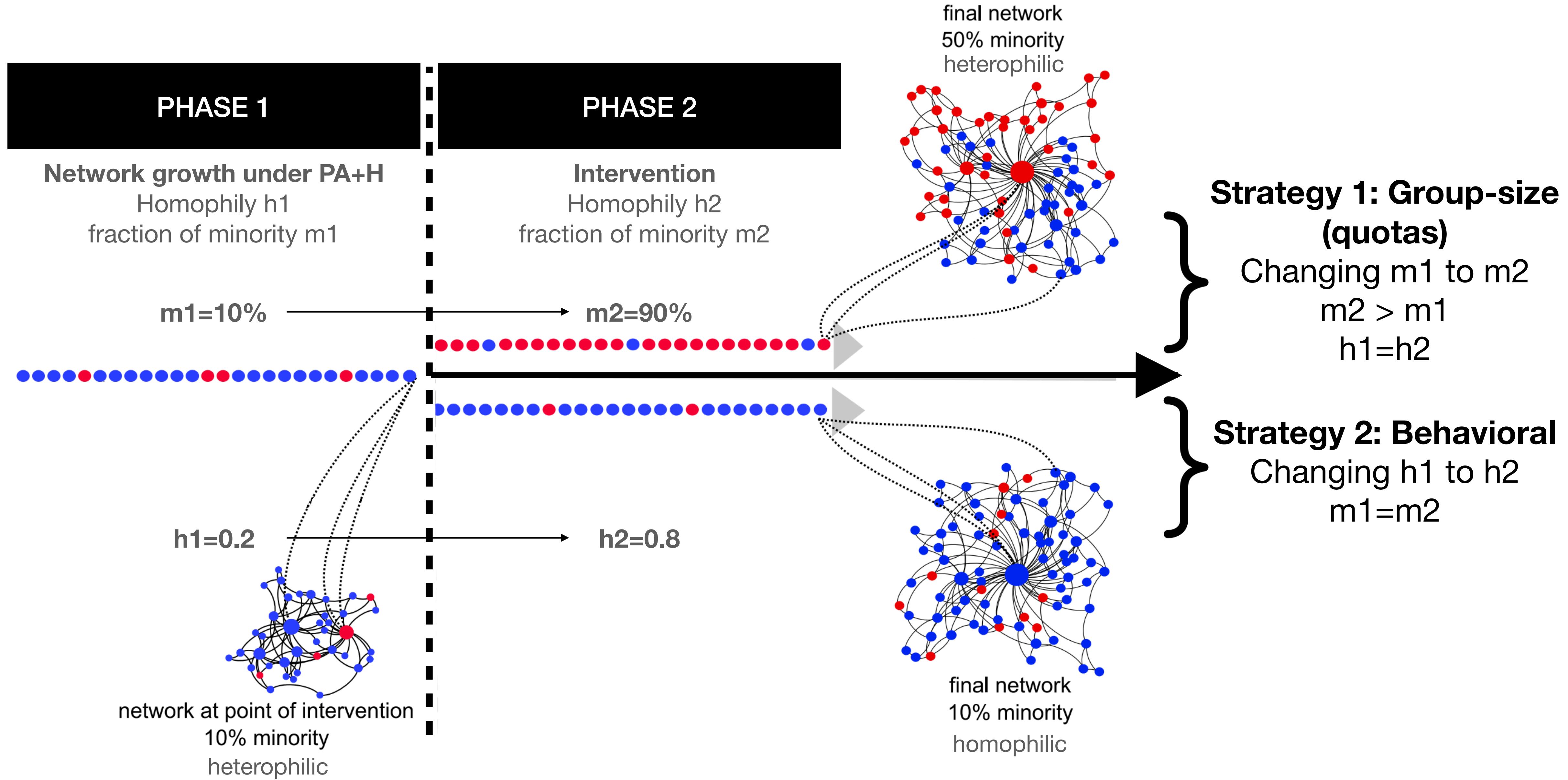
network at point of intervention

10% minority

heterophilic







The effects of changing homophily on minority representation in rankings

..... $h_1 = 0.1$ $h_1 = 0.5$ $h_1 = 0.9$

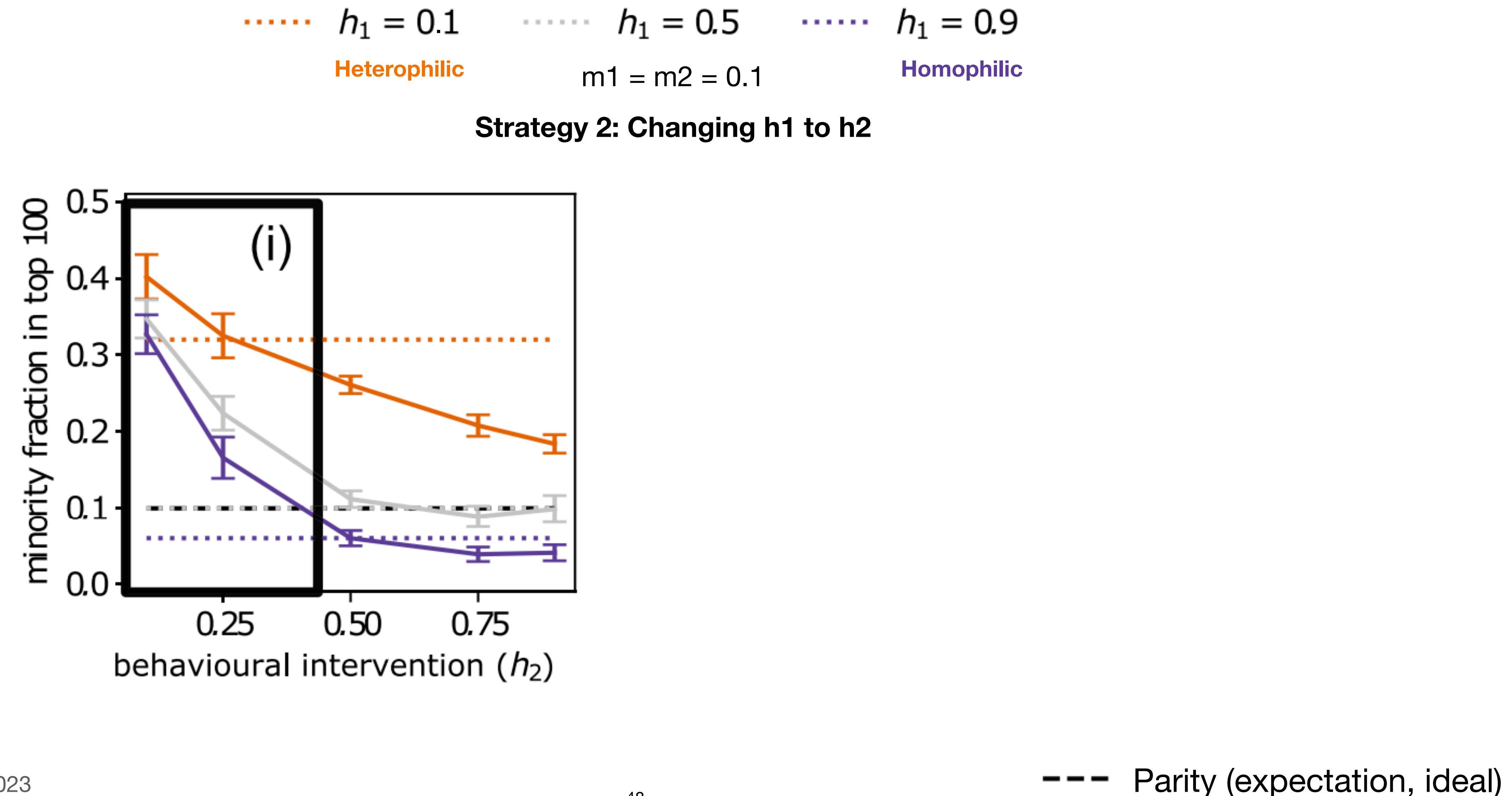
Heterophilic

$m_1 = m_2 = 0.1$

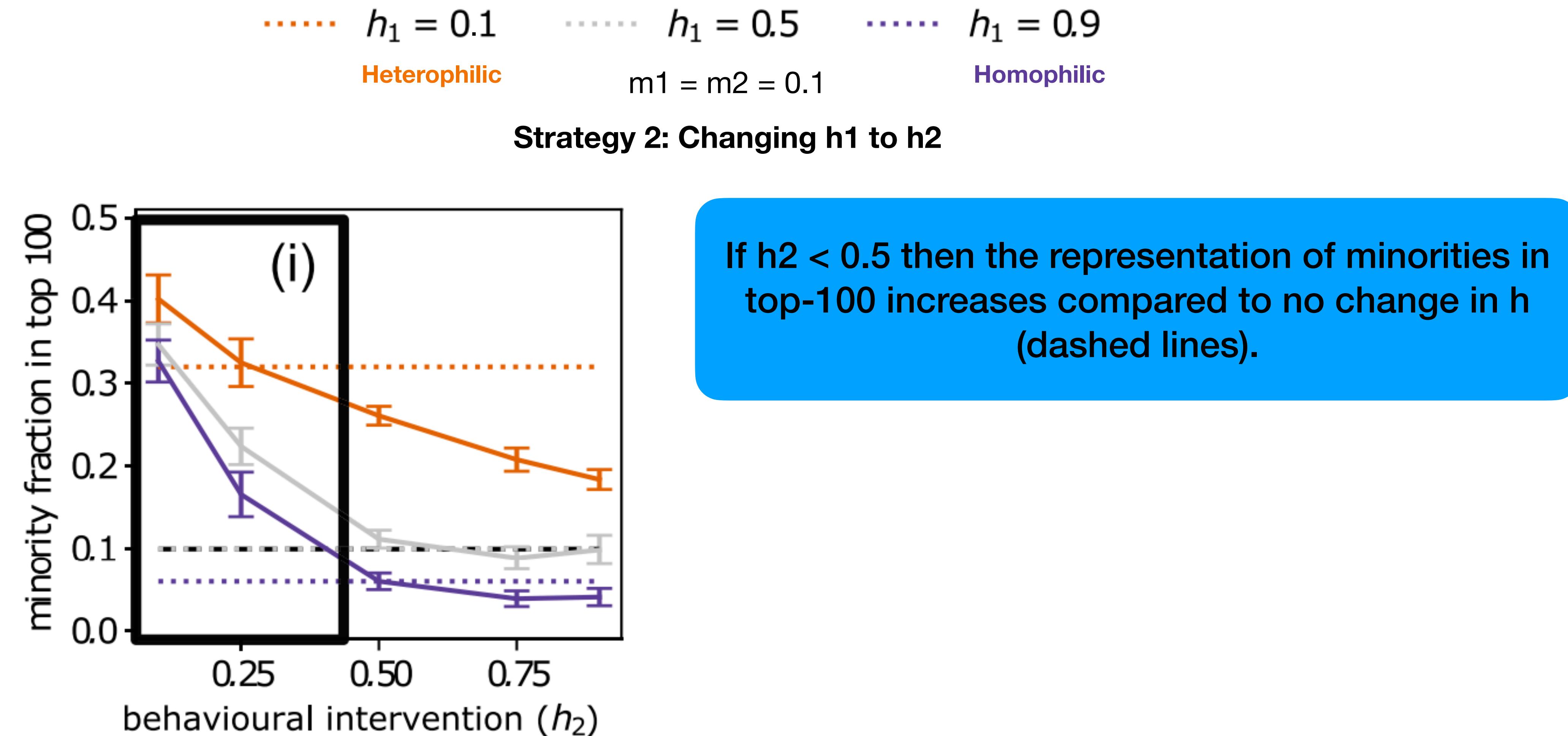
Homophilic

Strategy 2: Changing h_1 to h_2

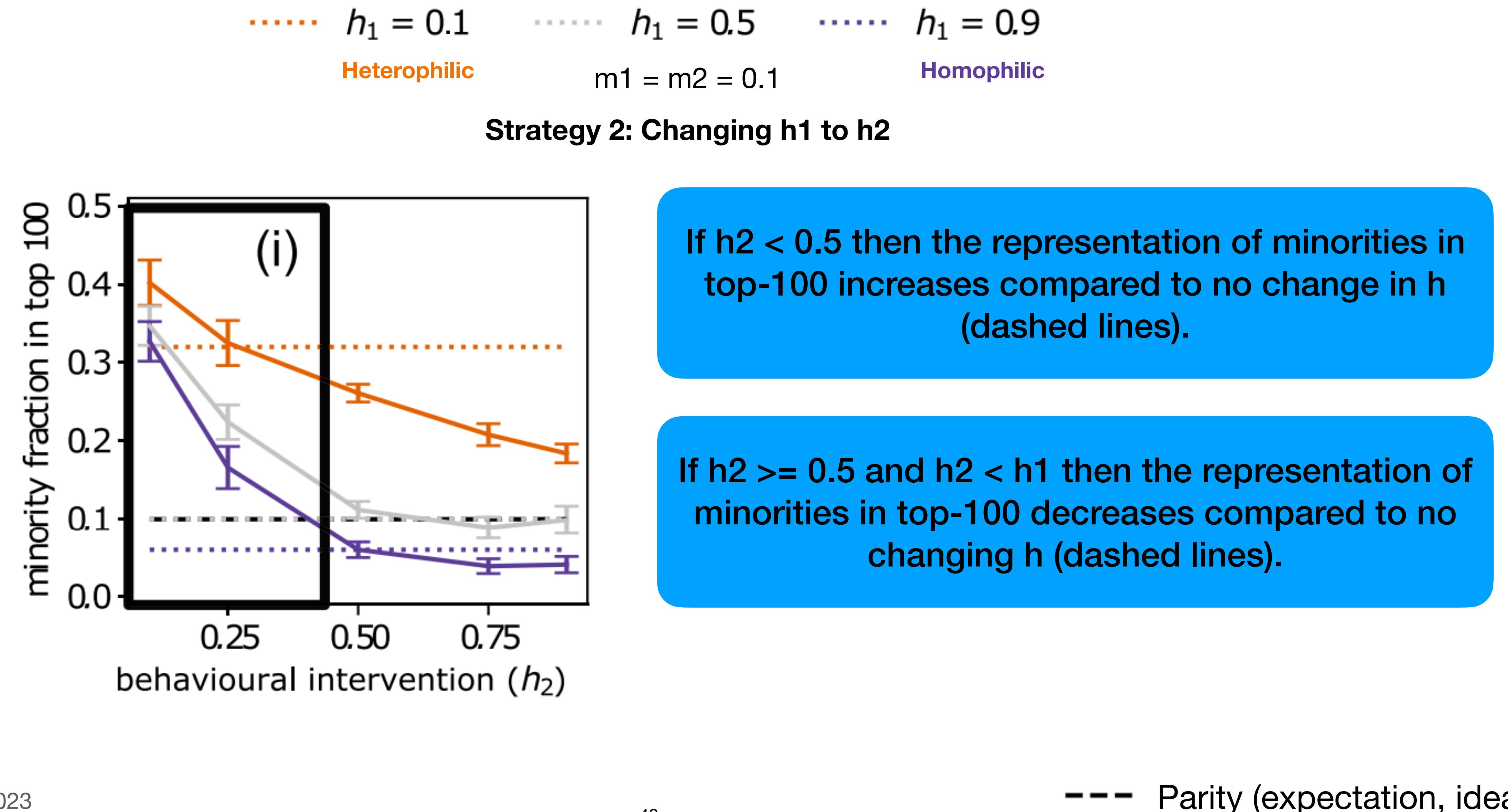
The effects of changing homophily on minority representation in rankings



The effects of changing homophily on minority representation in rankings



The effects of changing homophily on minority representation in rankings



The effects of “quotas” on minority representation in rankings

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Heterophilic

$h_1 = h_2$

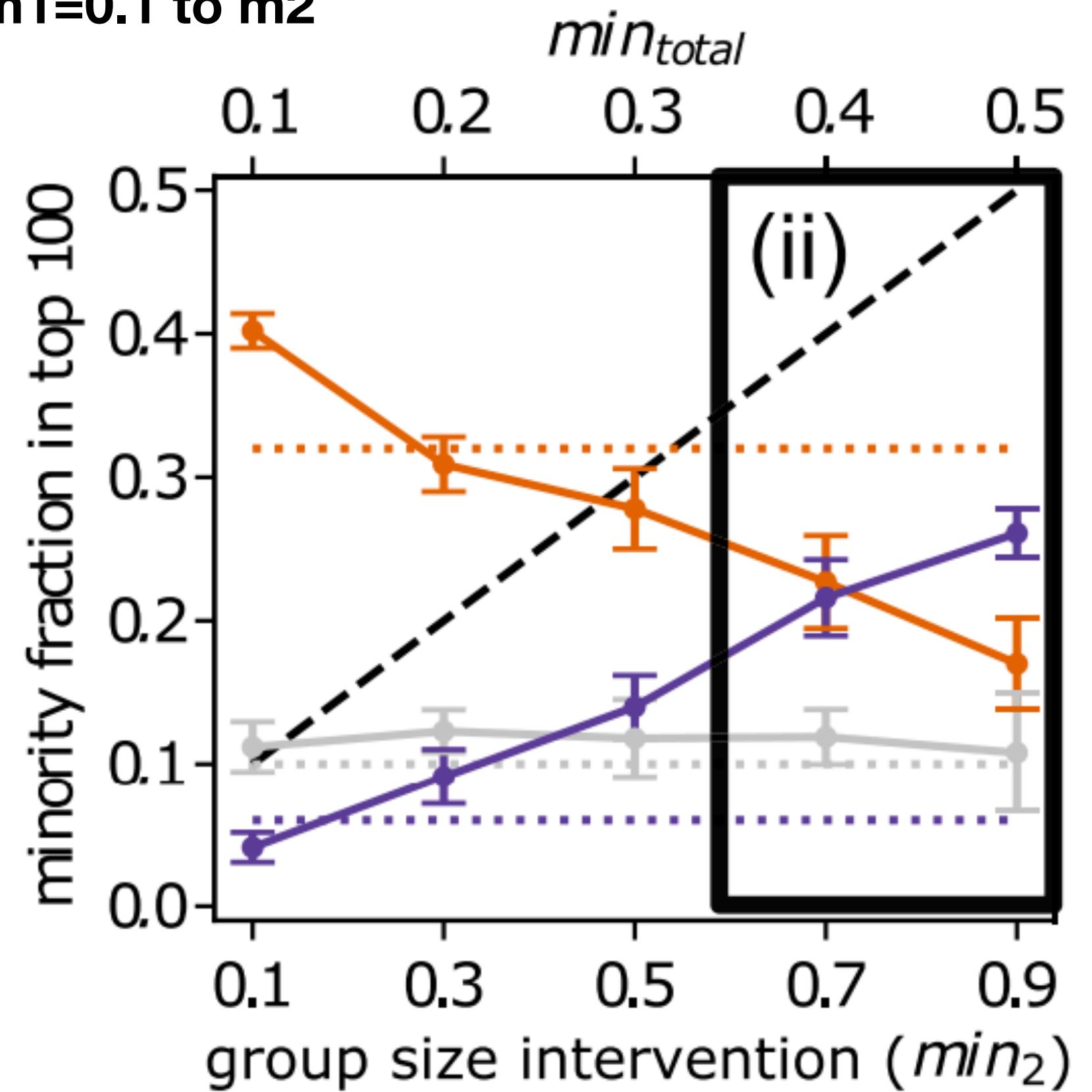
Homophilic

Strategy 1: Changing $m_1=0.1$ to m_2

The effects of “quotas” on minority representation in rankings

..... $h_1 = 0.1$ $h_1 = 0.5$ $h_1 = 0.9$
 Heterophilic h1 = h2 Homophilic

Strategy 1: Changing $m_1=0.1$ to m_2



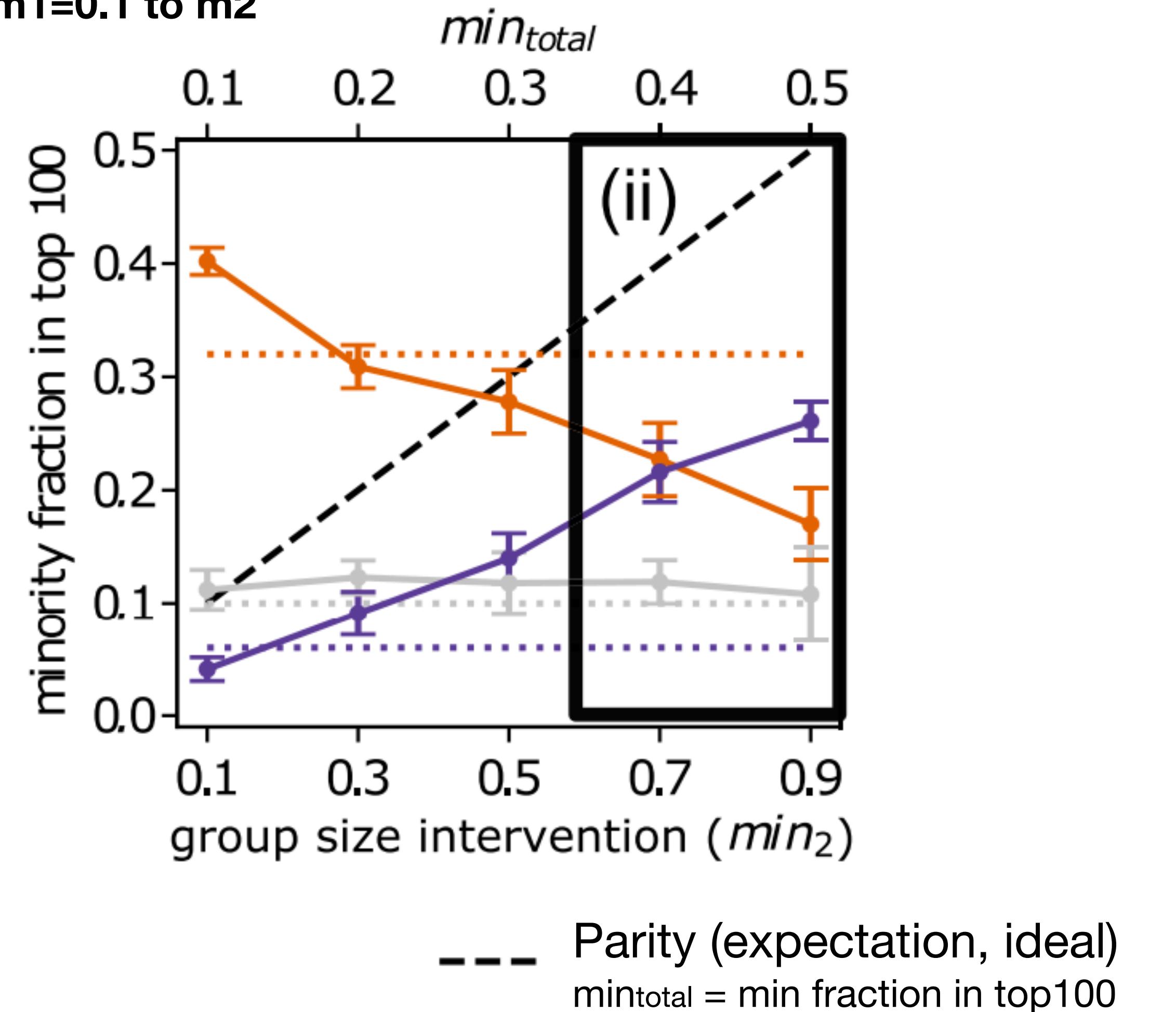
---- Parity (expectation, ideal)
 $min_{total} = \text{min fraction in top100}$

The effects of “quotas” on minority representation in rankings

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Heterophilic $h_1 = h_2$ **Homophilic**

Strategy 1: Changing $m_1=0.1$ to m_2

In the homophilic setting (purple $h=0.9$), the minority representation grows with the final minority size (min_{total}) and quota m_2 .



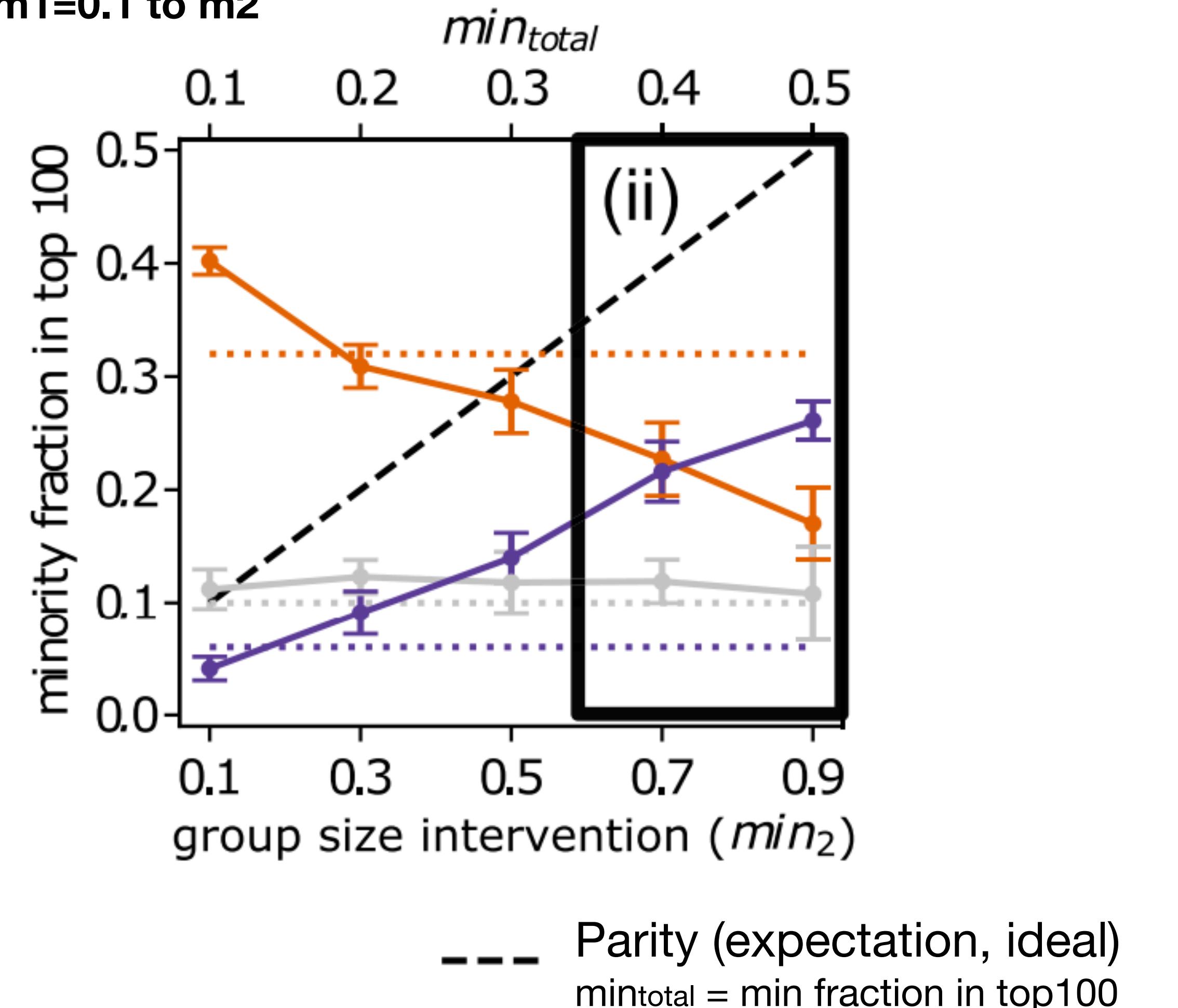
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In the heterophilic setting (orange $h=0.1$), the minority representation decreases with the final minority size (min_{total}) and quota m_2 .



The effects of “quotas” on minority representation in rankings

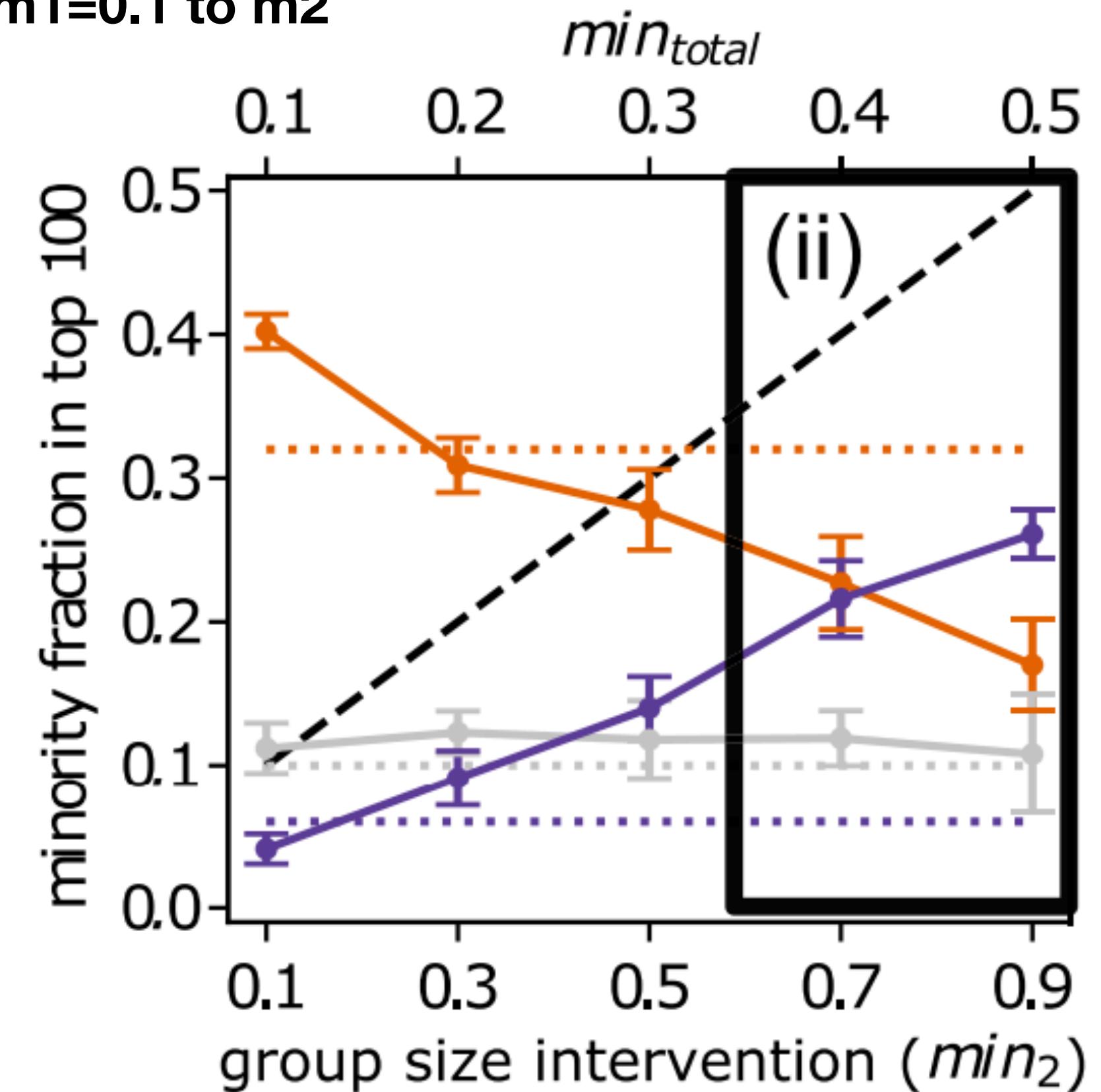
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In the homophilic setting (purple $h=0.9$), the minority representation grows with the final minority size (min_{total}) and quota m_2 .

In the heterophilic setting (orange $h=0.1$), the minority representation decreases with the final minority size (min_{total}) and quota m_2 .

In the neutral case (grey $h=0.5$), we see no impact of a quota at all



---- Parity (expectation, ideal)
 $min_{total} = \text{min fraction in top100}$

Recap!



Inequalities on networks

Inequalities on networks

- Networks are biased because their nodes and edges are biased!

Inequalities on networks

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 - Multiple mechanisms of edge formation can occur at the same time in one network

Inequalities on networks

- Networks are biased because their nodes and edges are biased!
 - Groups are unbalanced
 - Mechanisms of edge formation are biased towards:
 - Popular nodes
 - Similar nodes
 - Multiple mechanisms of edge formation can occur at the same time in one network
 - The `netin` python package offers multiple network models with homophily and preferential attachment

Inequalities on algorithms

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- Algorithms can be biased for multiple reasons

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- Algorithms can be biased for multiple reasons
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 - The algorithm is biased
 - The output is biased

Inequalities on algorithms

- Algorithms can be biased for multiple reasons
 - The data is biased
 - The algorithm is biased
 - The output is biased
 - Human assessment is biased

Inequalities on network-based algorithms

Inequalities on network-based algorithms

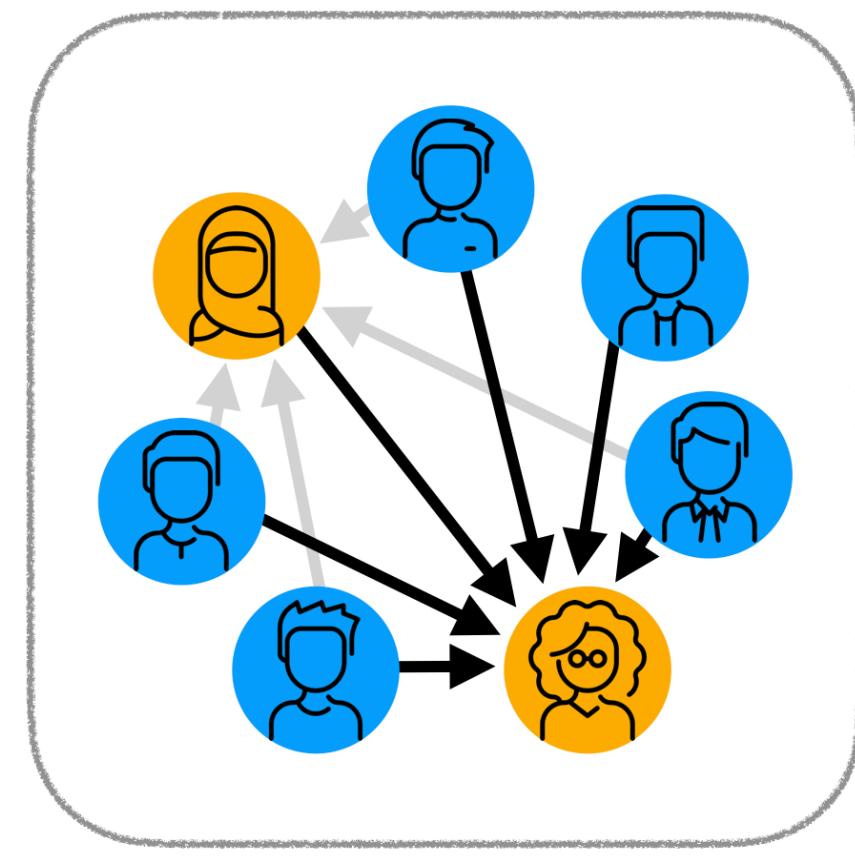
- Biases in network-based algorithms can be explained thanks to the structural nature of networks!

Inequalities on network-based algorithms

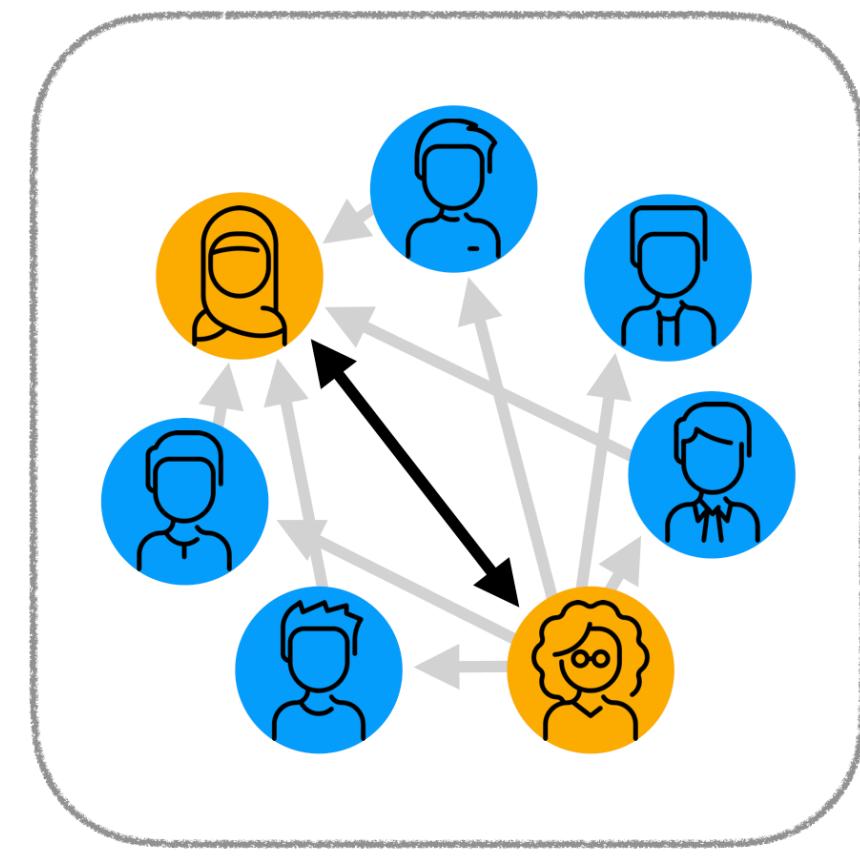
- Biases in network-based algorithms can be explained thanks to the structural nature of networks!
 - Certain mechanisms of edge formation can explain certain algorithmic biases

Inequalities on network-based algorithms

- Biases in network-based algorithms can be explained thanks to the structural nature of networks!
 - Certain mechanisms of edge formation can explain certain algorithmic biases
 - If we understand these correlations, we can propose better mitigation strategies to reduce inequalities

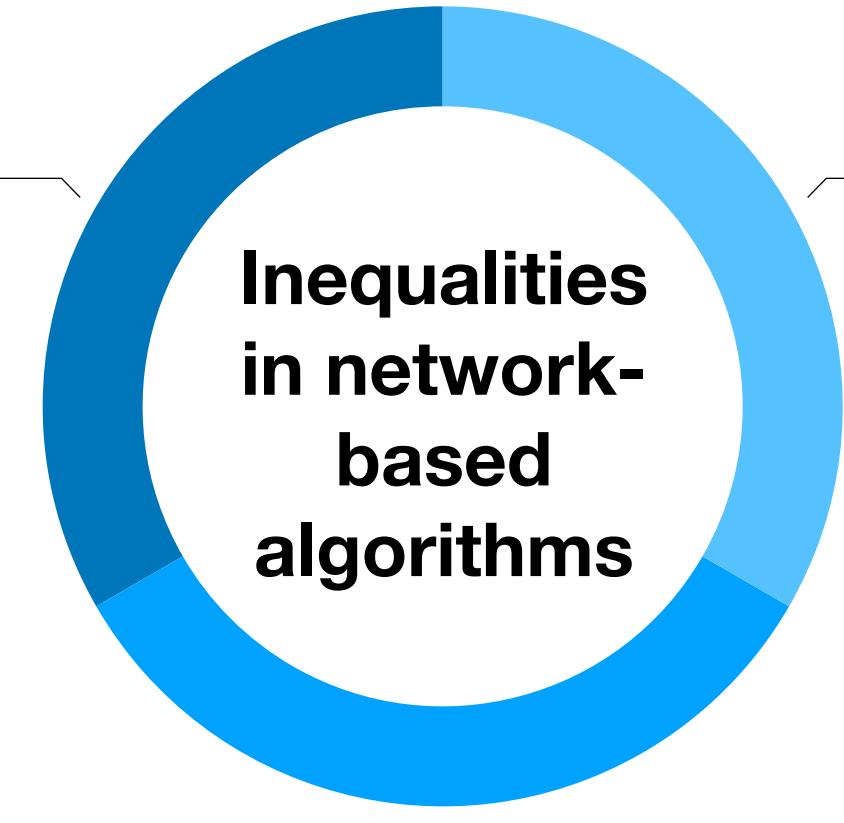


Popularity



Homophily

Mitigating
inequalities



Understanding
inequalities

Identifying
inequalities

Inequality II. Networks and Algorithms

Lisette Espín-Noboa | 31.May.2023 | TU Wien
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www.lisetteespin.info

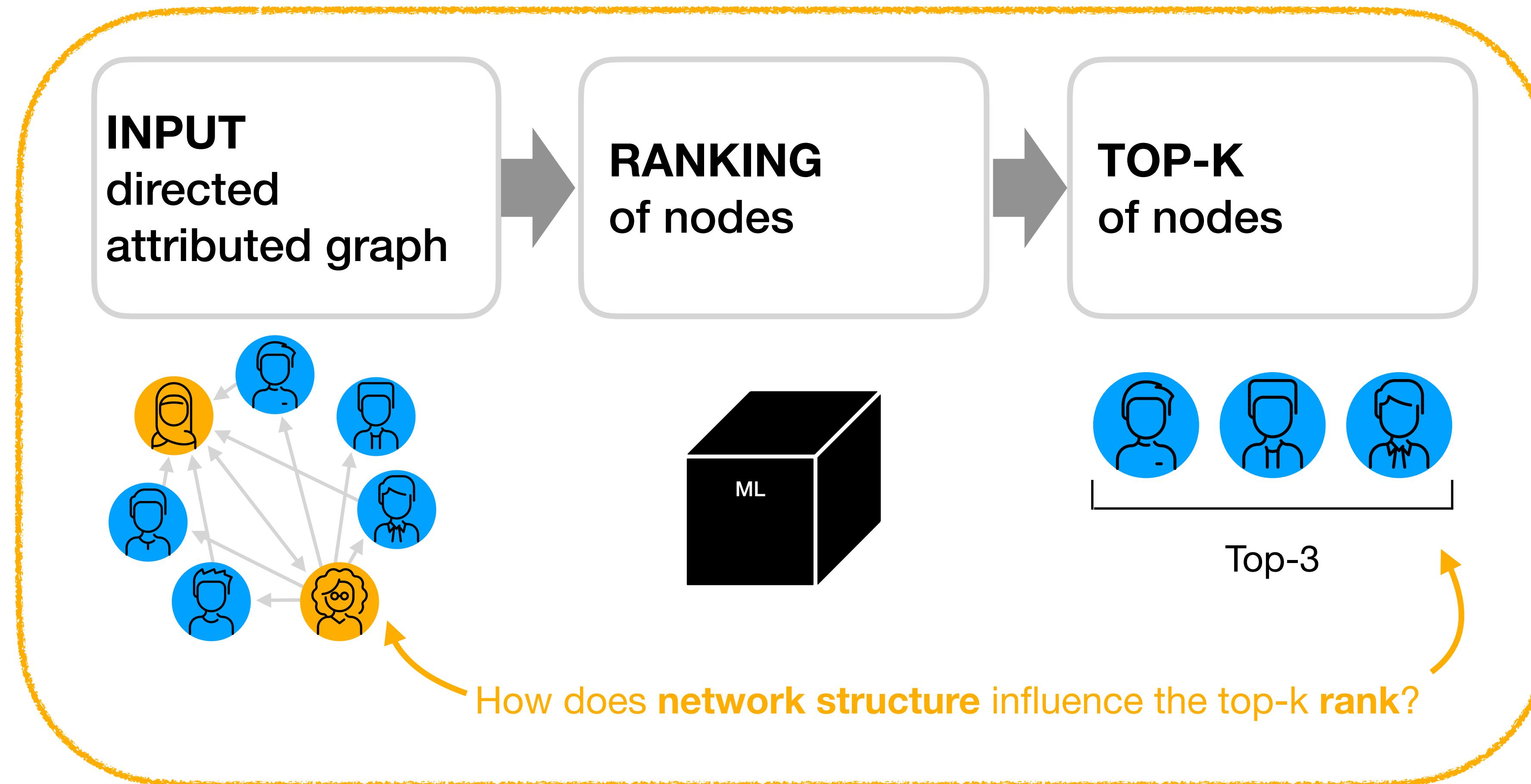
[Tutorial]
SOCIAL NETWORK MODELING AND APPLICATIONS
<https://bit.ly/snma2023>

Backups

Important properties of social networks

#	Graph	Node	Edge
1	Average and minimum degree (note: average degree does not make sense if you have power-law degree distribution)	Degree (in/out)	Weights
2	Degree distribution (the probability that a randomly selected node in the network has degree k)	Centrality (e.g., PageRank)	Shortest path
3	Adjacency matrix / Mixing matrix	Clustering coefficient	Homophilous type (MM, Mm, mm, mM)
4	Sparsity (out of the total possible number of edges, how many actually exist)	Activity (high activity = high outdegree)	
5	Diameter		
6	Average Path Length		
7	Connected components		

Evaluation benchmarks in “ranking inequalities”

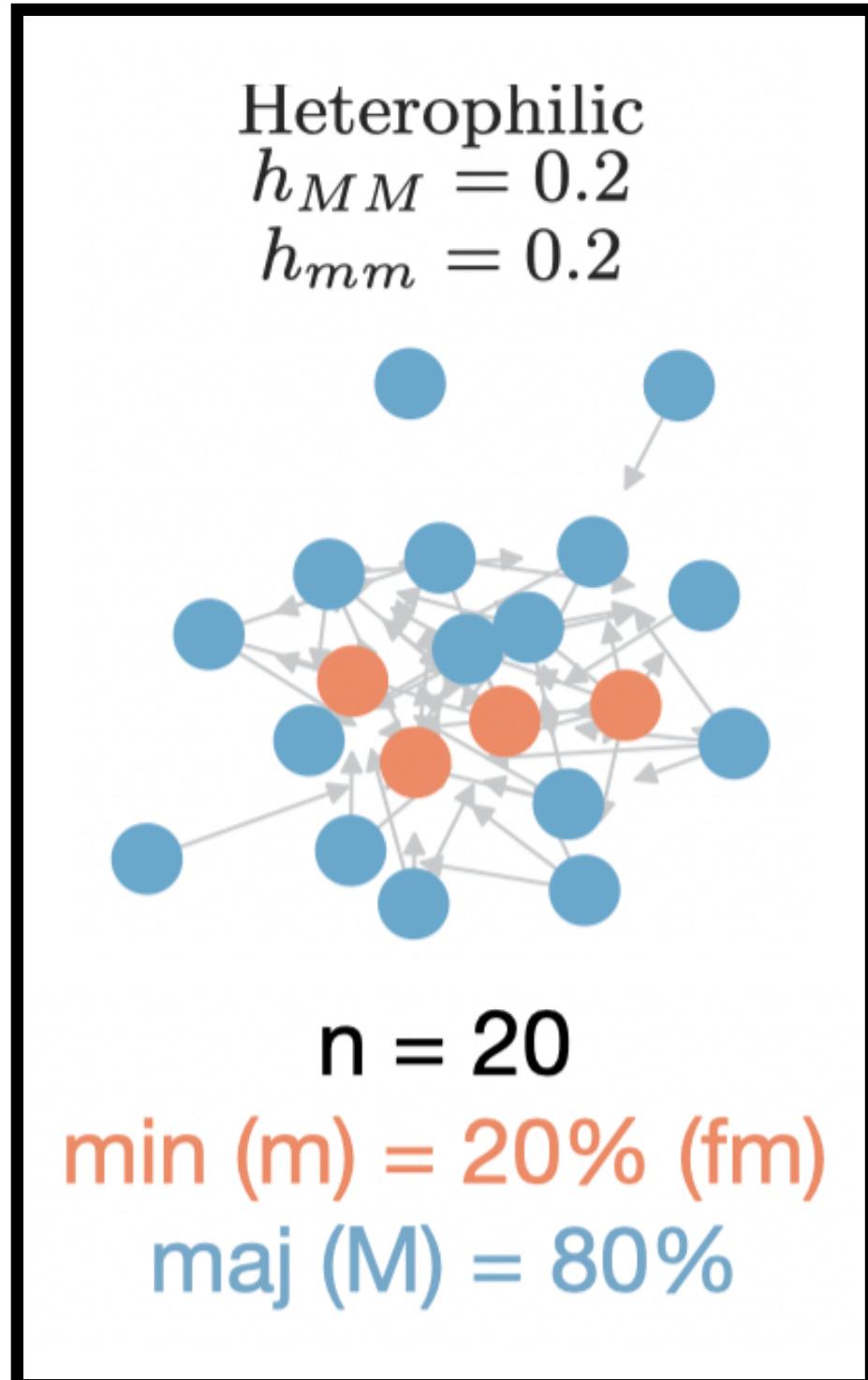


Espín-Noboa et al. SciRep'2022

Inequality, inequity, and disparity

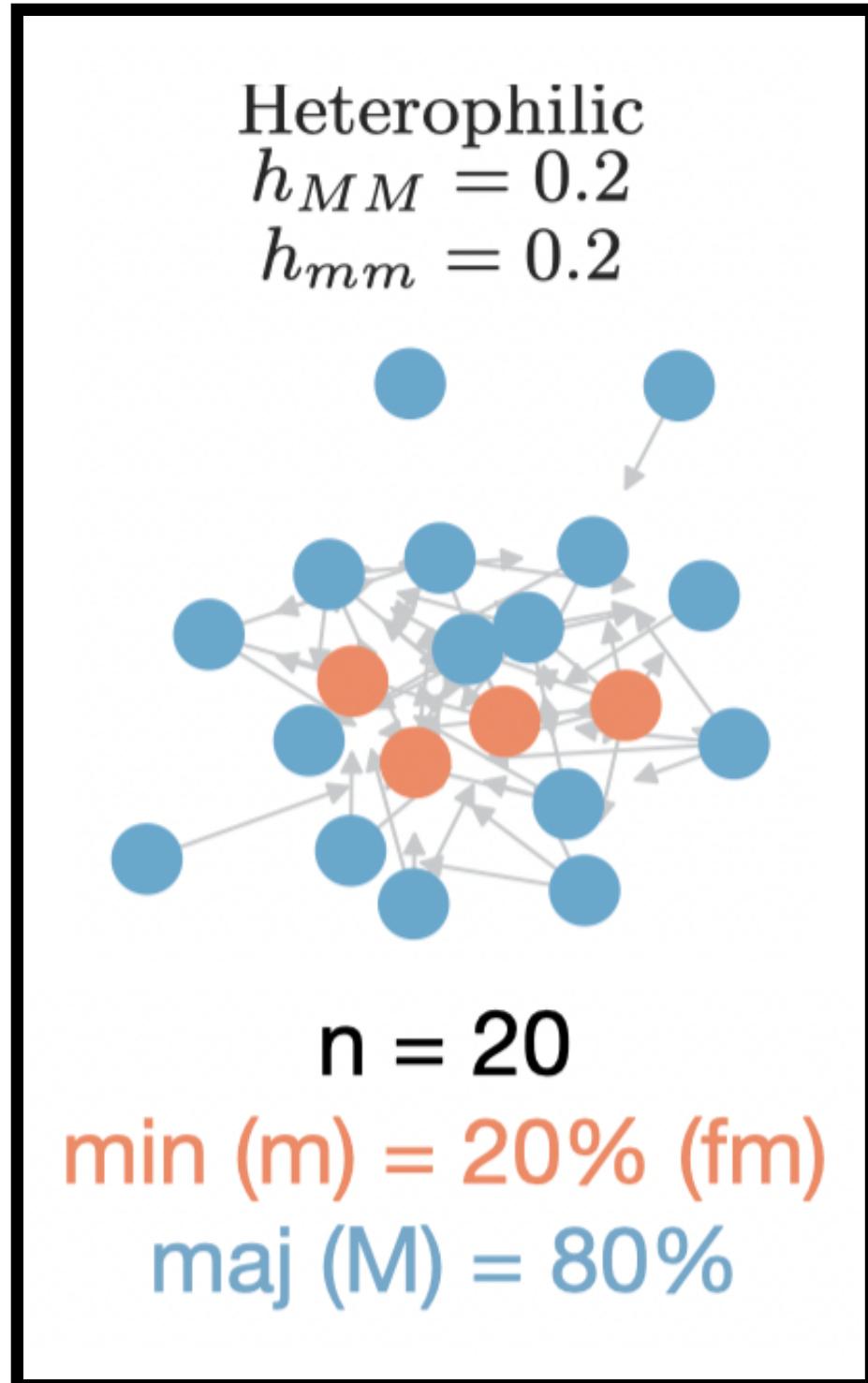
Inequality, inequity, and disparity

Given a network,

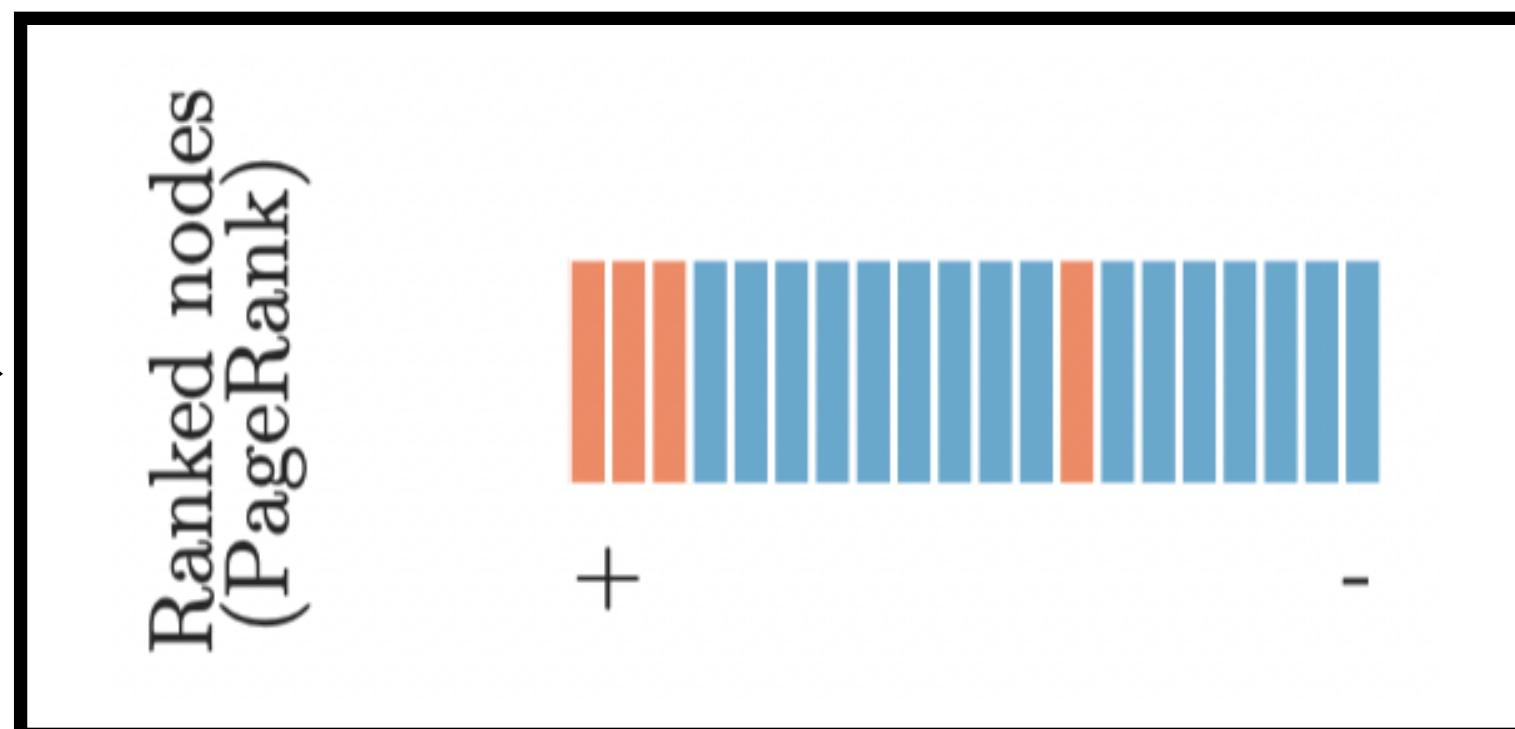


Inequality, inequity, and disparity

Given a network,

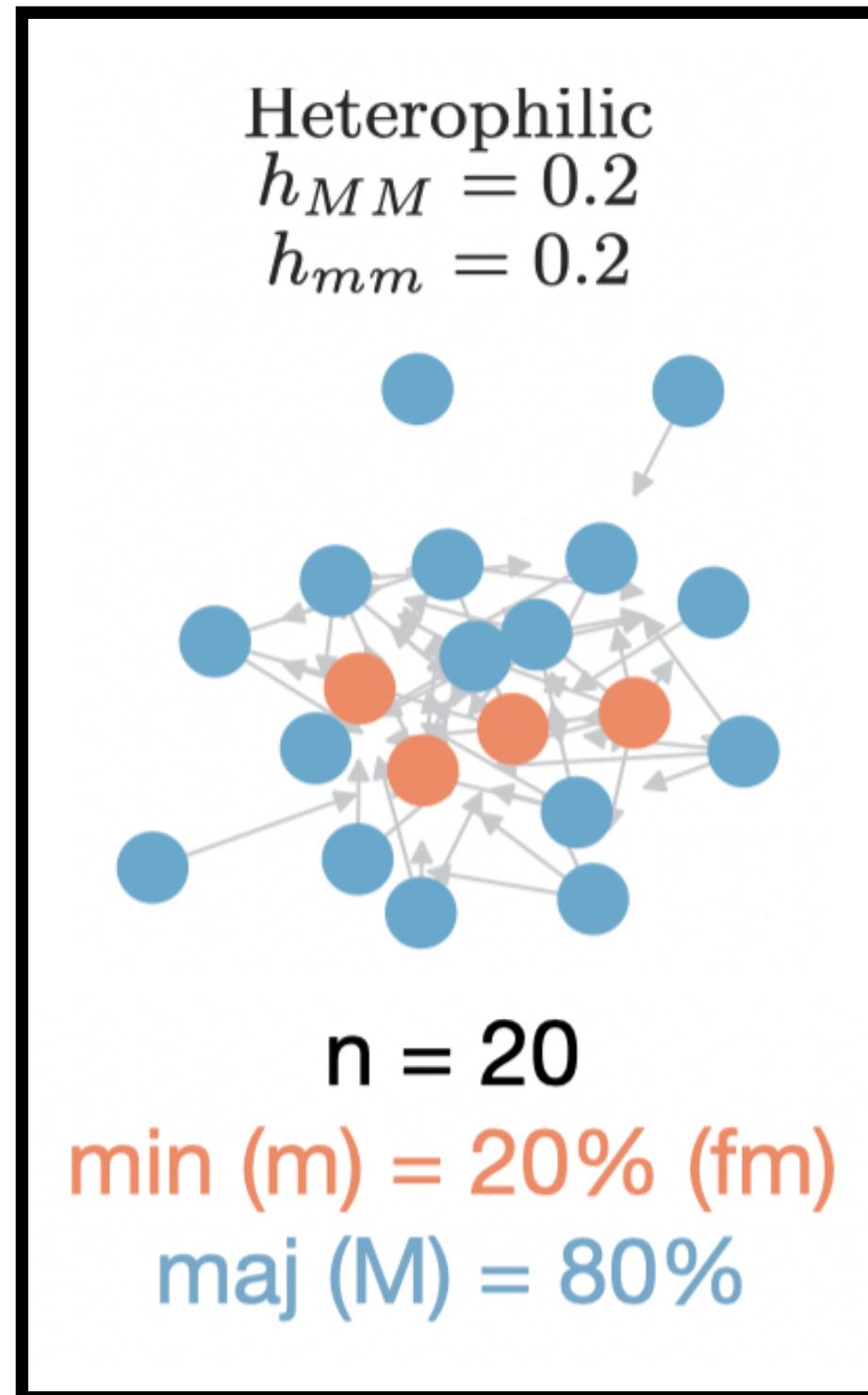


... and a ranking of its nodes

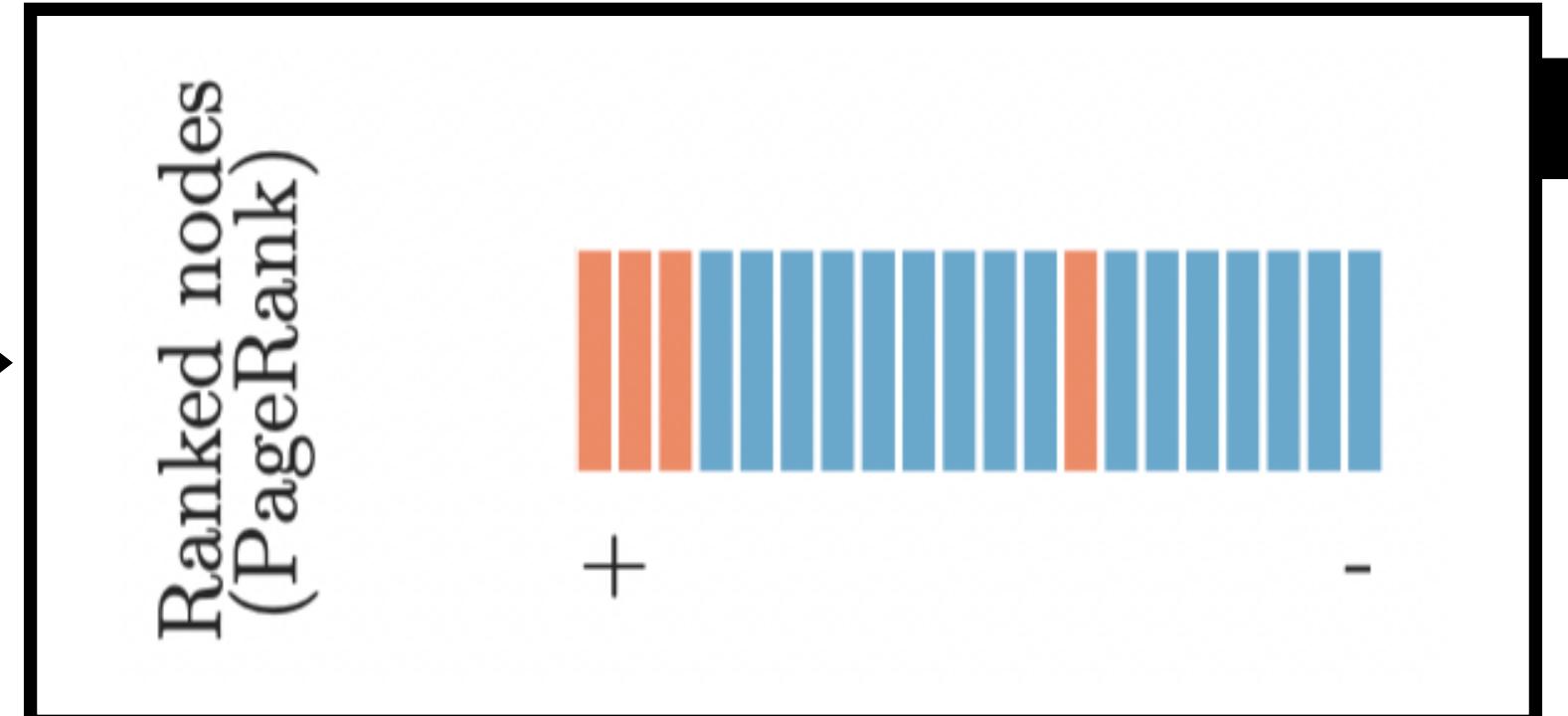


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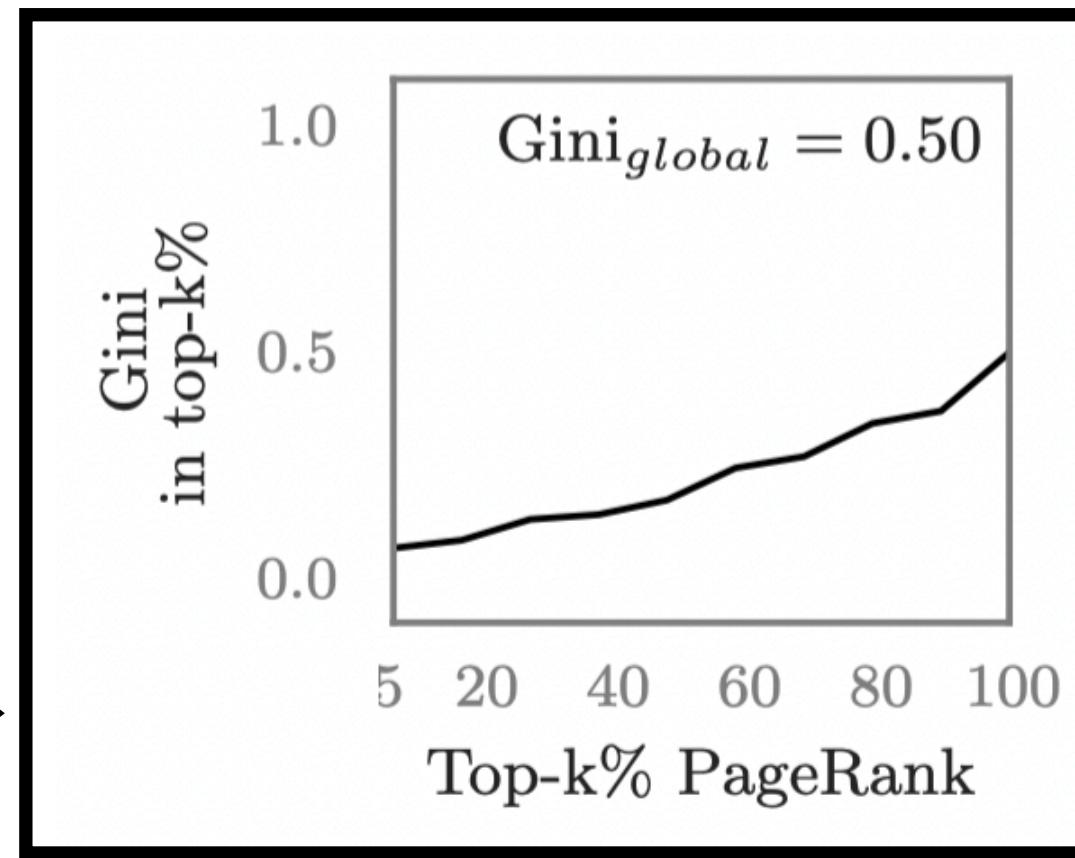
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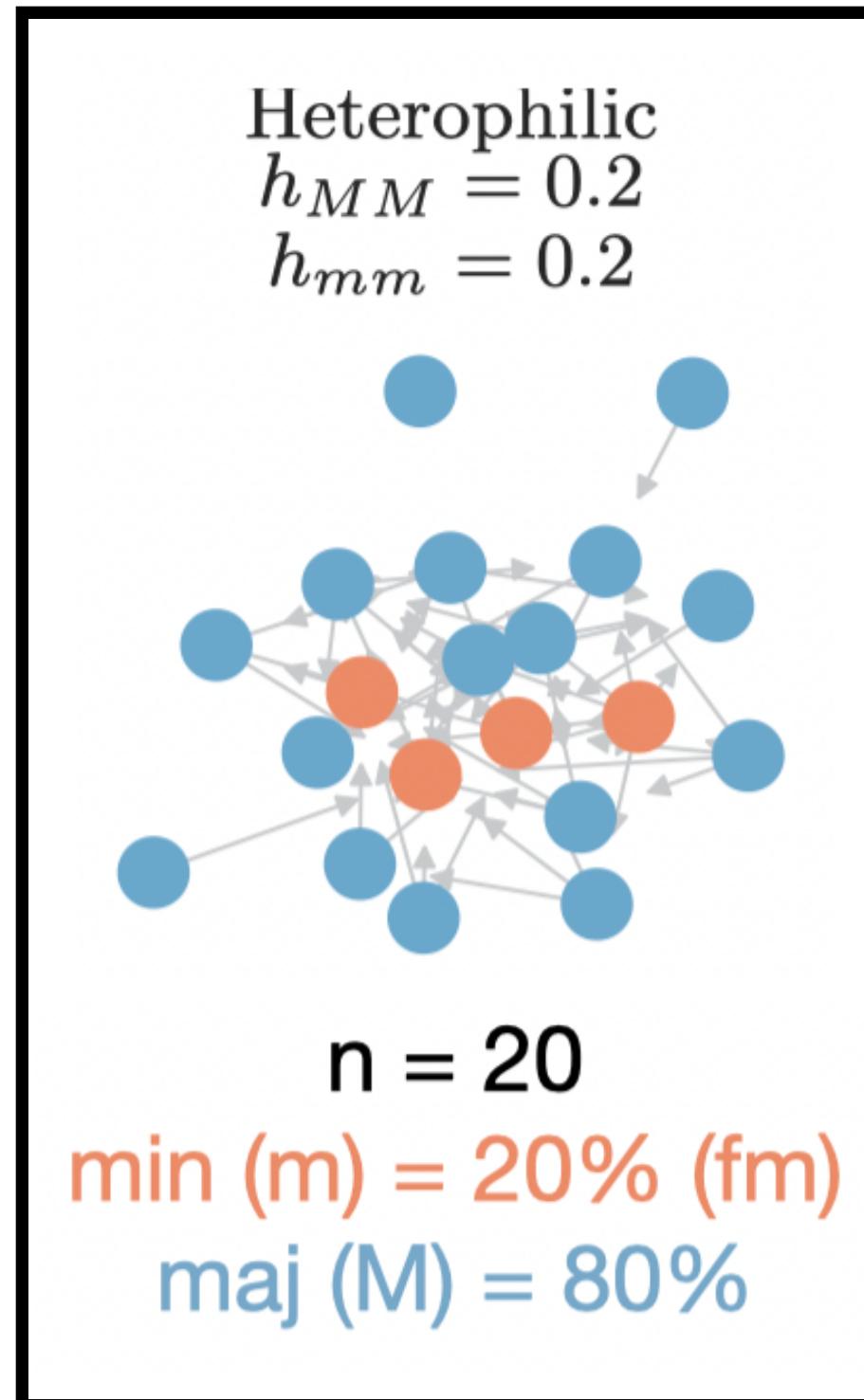
Measure:



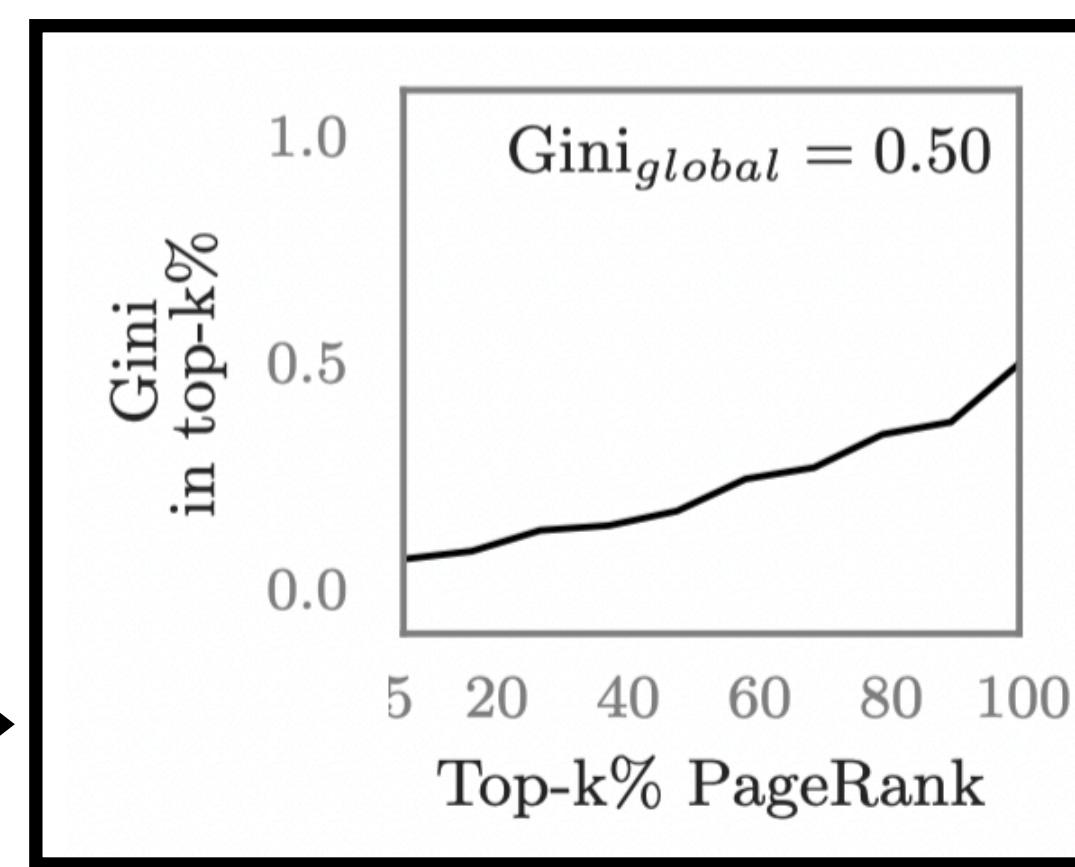
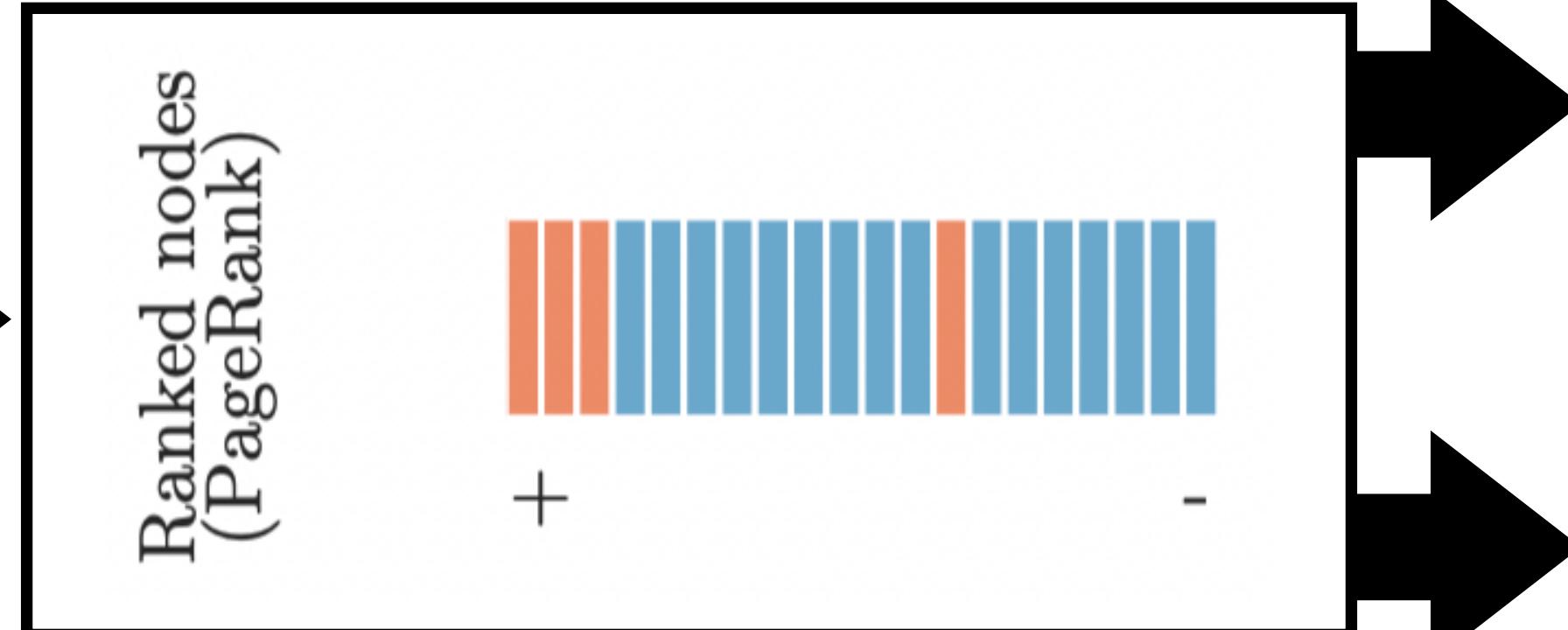
Inequality

Inequality, inequity, and disparity

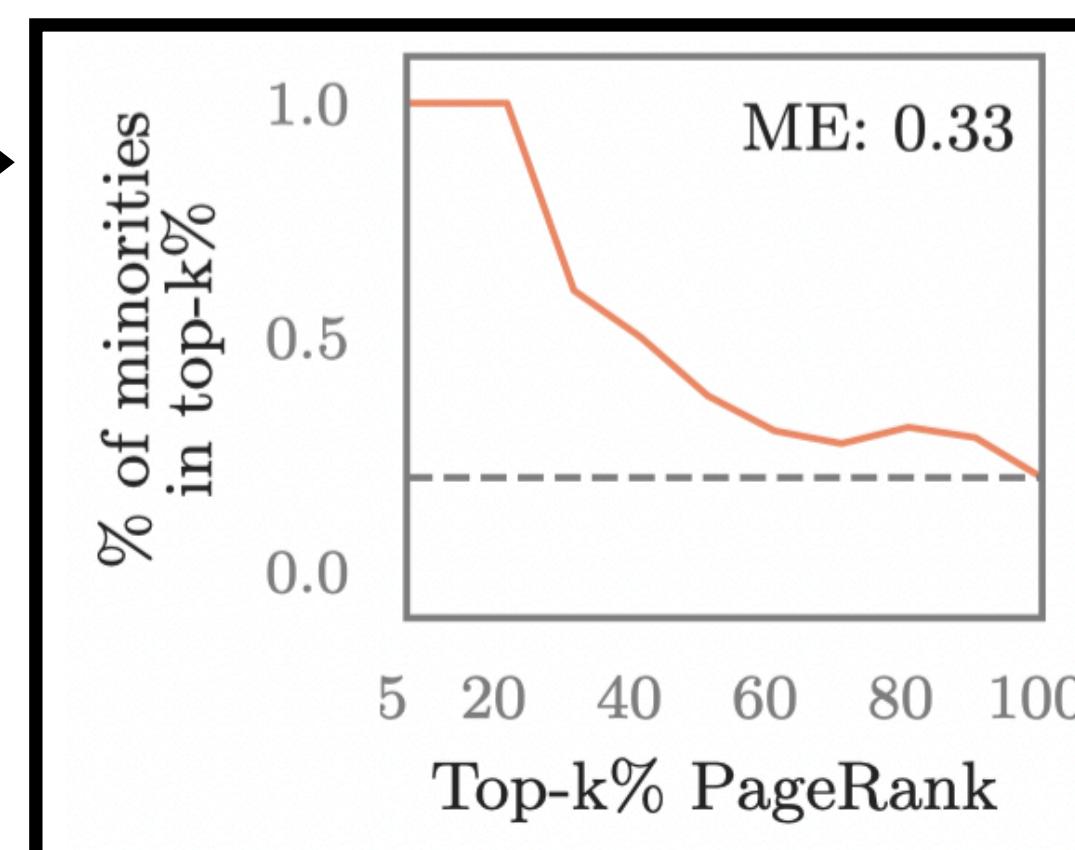
Given a network,



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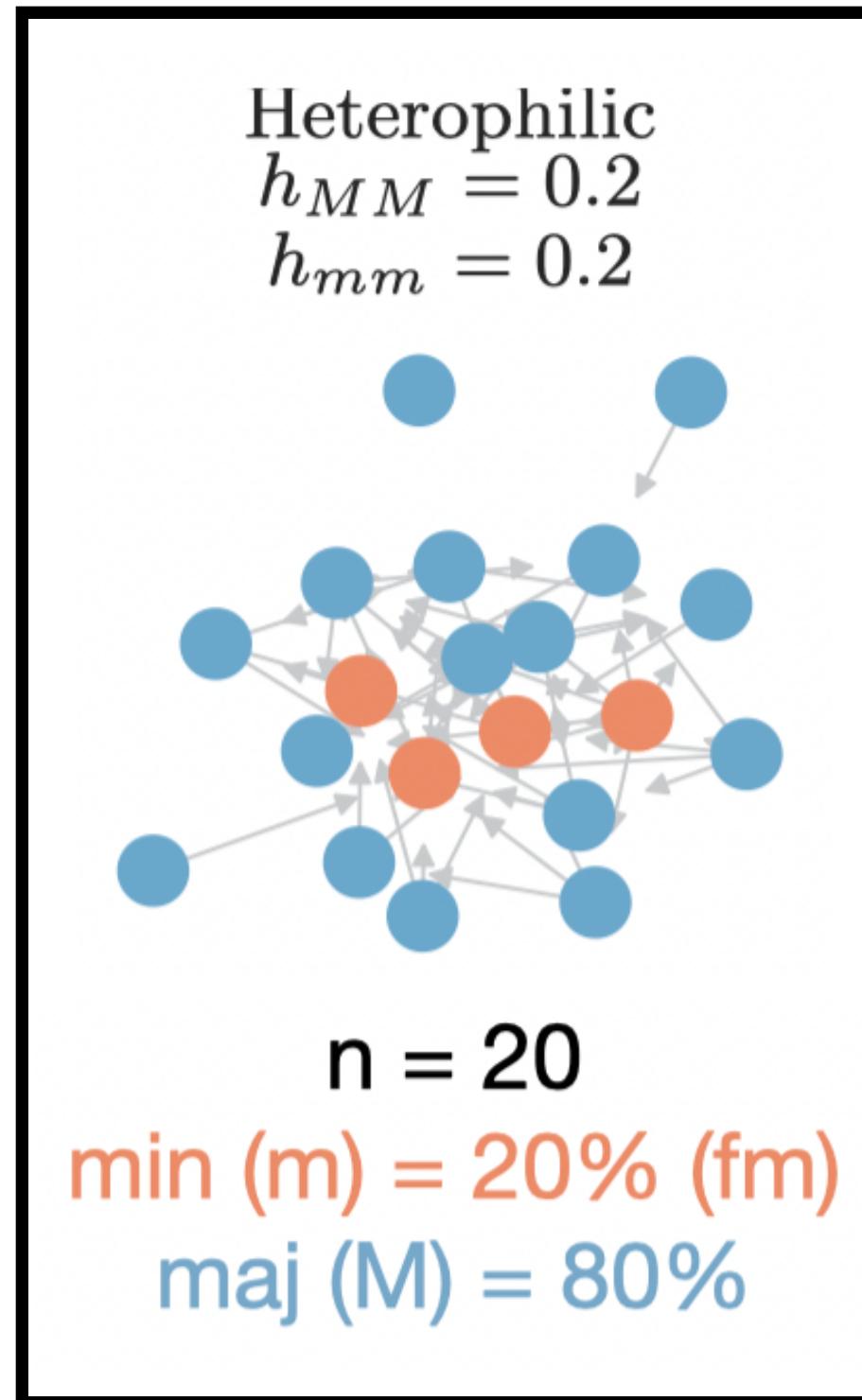
Inequality



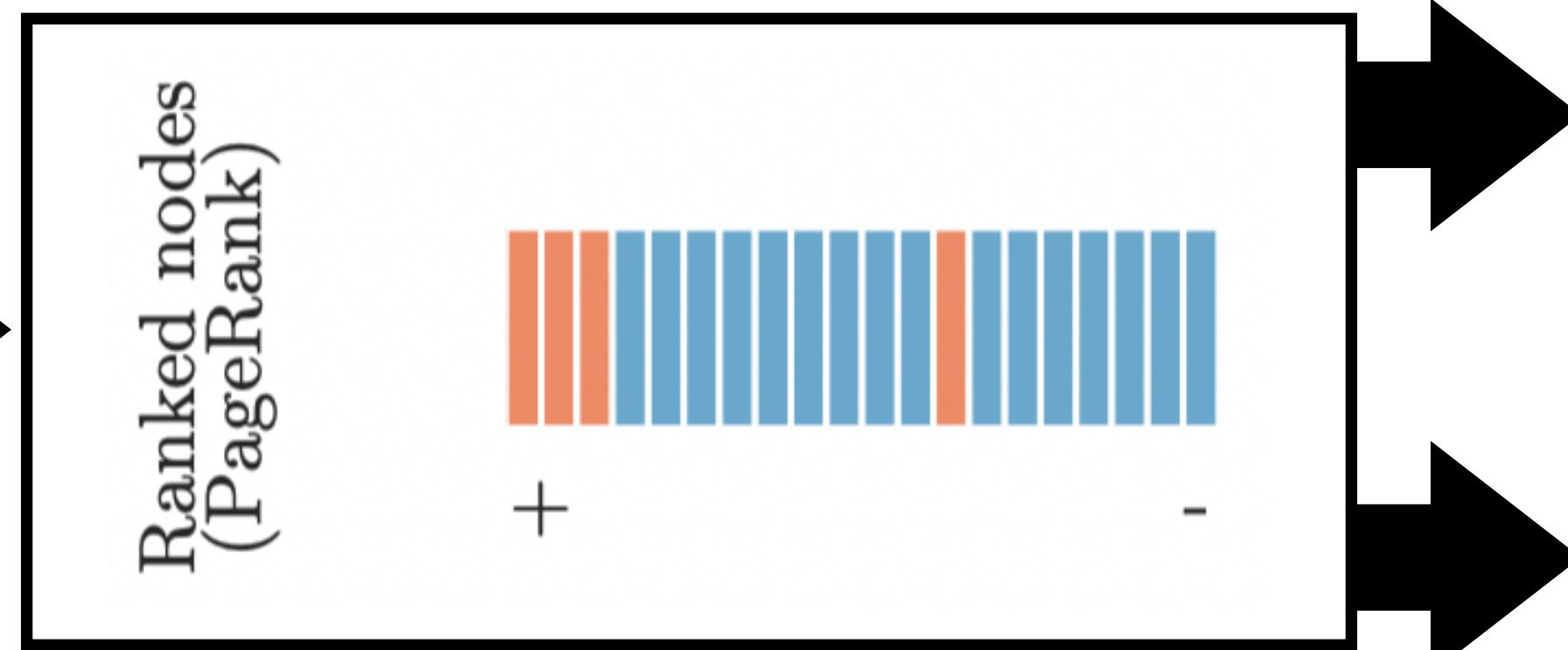
Inequity

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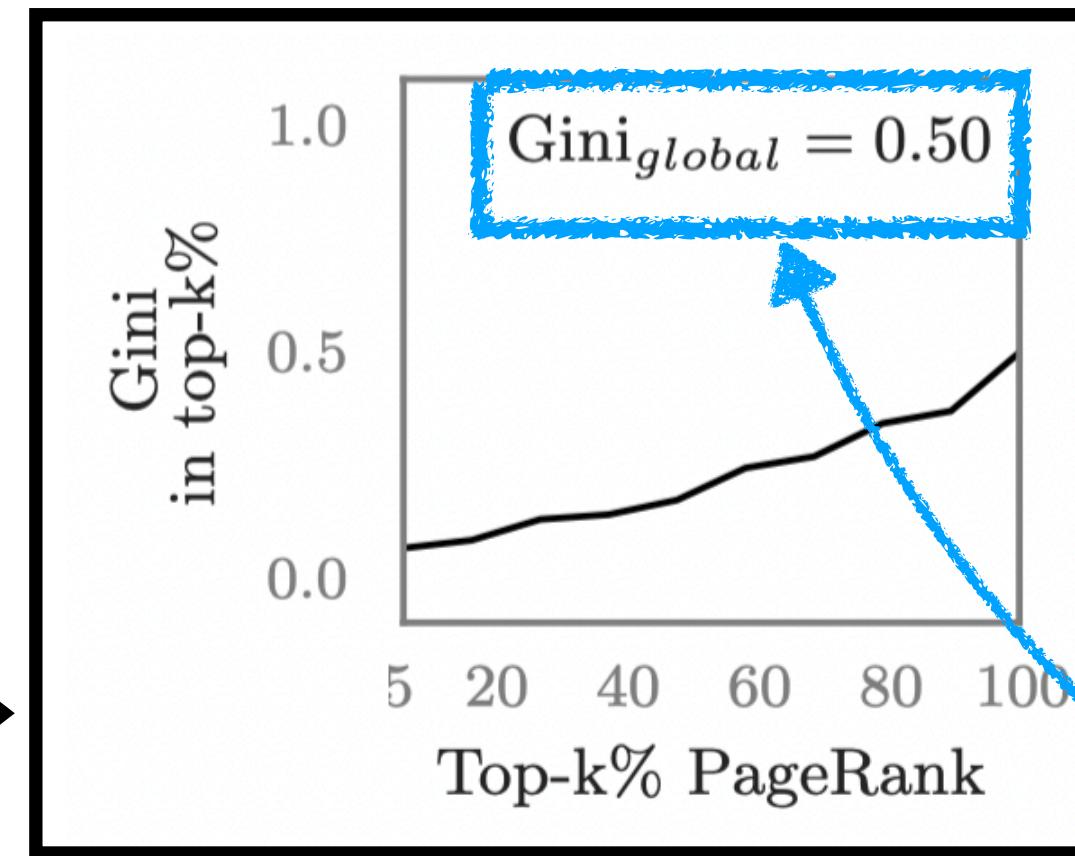
Given a network,



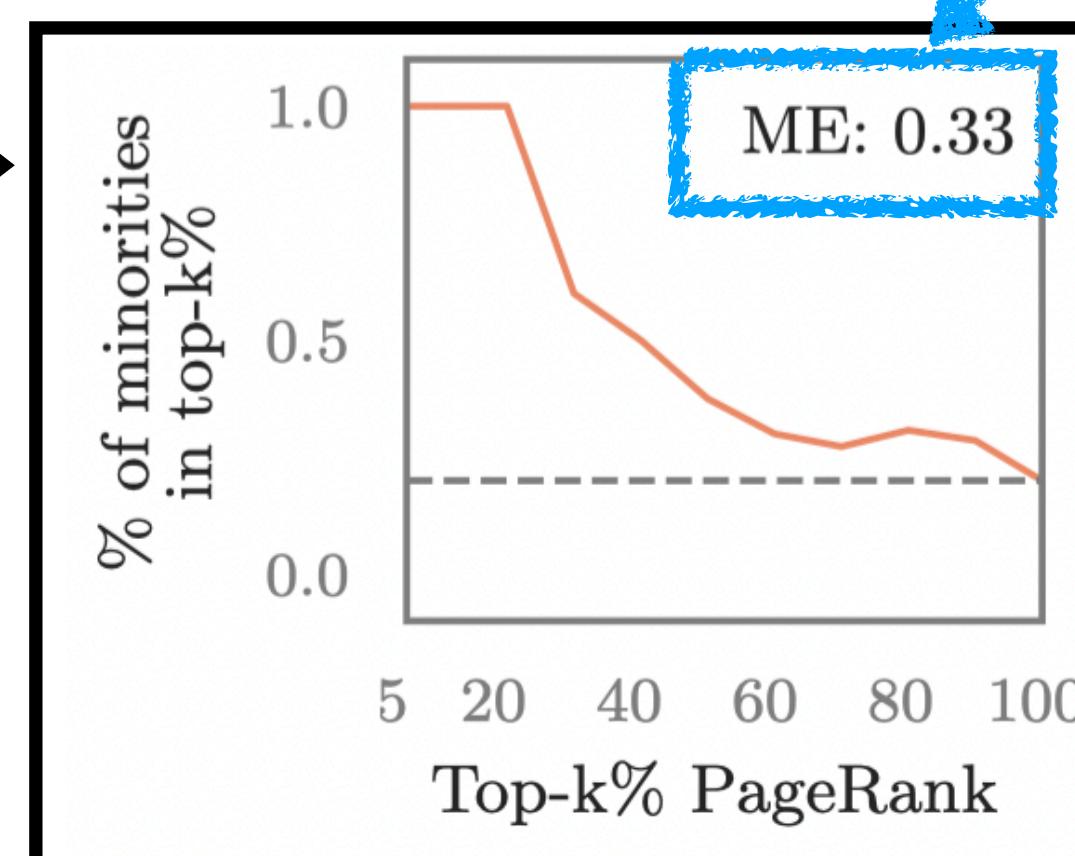
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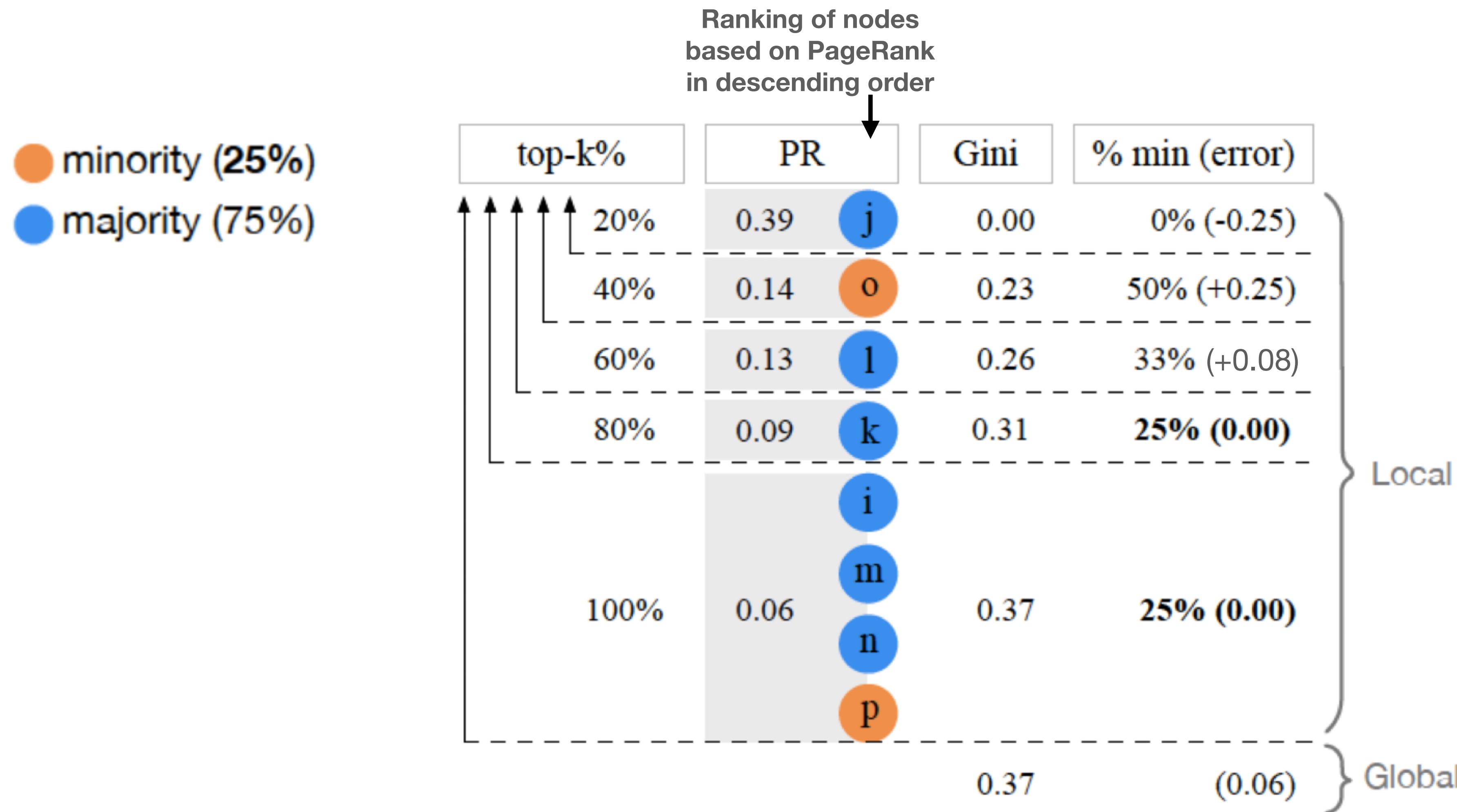
Inequality



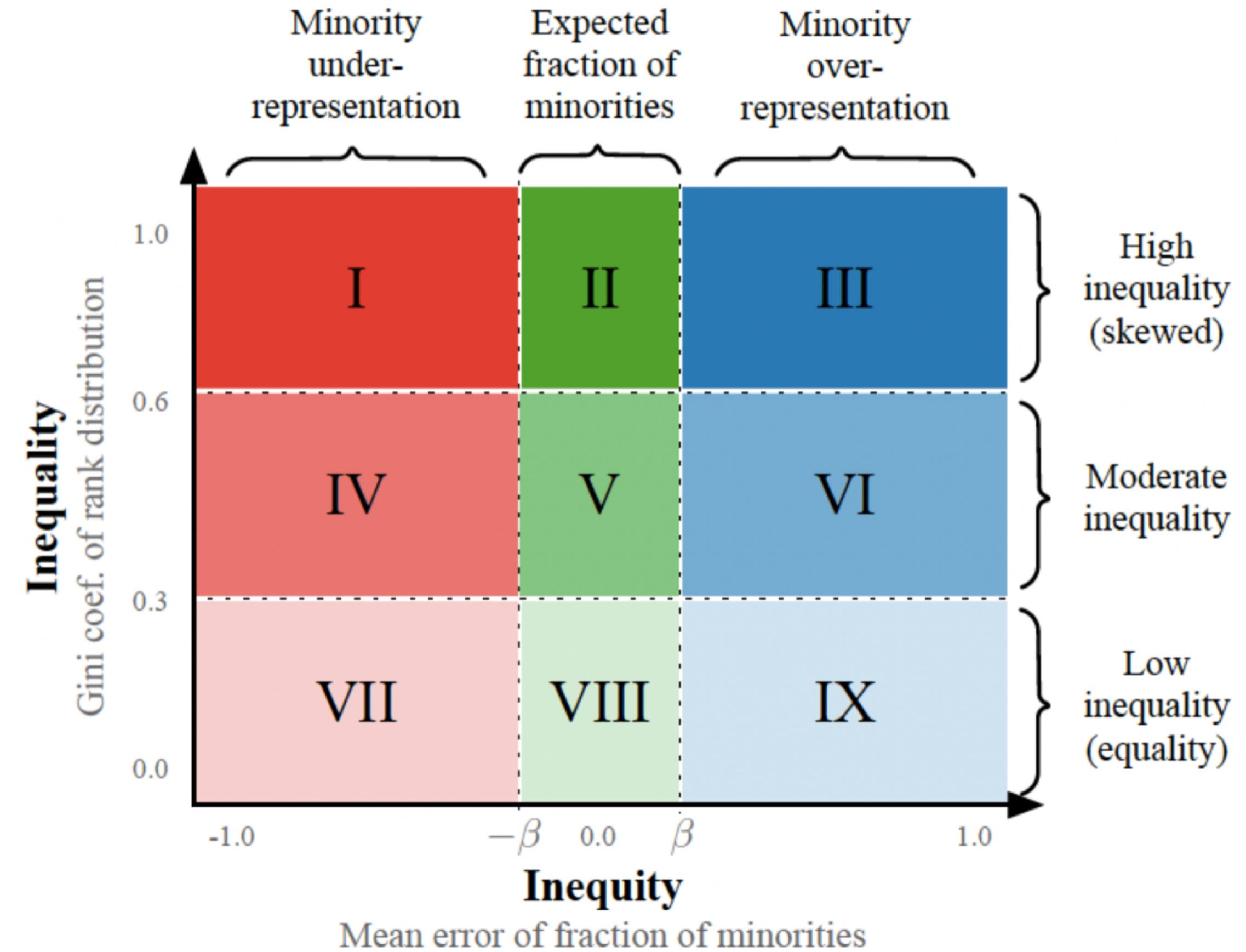
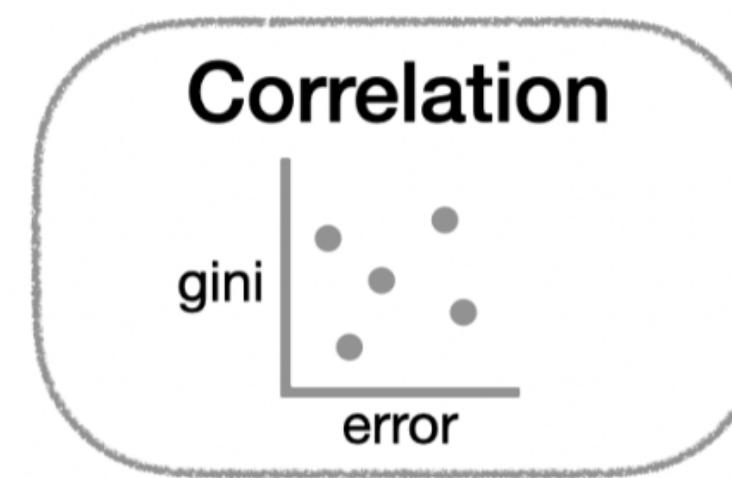
Disparity
ME vs. $Gini_{global}$

Inequity

Inequality, inequity, and disparity

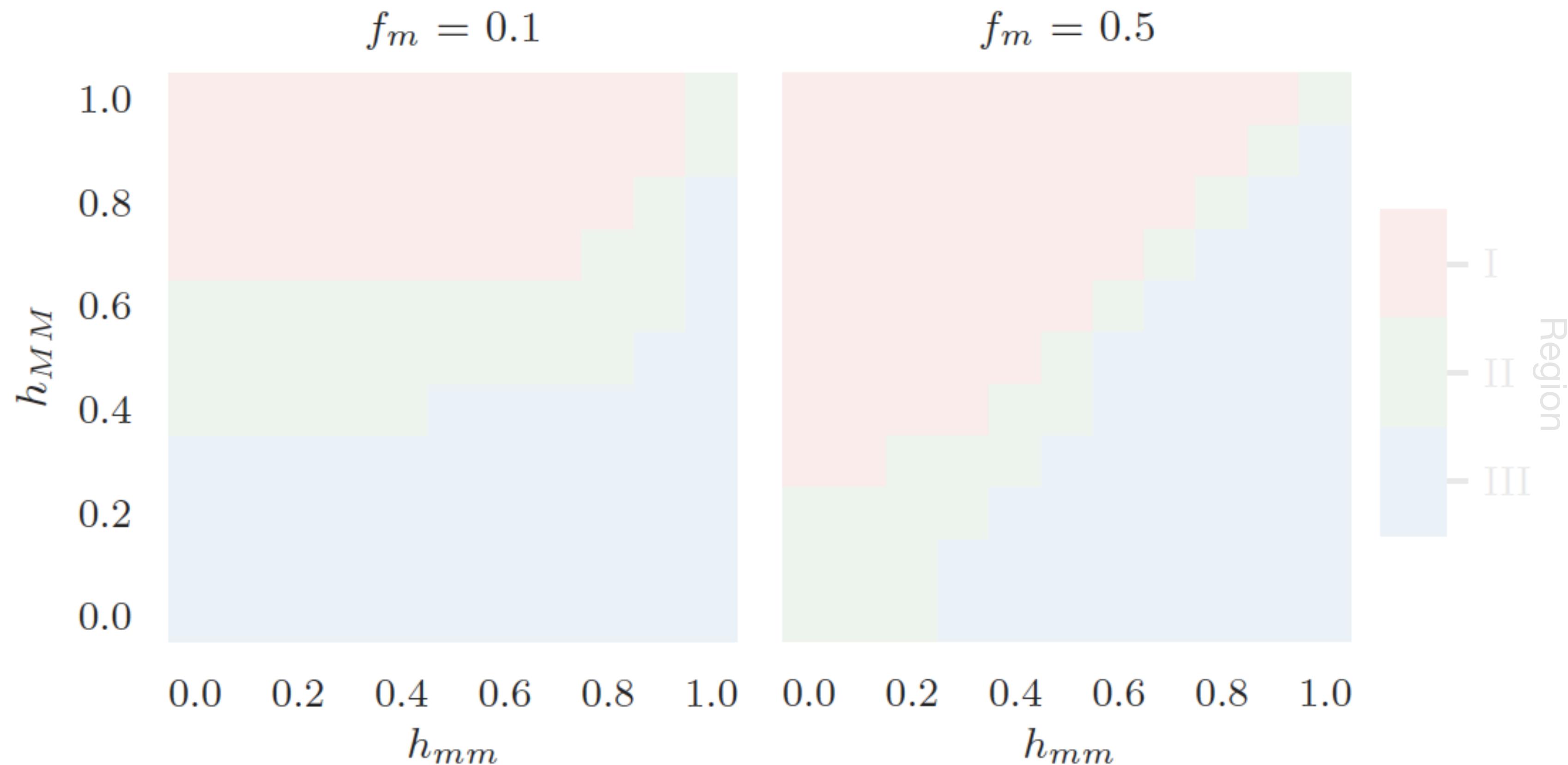
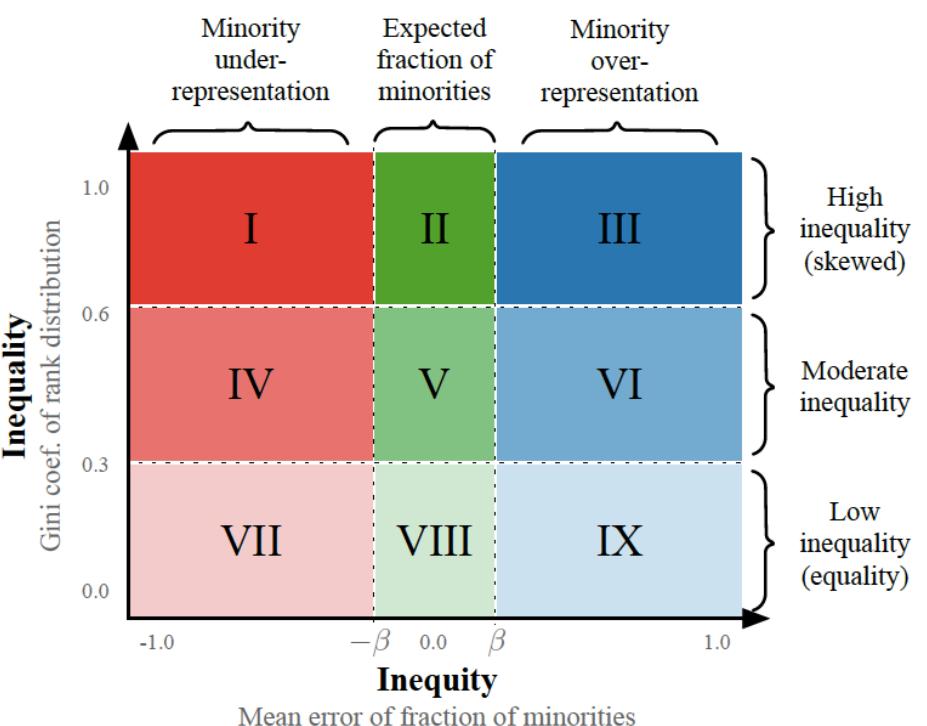


Inequality vs. inequity



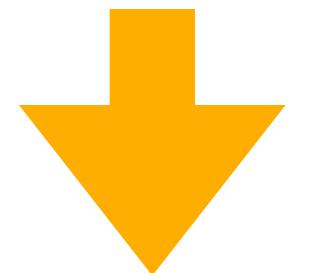
Inequality vs. inequity in PageRank

As a function of homophily and fraction of minorities

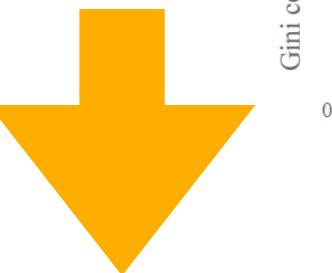


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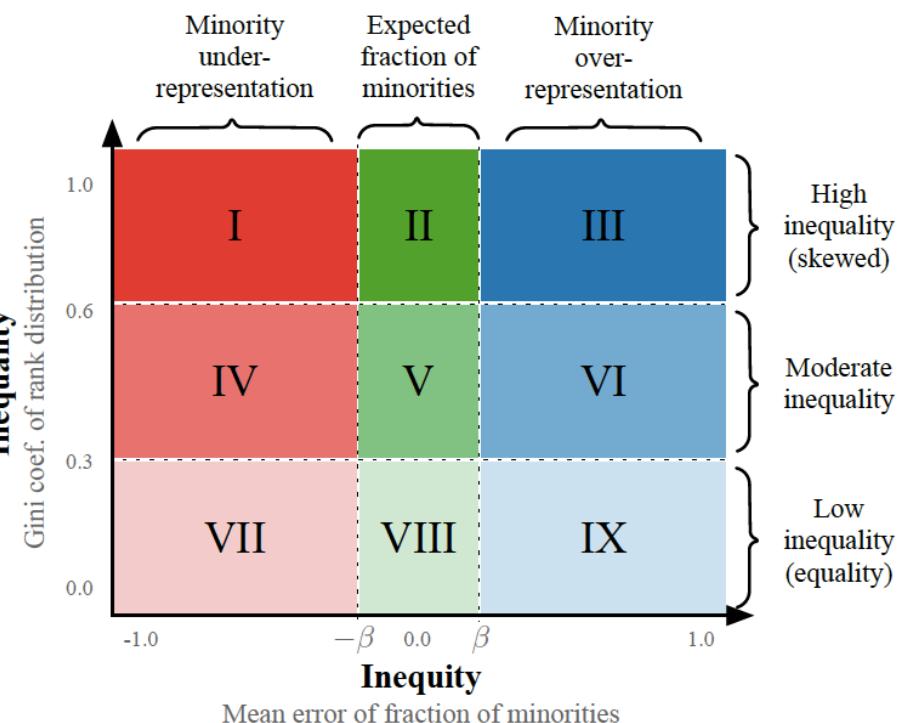
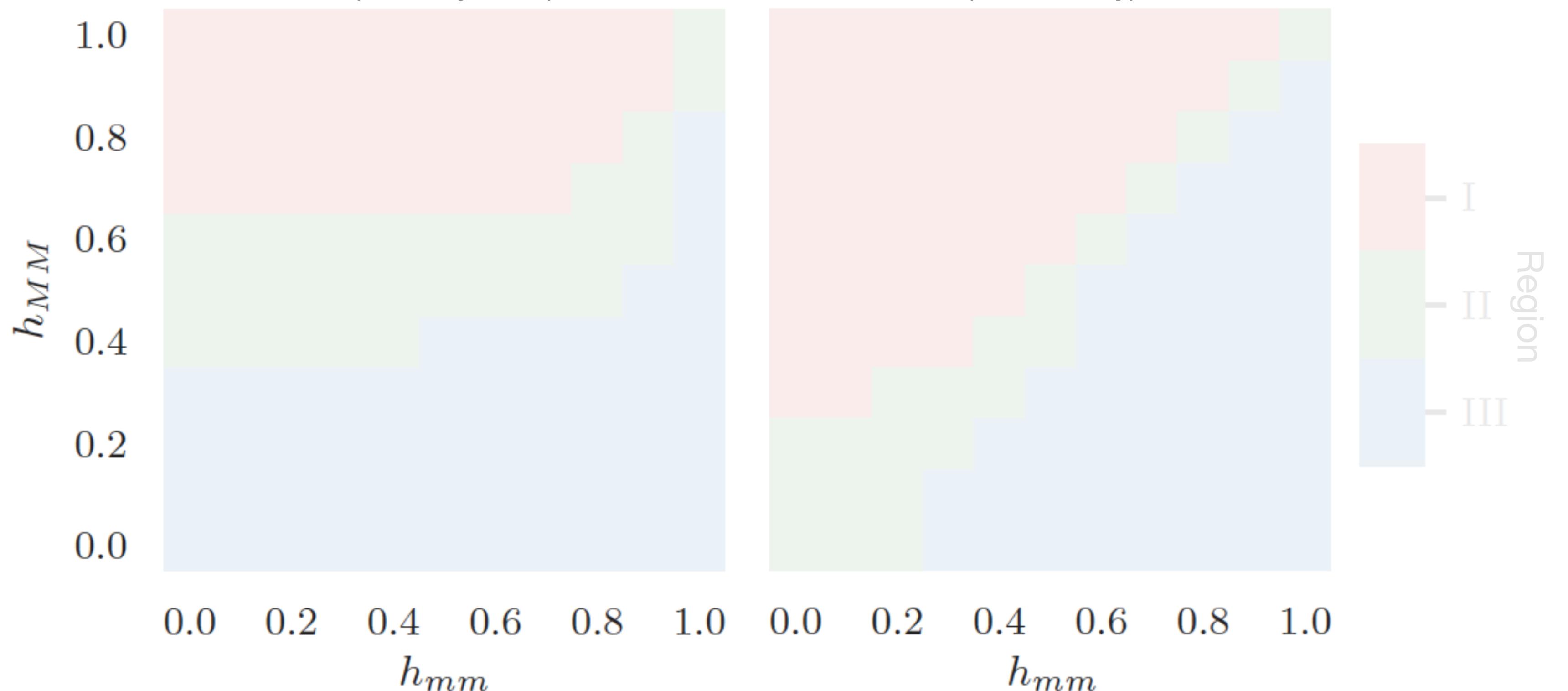
As a function of homophily and fraction of minorities



Columns
Fraction of minority group

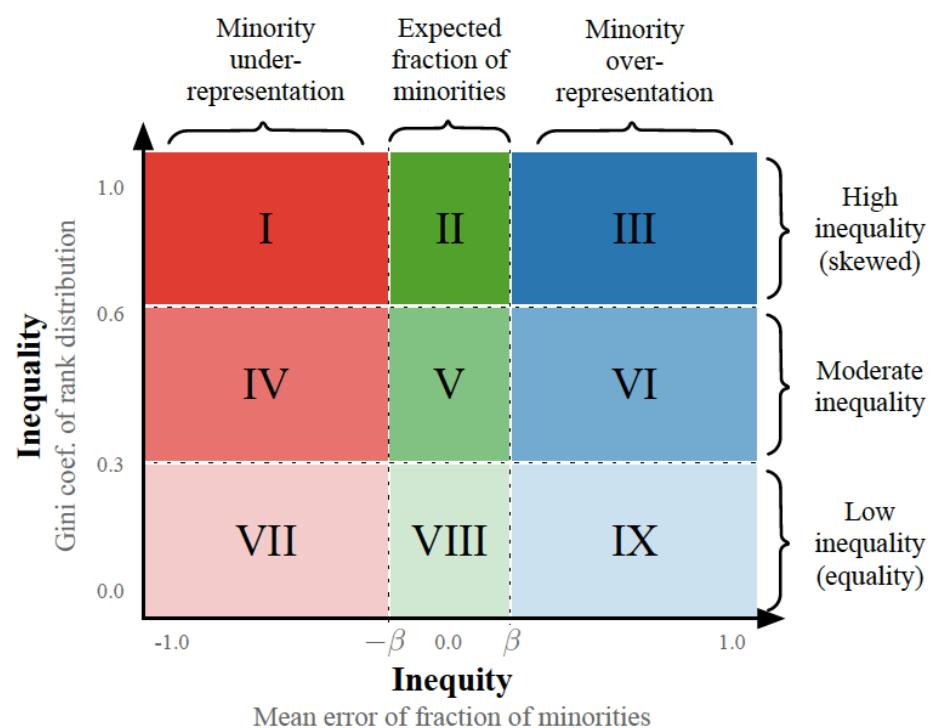


unbalance
(minority 10%)

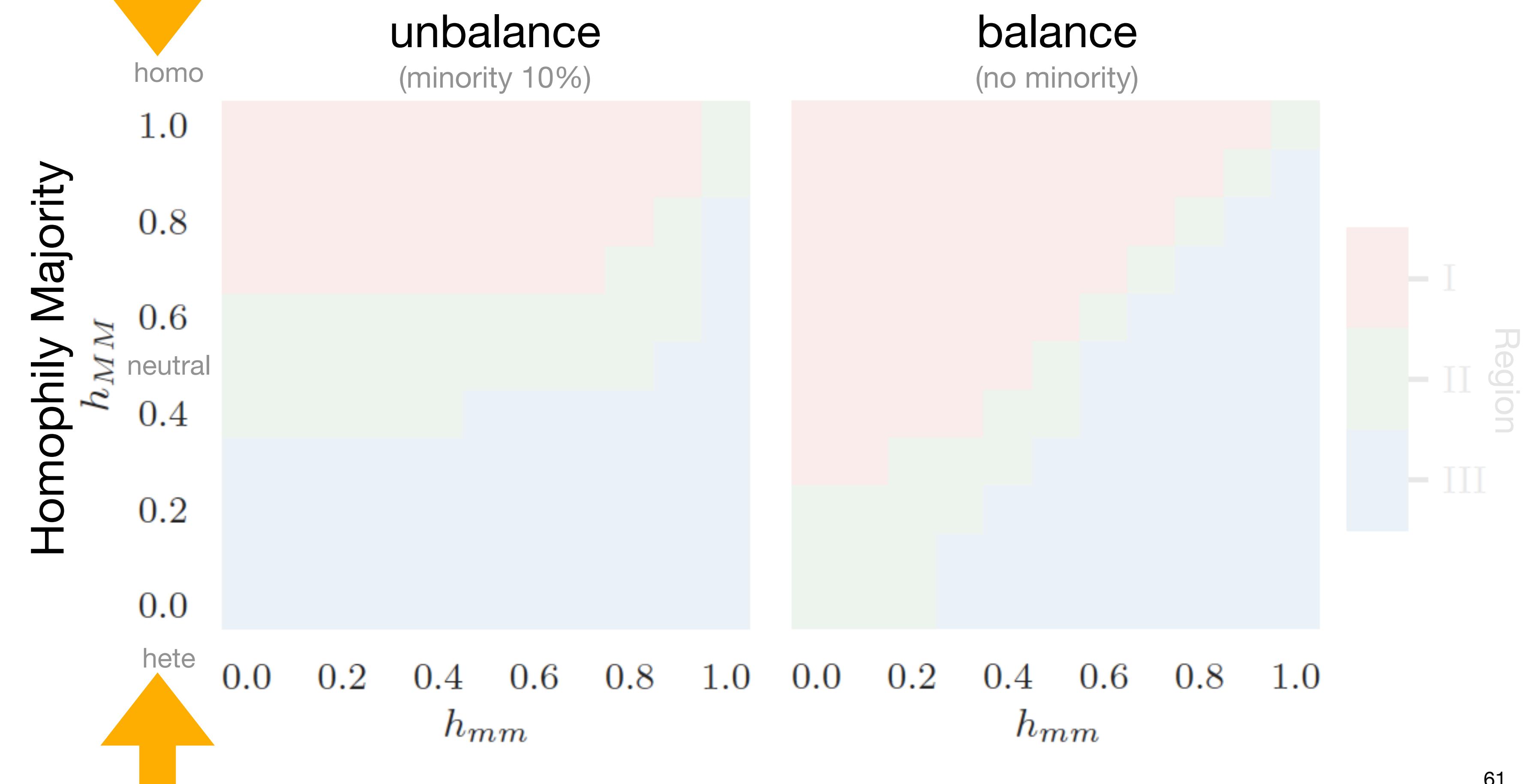


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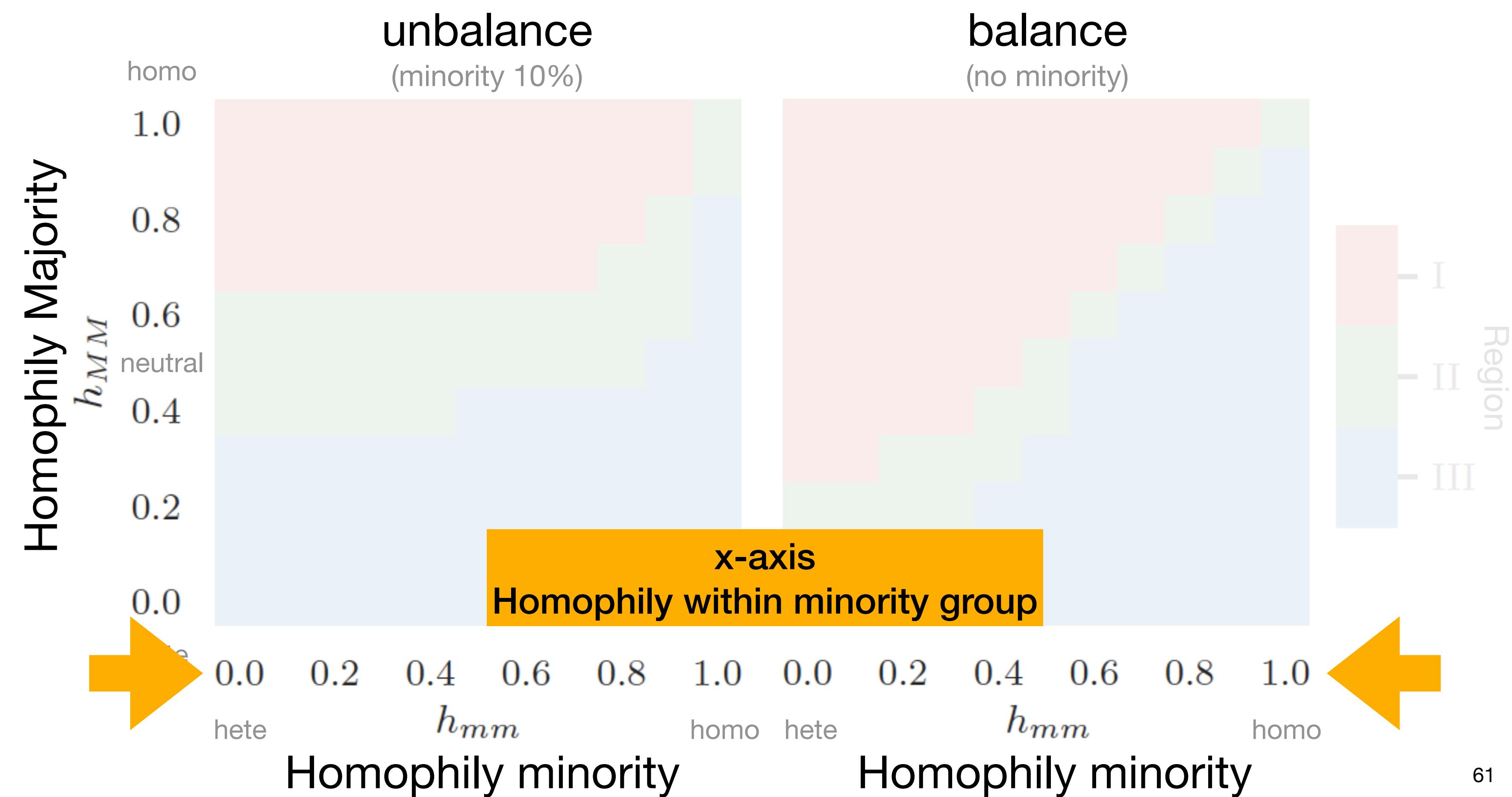
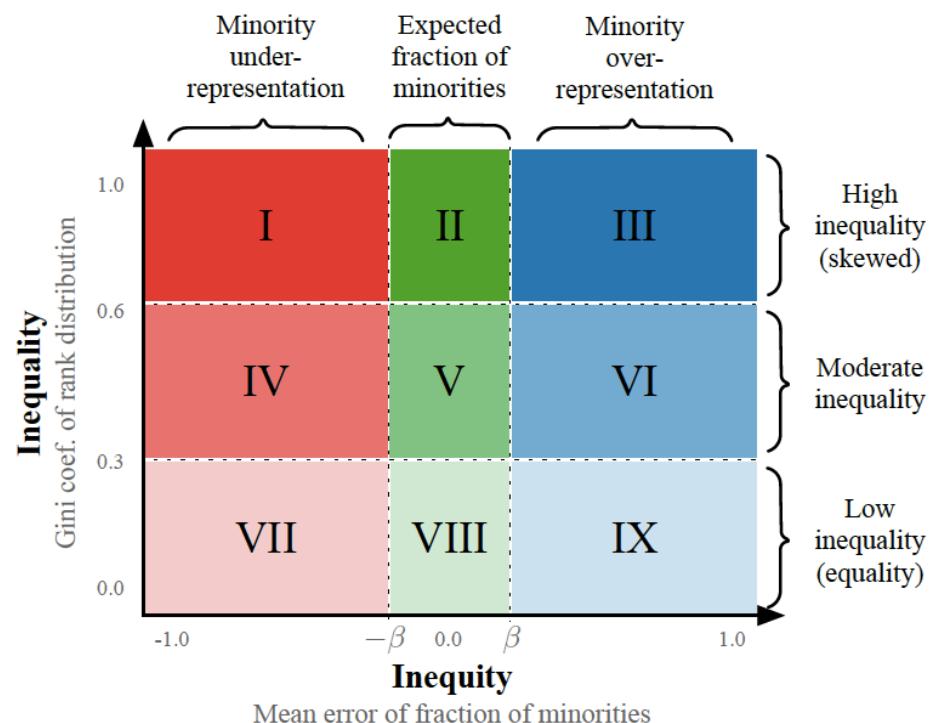


y-axis
Homophily within majority group



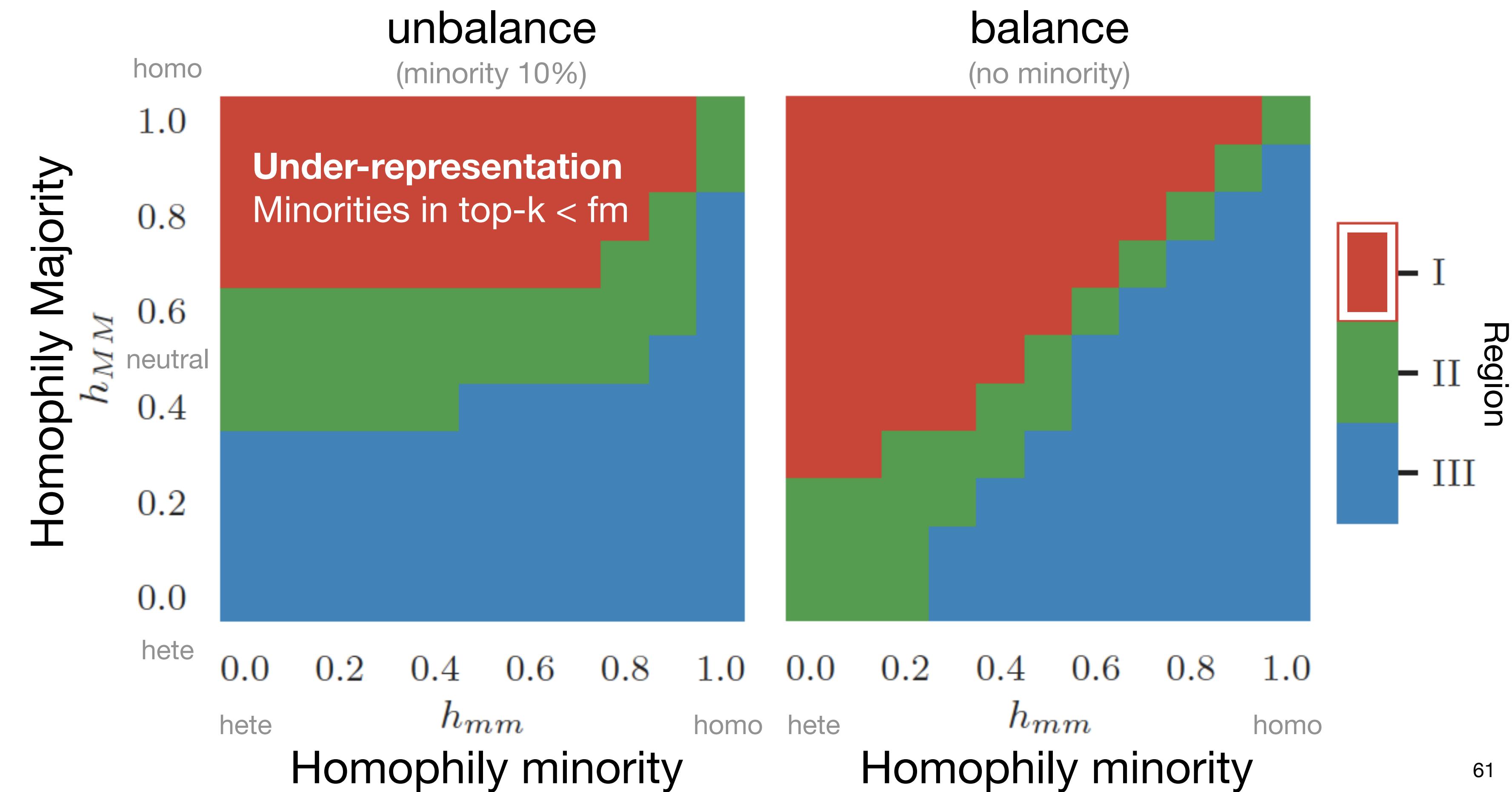
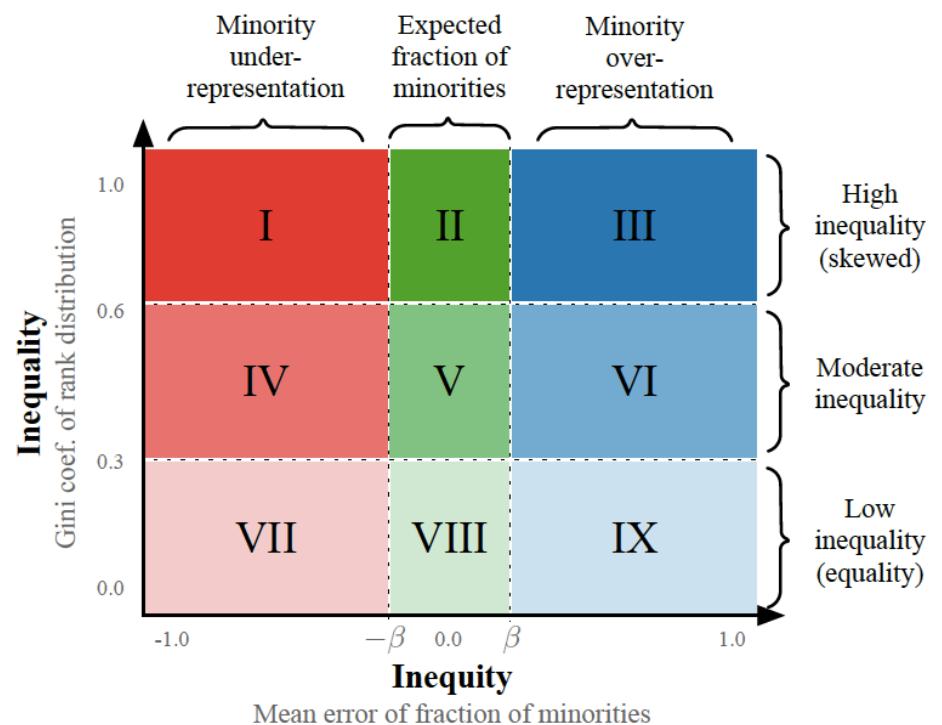
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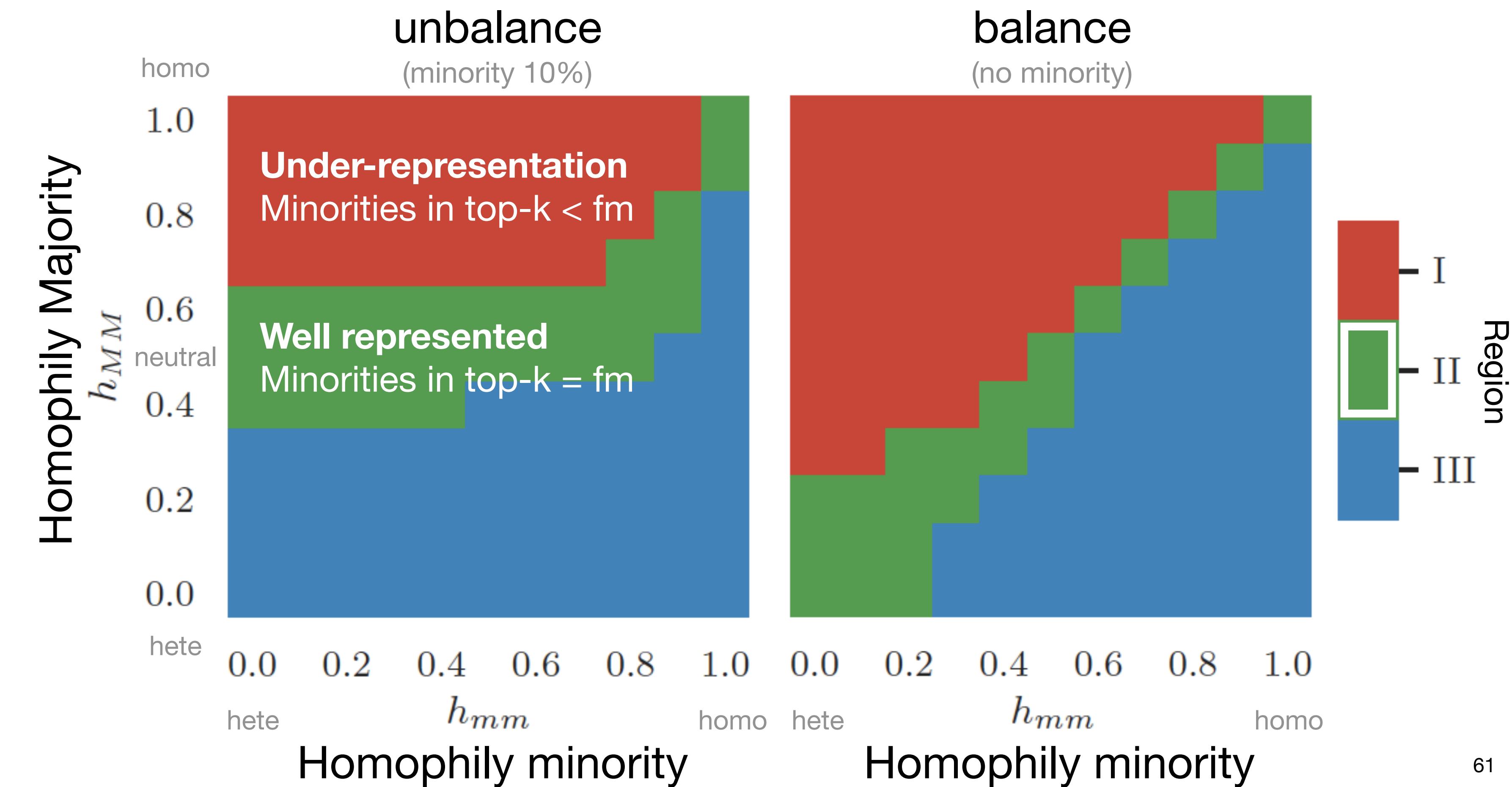
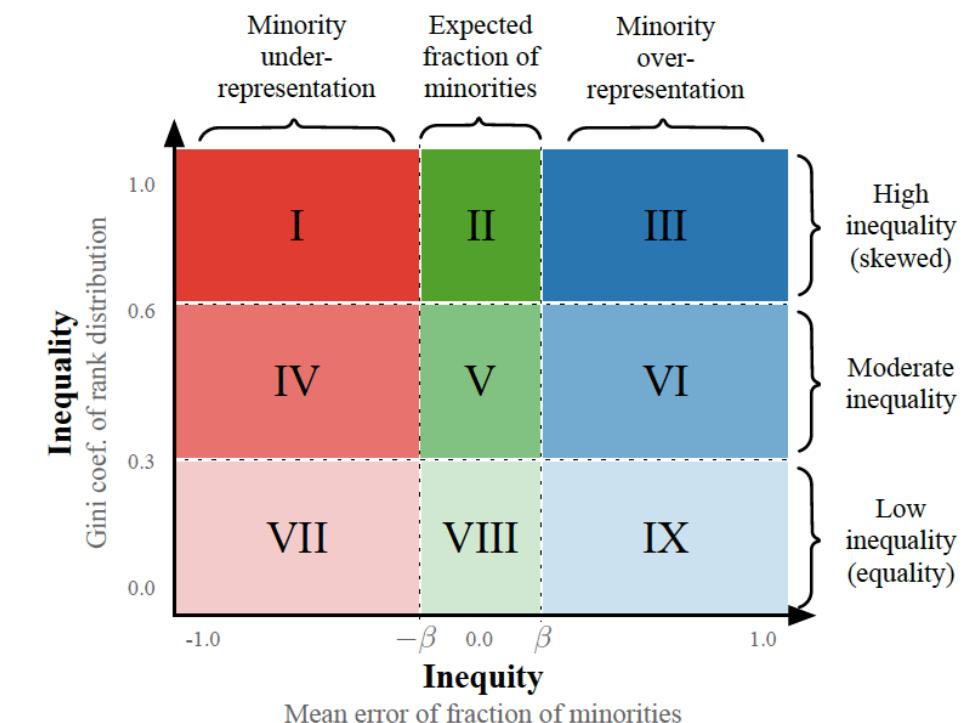
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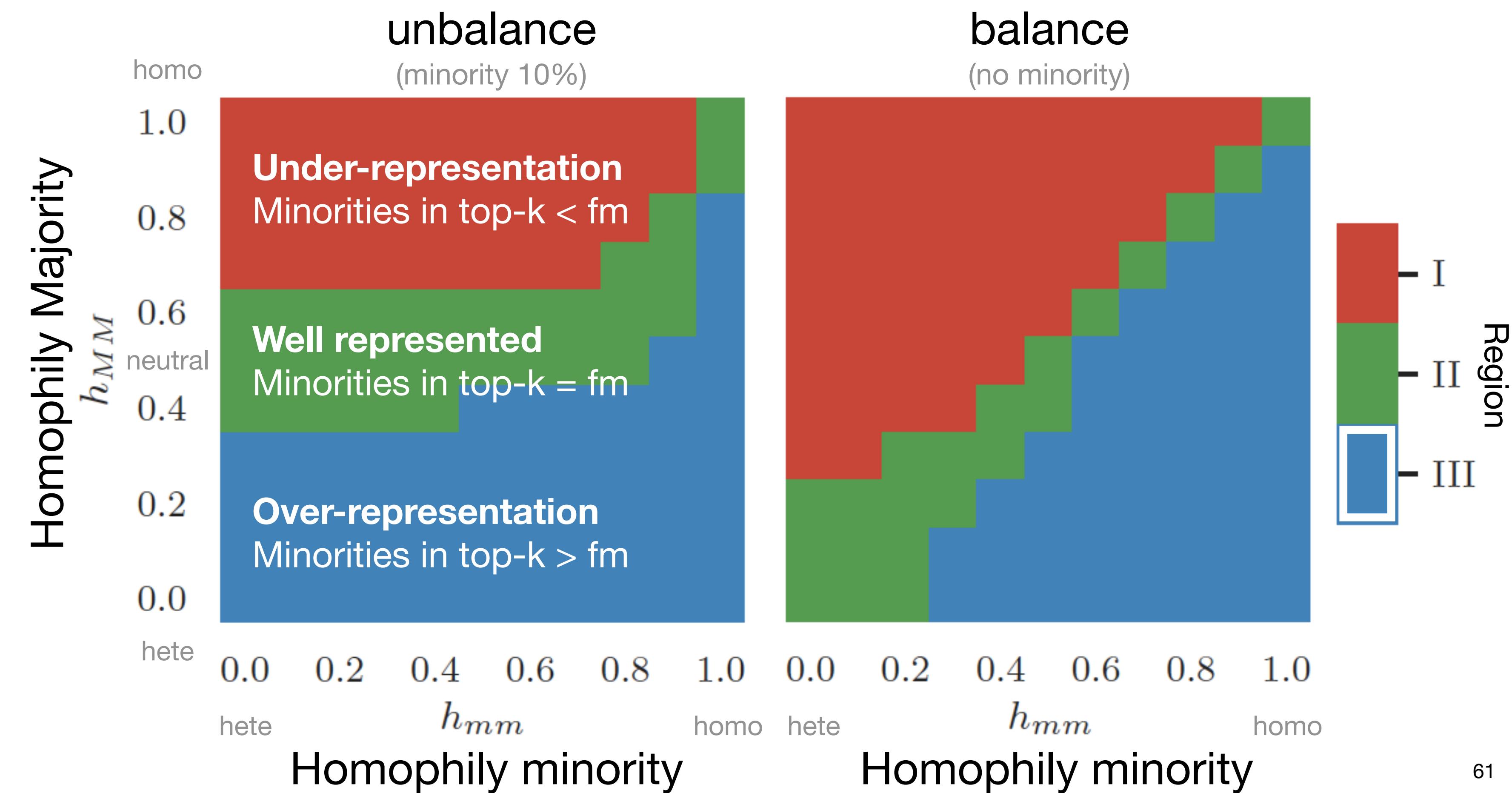
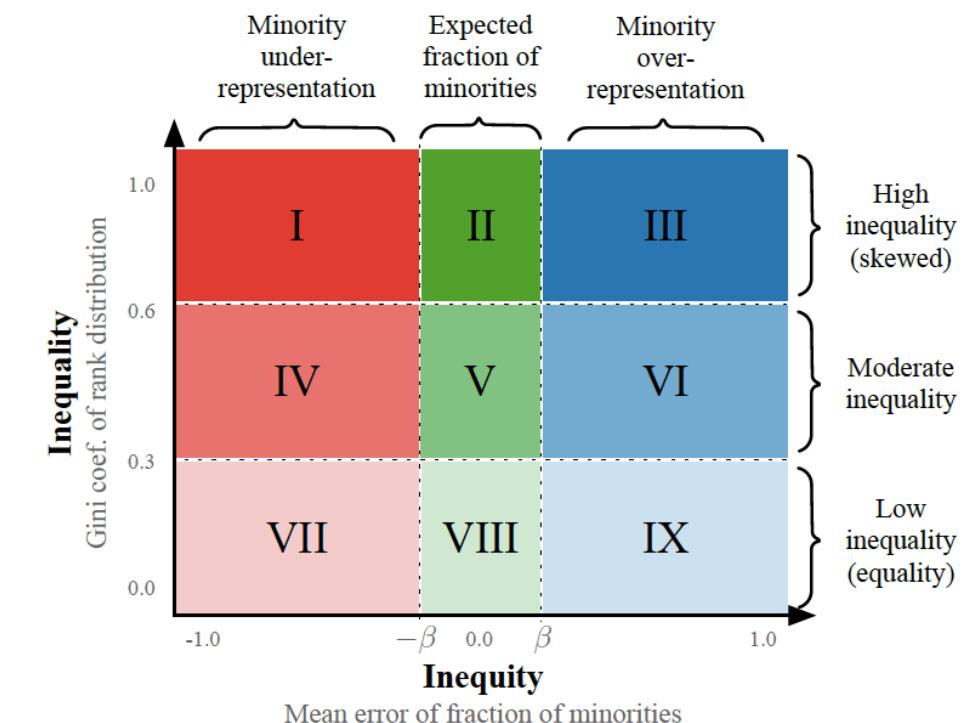
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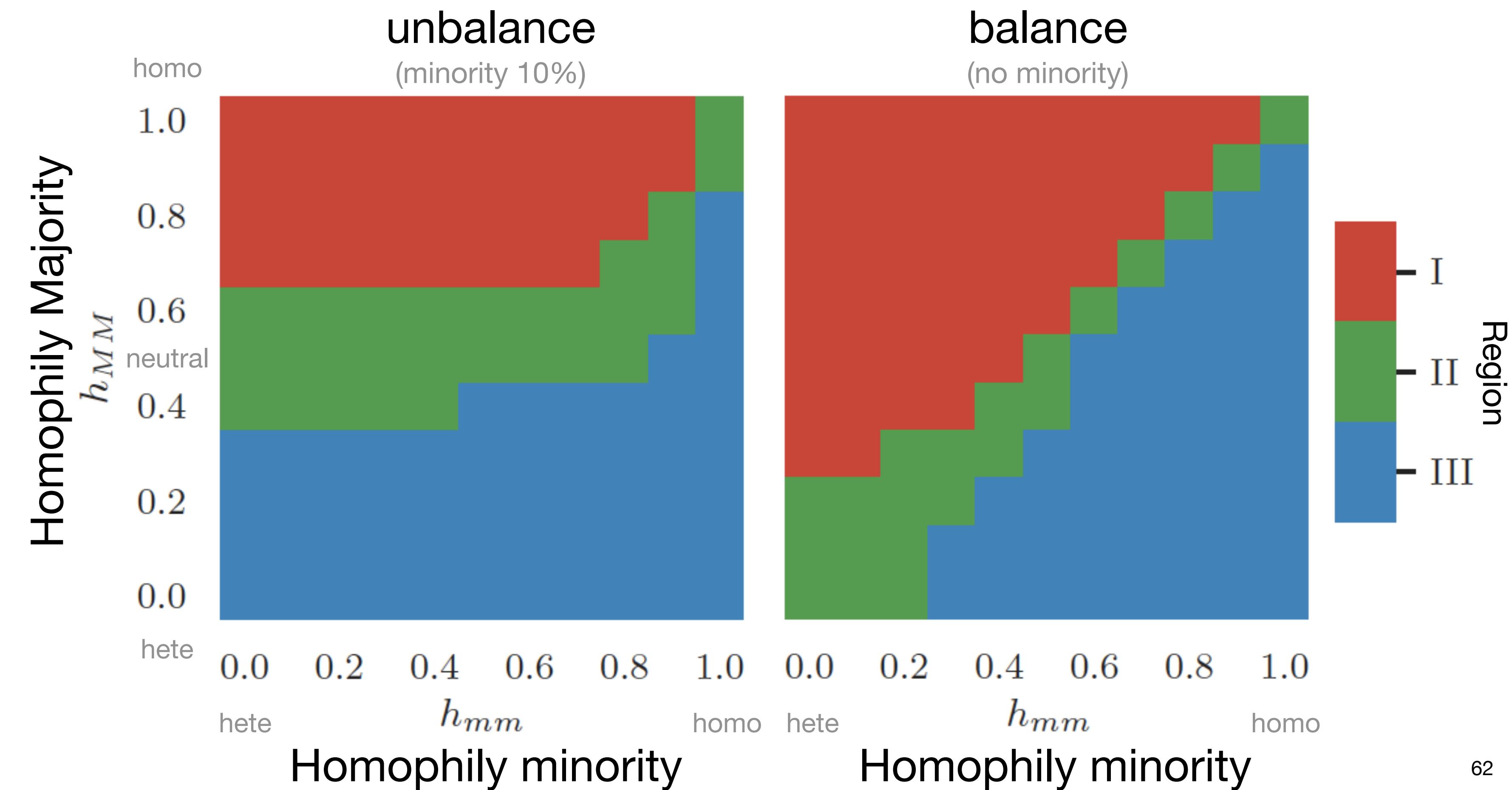
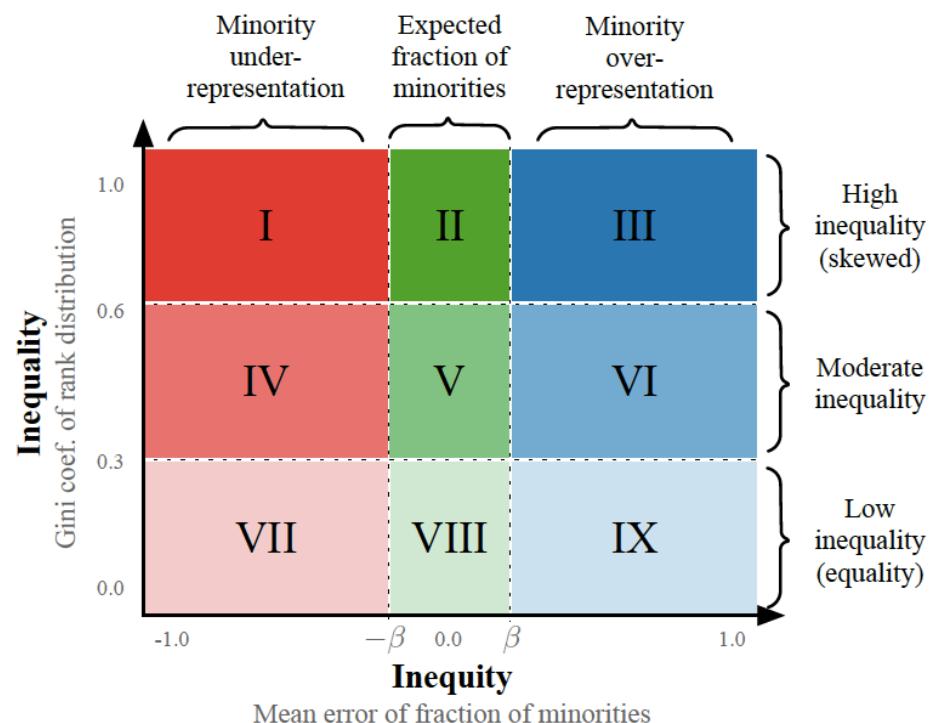
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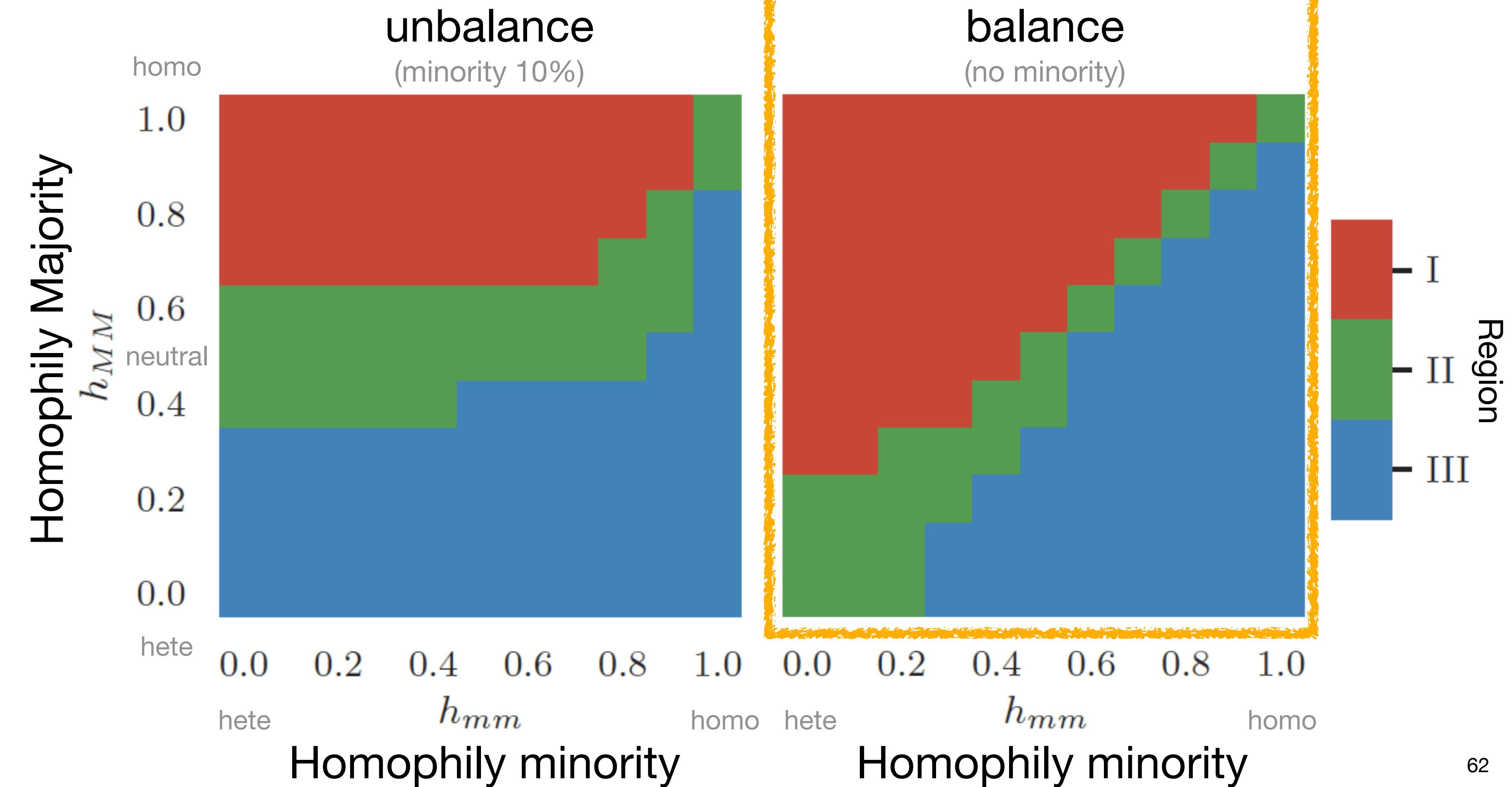
As a function of homophily and fraction of minorities



Inequality vs. inequity in PageRank

As a function of homophily and fraction of minorities

1. In balanced networks, both groups are well represented if $h_{MM} = h_{MM}$

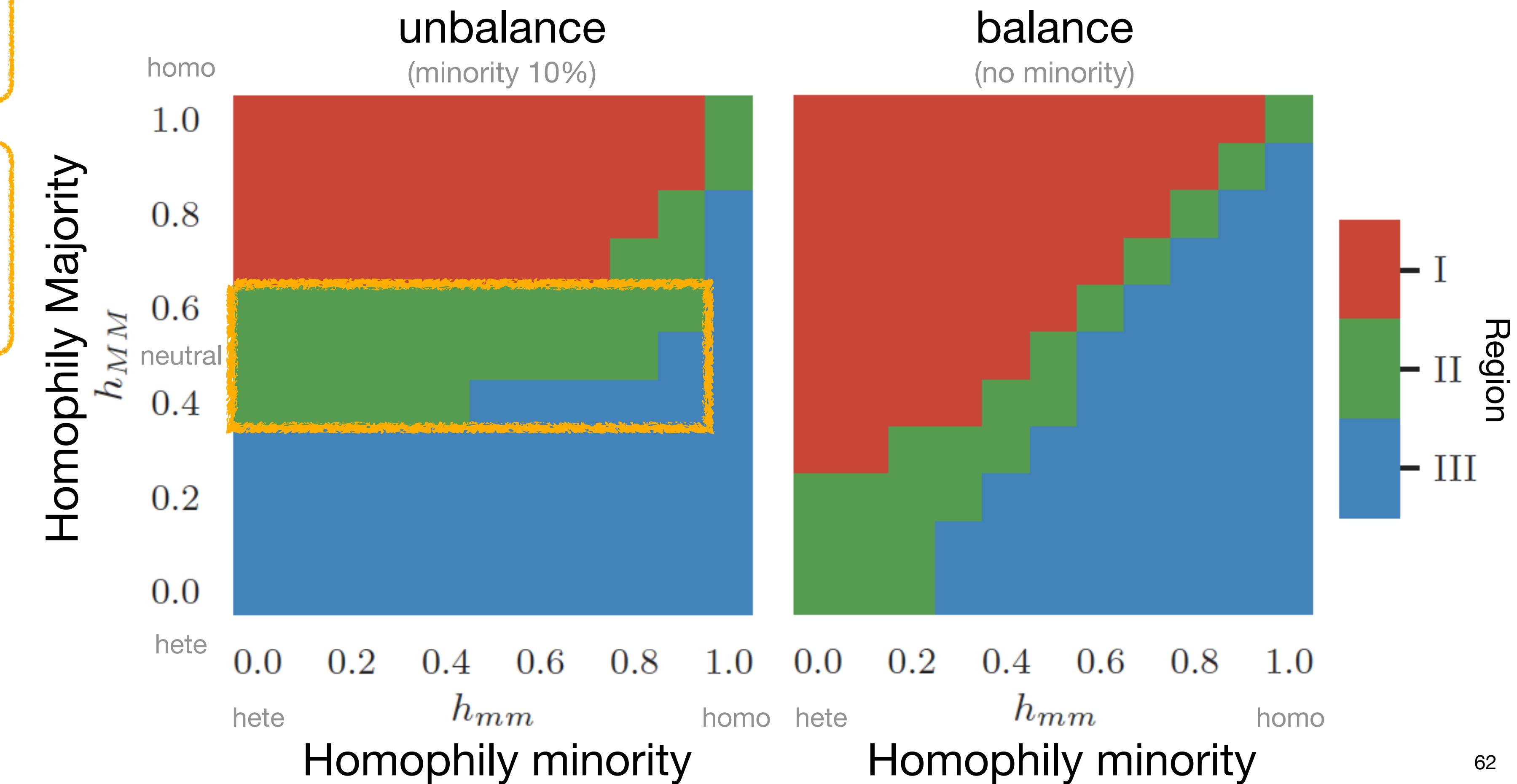


Inequality vs. inequity in PageRank

As a function of homophily and fraction of minorities

1. In balanced networks, both groups are well represented if $h_{MM} = h_{MM}$

2. In unbalanced networks, minorities are well represented when majority is neutral and the minority is not too homophilic.



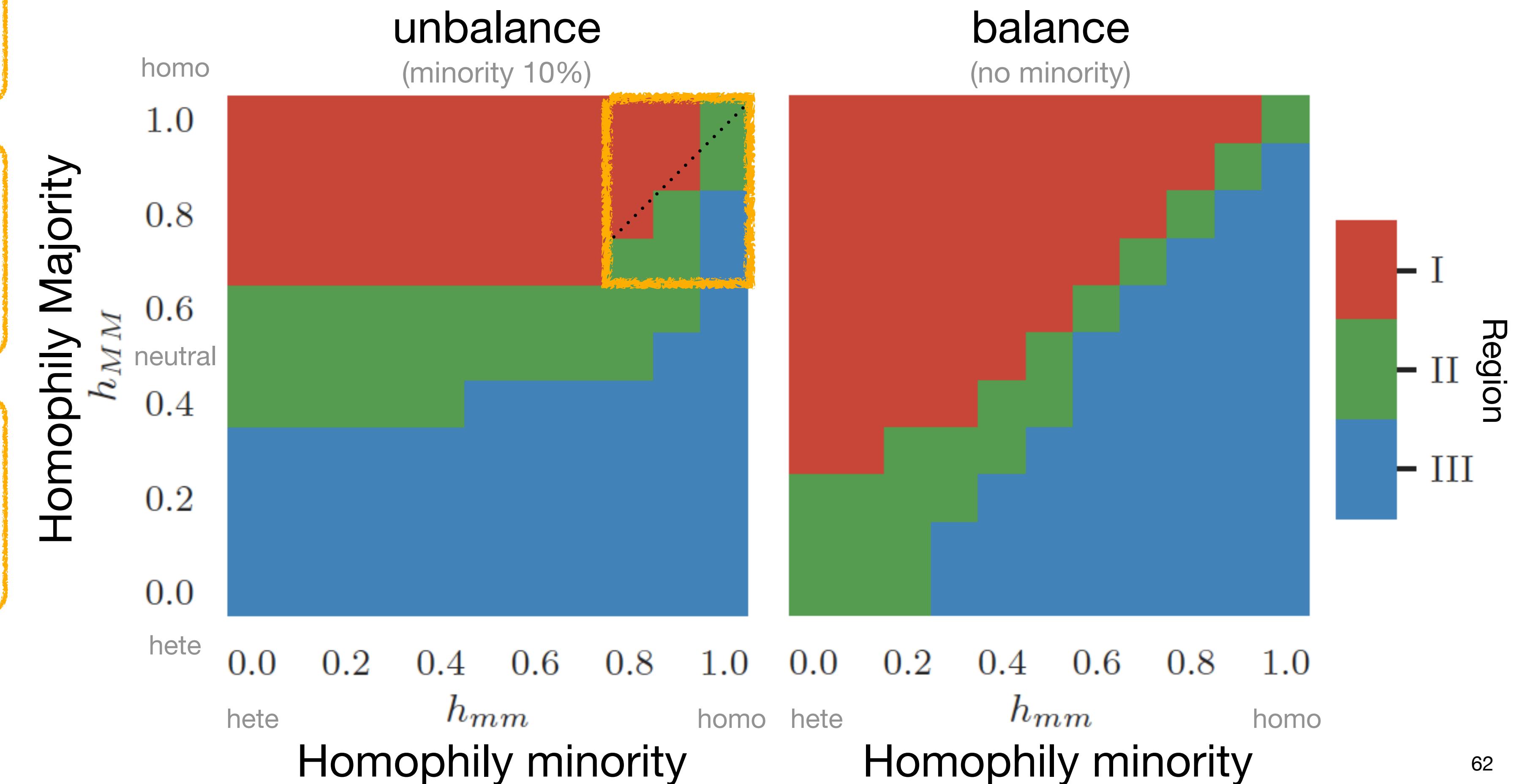
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As a function of homophily and fraction of minorities

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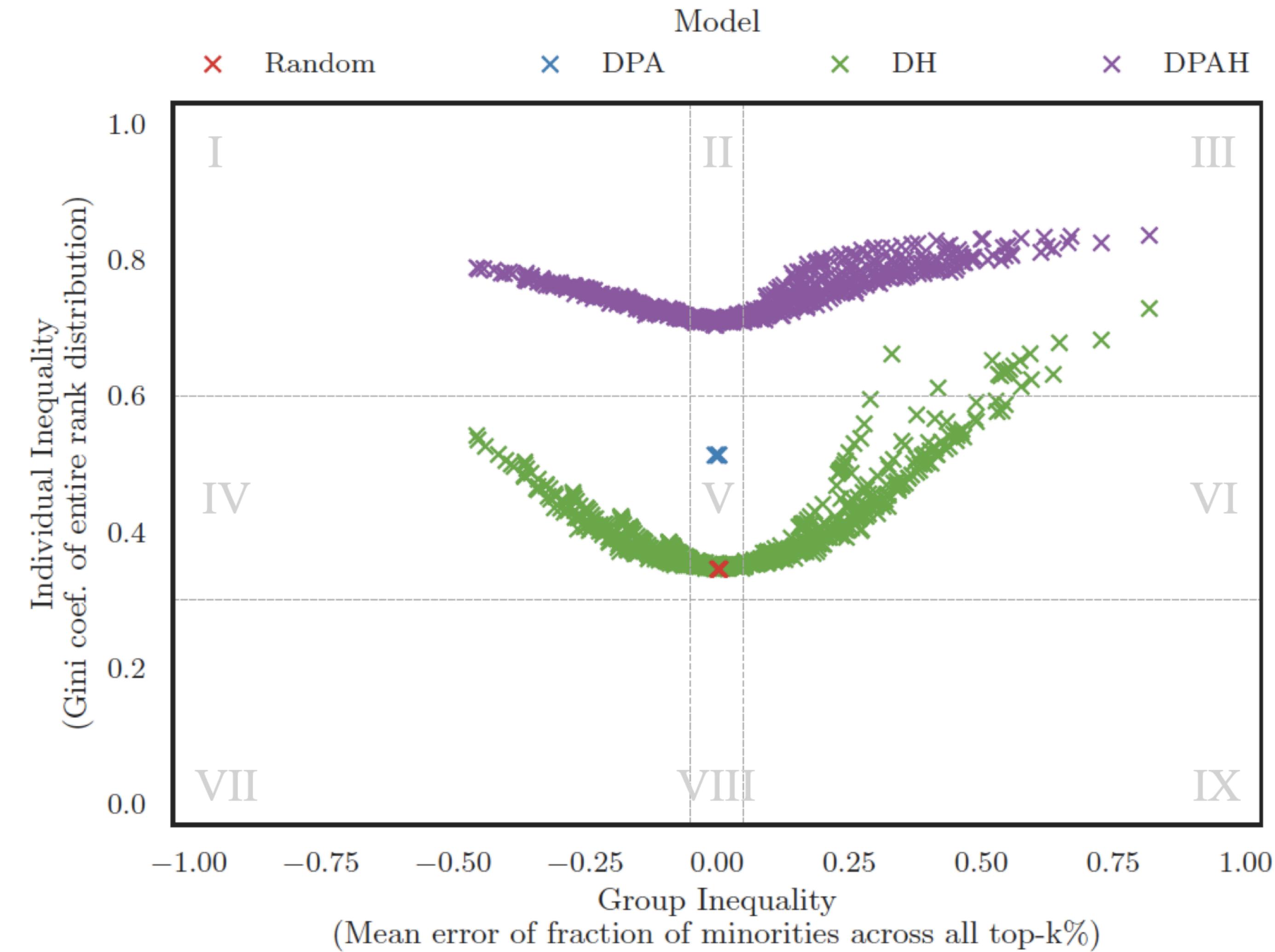
2. In unbalanced networks, minorities are well represented when majority is neutral and the minority is not too homophilic.

3. In unbalanced and homophilic networks, minorities are well represented when $h_{mm} > hMM$.



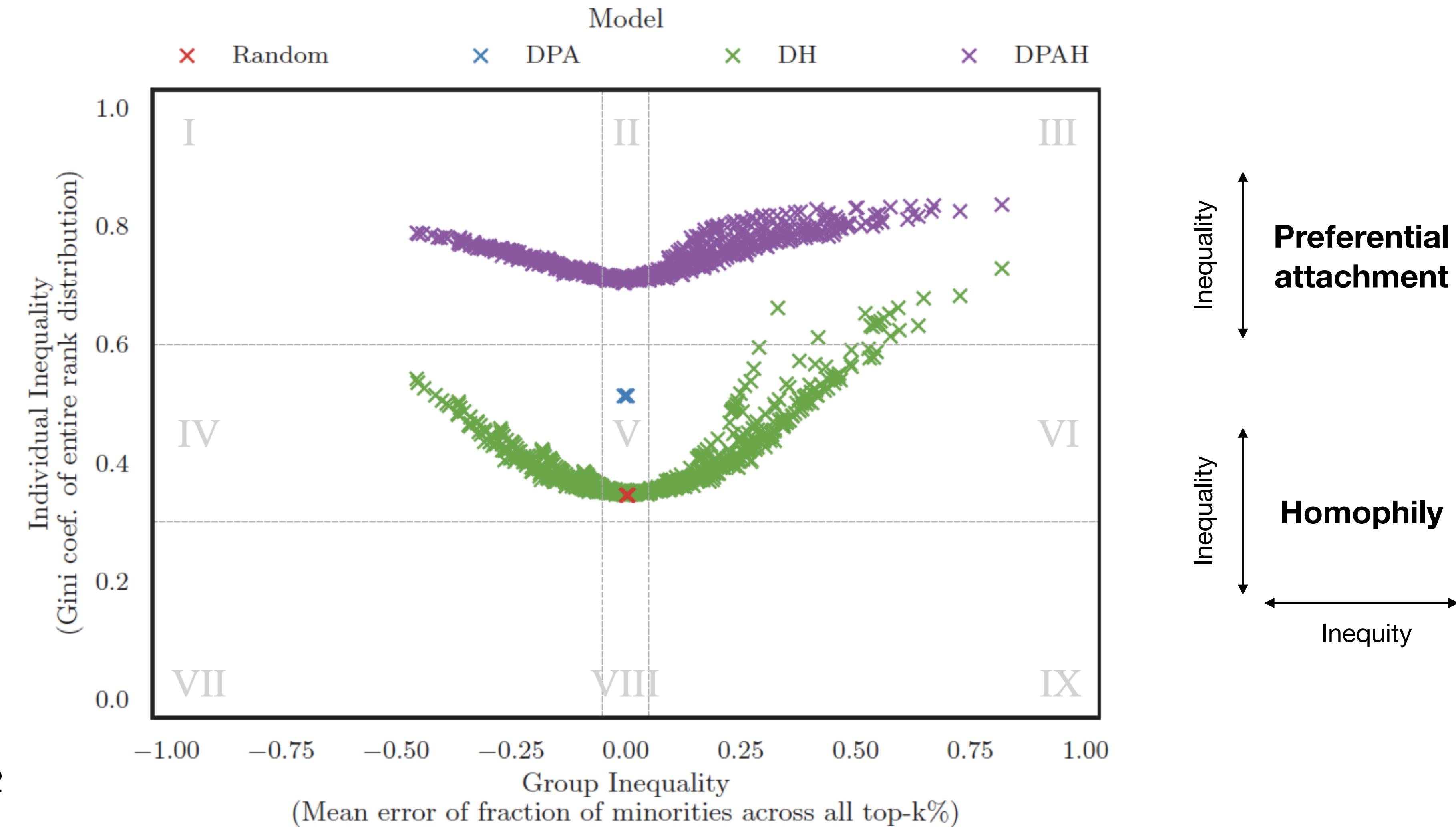
Inequality vs. inequity in PageRank

What mechanism of edge formation contributes to ranking inequality and inequity?



Inequality vs. inequity in PageRank

What mechanism of edge formation contributes to ranking inequality and inequity?



So what?

Real-world scenario

So what?

Real-world scenario



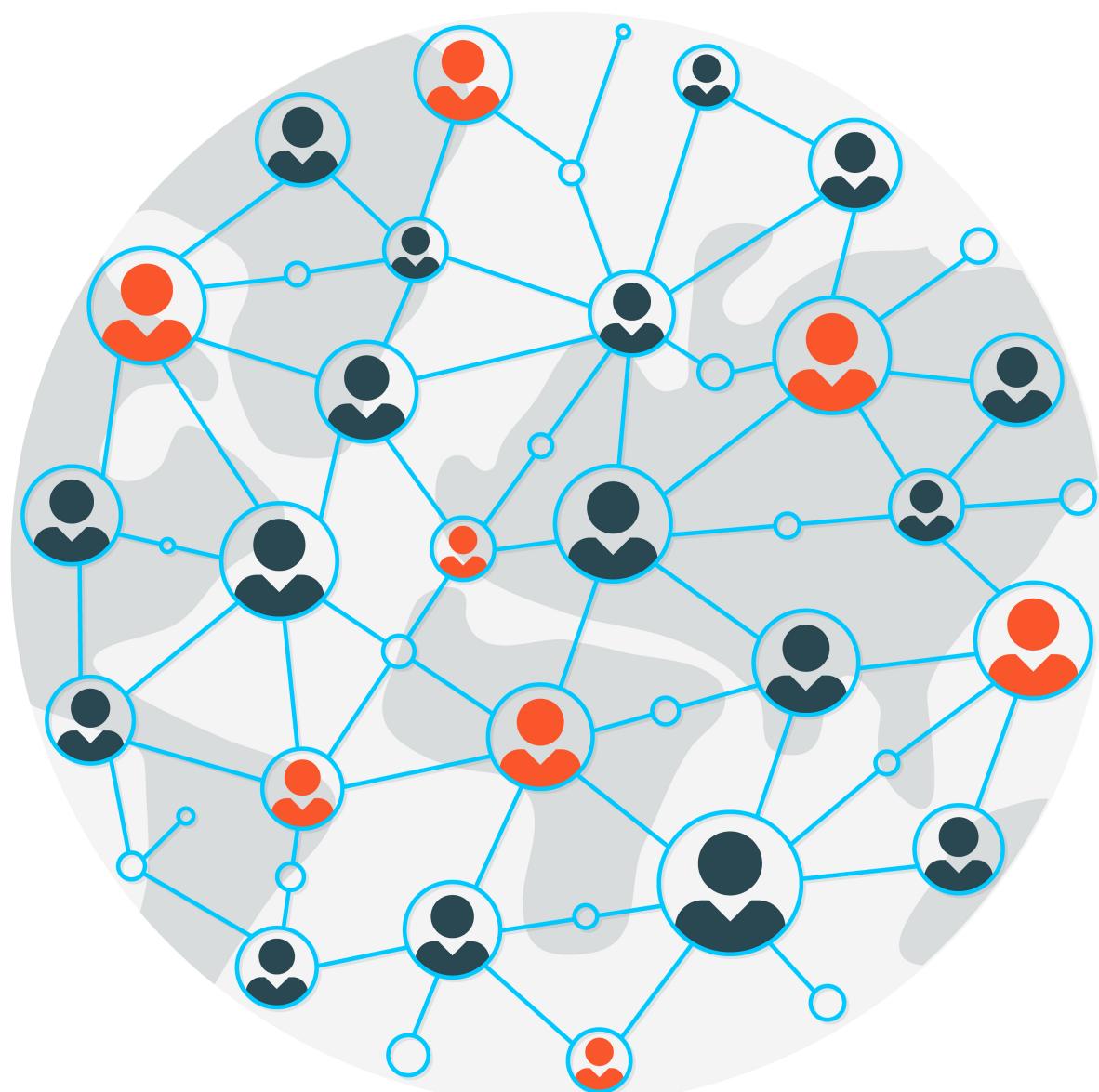
Real-world social network
(people with attributes)



Ranking / RecSys.
(PageRank or WTF)

So what?

Real-world scenario



Real-world social network
(people with attributes)

1. Identify network structure

Fraction min.
 $f_m=0.3$

Node activity
 $\gamma_M = \gamma_m = 3$

Density
 $d=0.0015$

Homophily Maj.
 $H_{MM}=0.8$

Homophily min.
 $H_{mm}=0.4$

(Inequity is driven by homophily and fraction of minorities)



Ranking / RecSys.
(PageRank or WTF)

So what?

Real-world scenario



Real-world social network
(people with attributes)



Ranking / RecSys.
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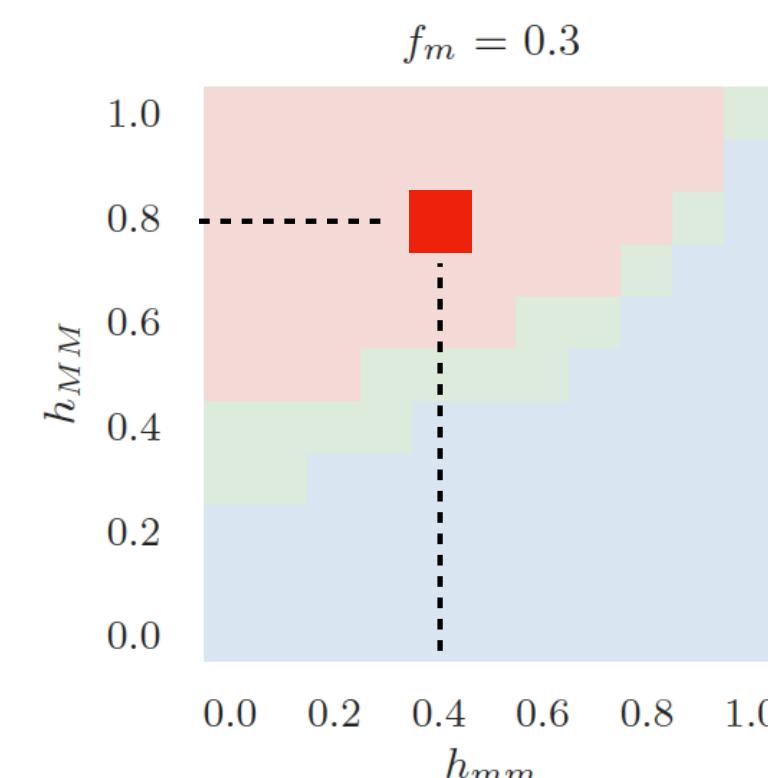
Homophily min.
 $H_{mm}=0.4$

(Inequity is driven by homophily and fraction of minorities)

2. Identify inequality and inequity in ranking

OPEN Inequality and inequity
in network-based ranking
and recommendation algorithms

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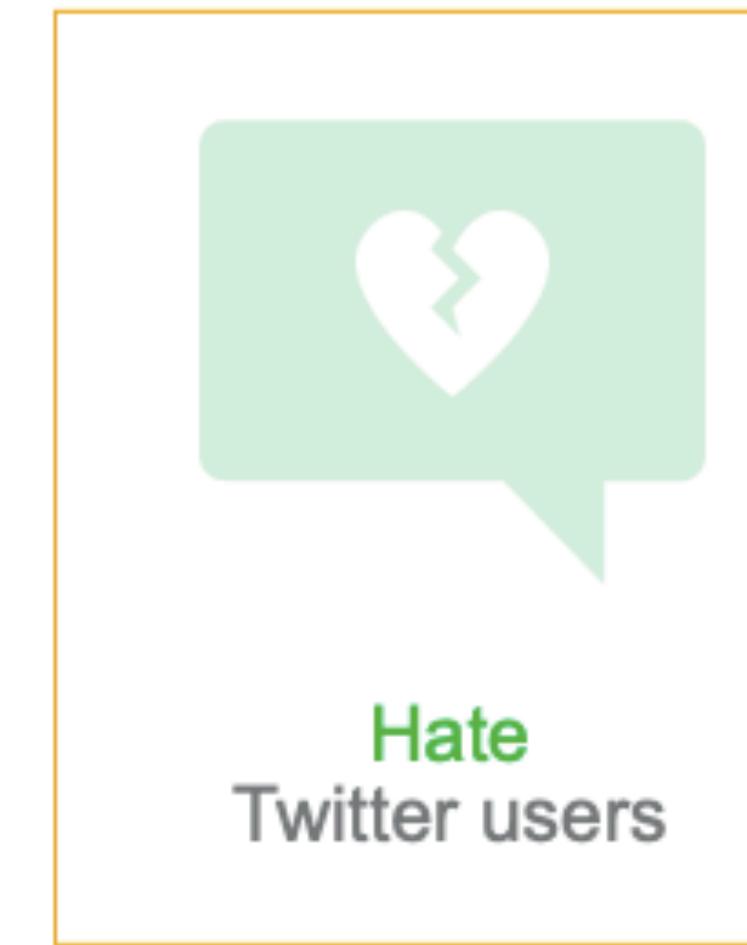
On average minorities are
under-represented in top-k's
(Interventions needed)

Real-world (empirical) networks

Network properties



38% Classical
statistical mechanics
62% Quantum
statistical mechanics



11% haters
80% normal



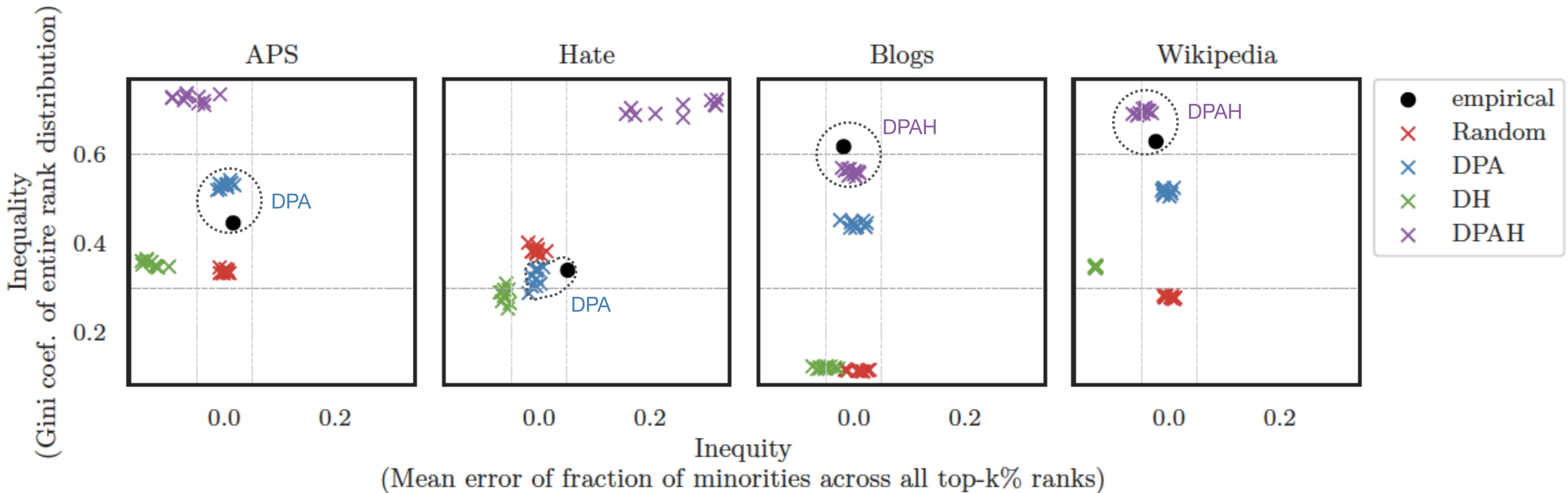
48% left-wing
52% right-wing



15% women
85% men

Empirical networks

Model fitting (which model explains best the disparity?)



Disparities in vaccination (Agarwal 2021)

Social and Community Context

Political Ideology. To model political ideology, we used the share of votes cast for the Republican candidate (President Donald J. Trump) in the 2020 election collected from USA Today (34). We use Republican vote share because survey evidence suggests that political affiliation is an important predictor of attitudes toward COVID-19 and the COVID-19 vaccine in particular (35). This approach is also consistent with prior research that showed Democratic counties were more likely to reduce mobility in response to stay-at-home-orders for COVID-19 prevention, which used the vote margin in favor of President Trump as a predictor (36).

Segregation Index. We collected Black-White segregation index measures from the 2021 County Health Rankings (37). Based on data from ACS 2015 to 2019, the residential segregation index ranges from 0 (complete integration) to 100 (complete segregation). These values represent the percentage of either Black or White residents who would have to move to yield a distribution that is similar to that of the larger area. Segregation in communities has been associated with a number of important racial disparities in health (38).

Racial Bias. We modeled implicit racial bias using estimates published in prior research (39), which are based on responses collected from Project Implicit, a website where individuals voluntarily complete psychological attitude measures (40). We used the weighted measure of implicit bias, which accounts for the number of observations available for each county. Measures of implicit bias assess the automatic association between race (White and Black) and attitudes (good or bad), with larger values indicating greater bias against Blacks. Such measures of bias have previously been linked to racial disparities in school disciplinary actions (39).

Real-world (empirical) networks

Network properties

Table 1 Empirical networks: Structural properties of five real-world networks: Escorts, Swarthmore42, Caltech36, Wikipedia, and GitHub. In addition to the properties of interest, we report β , the power-law exponent of the degree distribution computed as described in [8]. N_{fit} and m_{fit} represent the number of nodes and minimum degree utilized to generate synthetic networks, respectively.

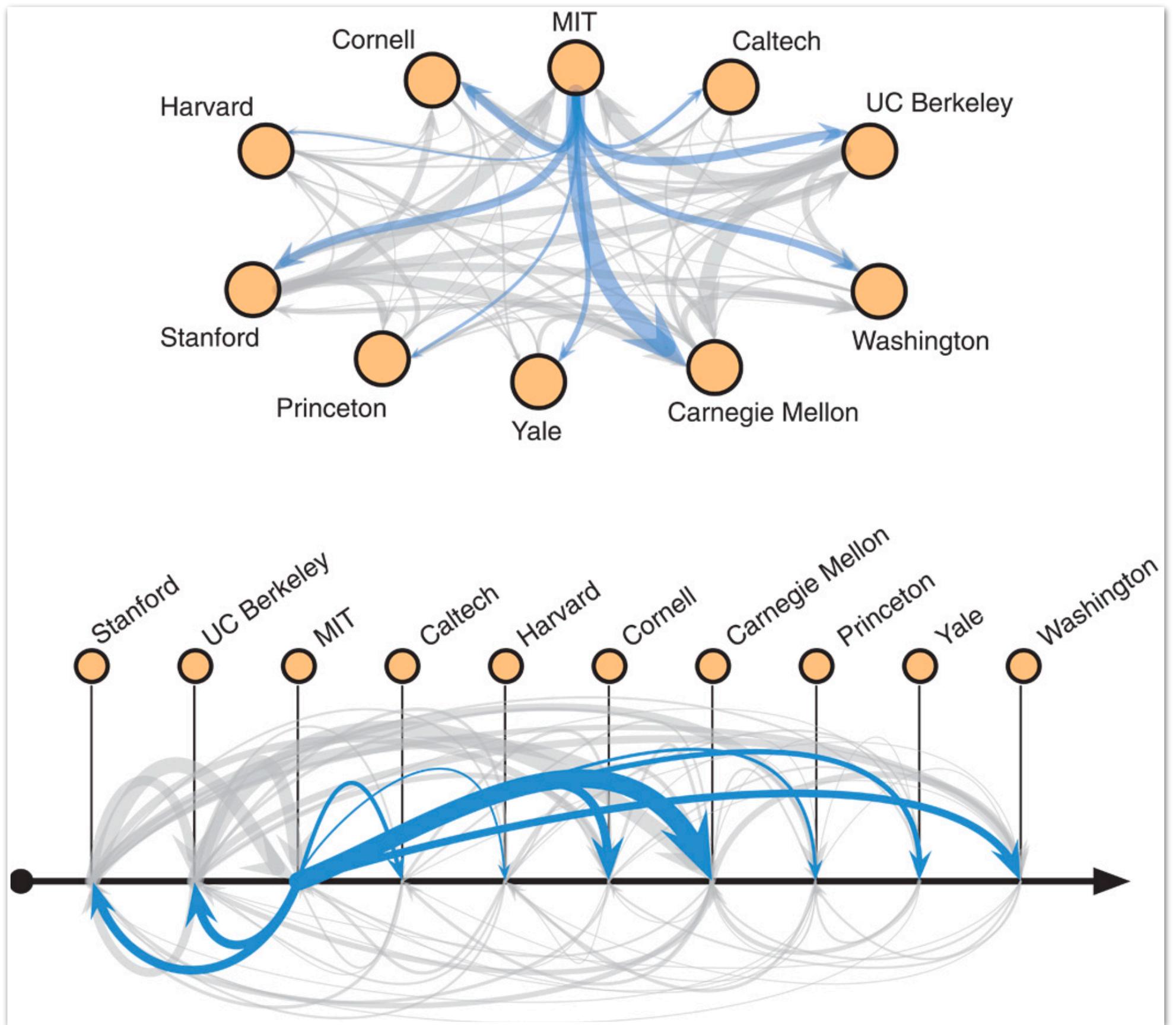
dataset	Escorts	Swarth.	Caltech	Wiki.	GitHub
N	16730	1519	701	2132	37700
m	1	1	1	1	1
class	role	gender	gender	gender	dev
minority	escort	2 (m)	1 (f)	female	1 (ML)
B	0.40	0.49	0.33	0.15	0.26
E	39044	53726	15464	3143	289003
d	0.0003	0.05	0.06	0.001	0.0004
β	2.87	5.50	4.90	2.87	2.54
H	0.00	0.52	0.54	0.64	0.84
N_{fit}	14338	208	179	2893	9830
m_{fit}	2	2	2	2	2

Inequalities in networks

Examples

Inequalities in networks

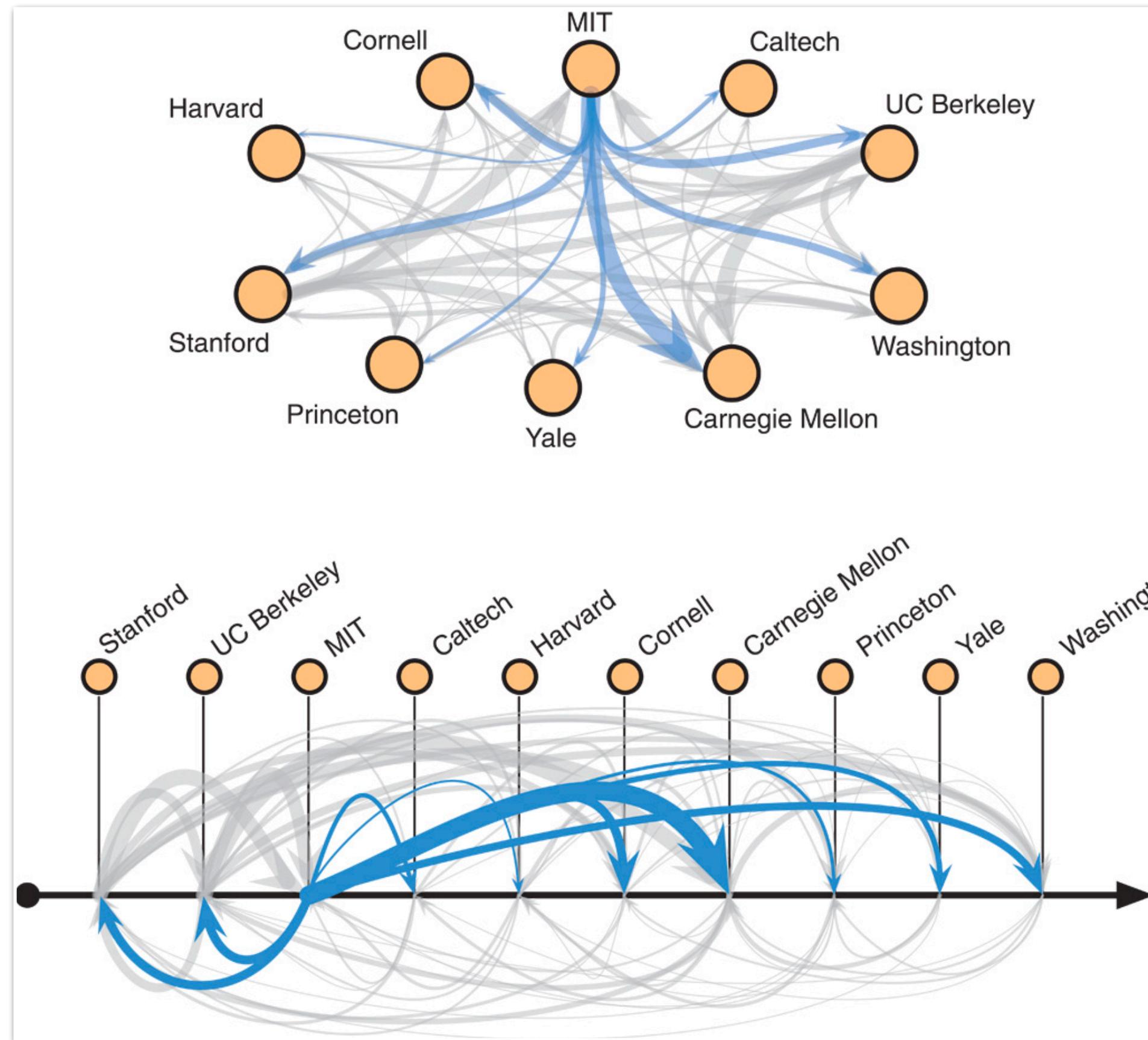
Examples



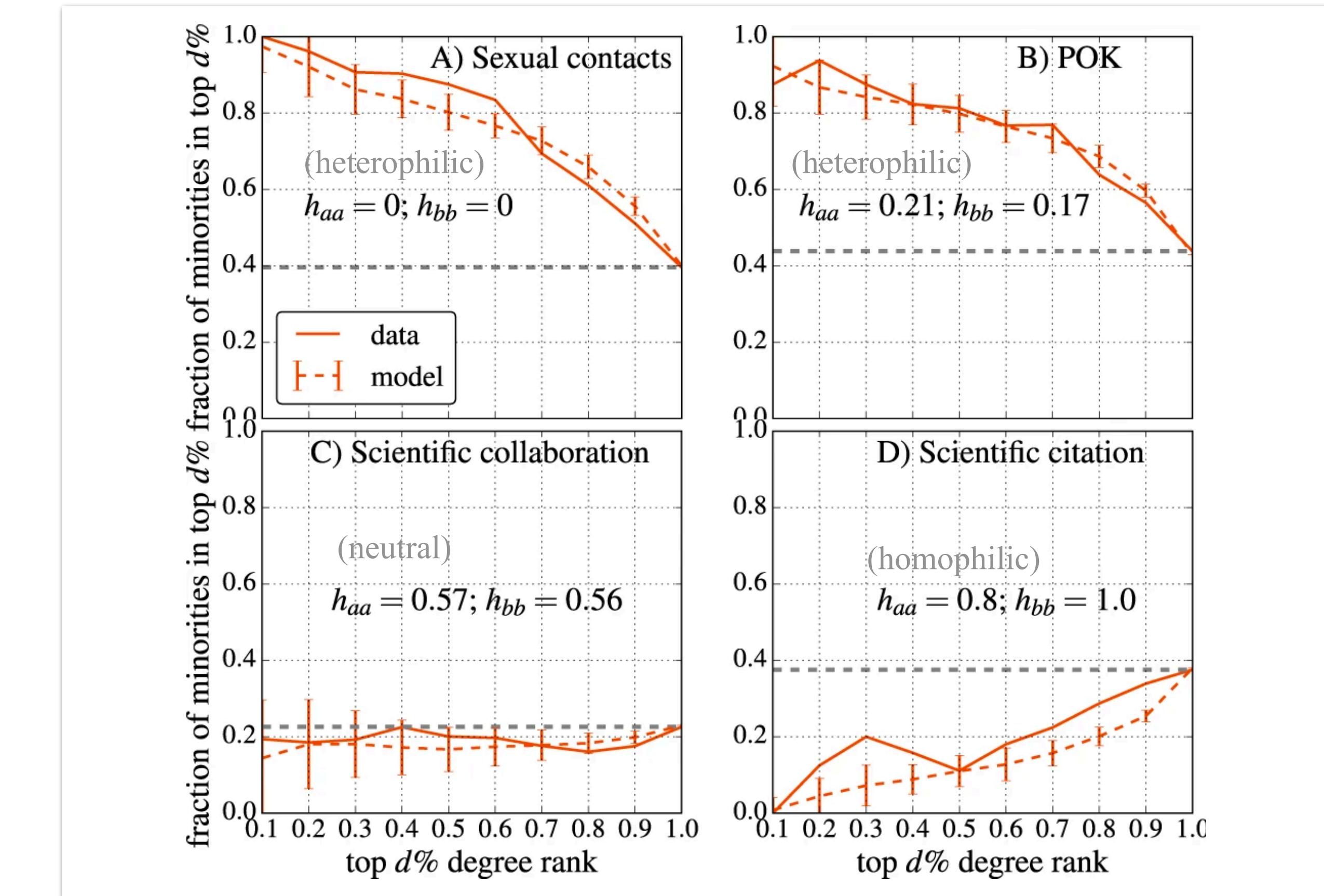
Systematic inequality and hierarchy in faculty hiring networks. Clauset et al. 2015.

Inequalities in networks

Examples



Systematic inequality and hierarchy in faculty hiring networks. Clauset et al. 2015.



Homophily influences ranking of minorities in social networks. Karimi et al. 2018.