

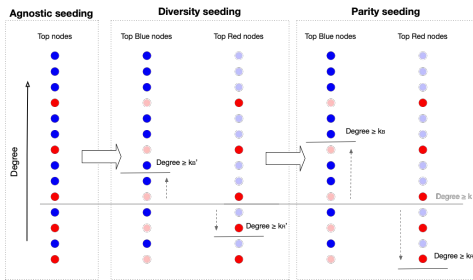


# Diversity and Bias in the Influence Maximization Problem

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## Introduction

We study diversity interventions in the problem of social influence maximization: choosing a set of seeds in a network that maximize the spread of a message, service, or technology. We work with a theoretical model of networks that exhibit community structure and homophily to show that community-aware seeding can lead to a better efficiency in certain conditions, which we analyze analytically in terms of the number of seeds. We propose heuristics to enhance diversity that illustrate the trade-off between diversity and outreach maximization on real networks.

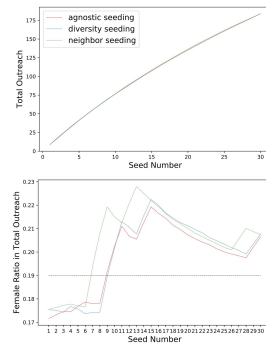


### Data from DBLP:

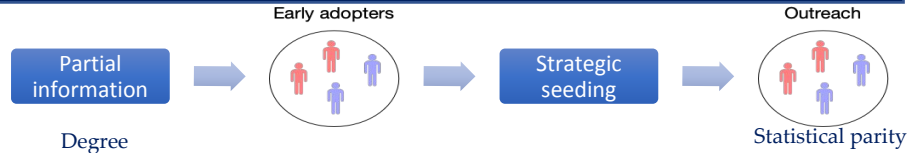
- Co-authorship graph ~50,000 people,
- 81% men, 19% women,
- Homophily: people cluster based on gender.

### Results:

- Diversity-enhancing heuristics improve equity in information access and **no cost** to total outreach.
- Can extend notions of equitable access beyond seed selection and outreach, ensuring diversity at different levels of information cascade.



## Problem formulation & Results

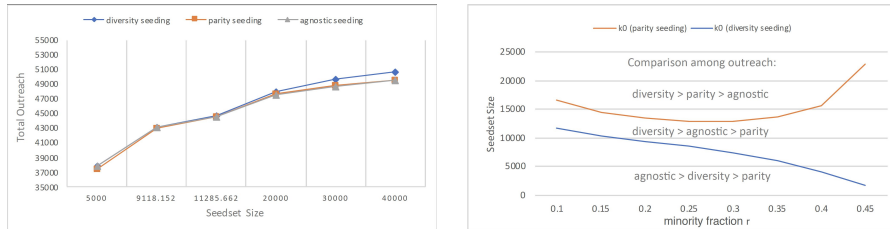


- Obtain statistical parity in the seed selection as a **tool** to get parity in outreach
- Can we be strategic in choosing seeds, while being as efficient?

**Theorem:** For a sufficiently large seedset\* we can achieve both parity in outreach and efficiency: strategic seeding can achieve

- A better R/B outreach ratio than the color agnostic strategy,
- Relaxed-statistical parity in seed selection with the same seed budget,
- Better outreach overall.

\*Corollary: We can analytically compute the seedset size as the root of a function computing marginal influence between diversity seeding ( $k_r$ ) and agnostic, and between parity ( $k_c$ ) seeding  $k_c$  and agnostic.



## Theory

Models of network evolution based on a bi-populated network (red and blue nodes) :  
• Fraction of red nodes =  $r < 1/2$

At timestep  $t$ , a new edge is formed:

### Organic growth model:

- A new node connects naturally:
- $\eta$ : randomly
  - $1 - \eta$ : preferential attachment

Homophily: if  $\neq$  labels, edge is accepted w.p.  $\psi$

### Diffusion model:

- Independent cascade model, each node accepts influence from a neighbor w.p.  $p$

Bias

Key idea: **Homophily** leads to a different degree distribution for the two communities.  
➔ Bias in centrality measures affects who receives the message

## Data

## Proof sketch & Conclusion

Power law dynamics of degree distribution:

$$top_k(R) \sim k^{-\beta(R)}$$

$$top_k(B) \sim k^{-\beta(B)}$$

The expected size of a seedset with nodes of degree at least  $k(n)$  can be computed:

$$\mathbb{E}(|S_{k(n)}|) = n \cdot \alpha \cdot d \cdot \frac{\beta(R) - 2}{\beta(R) - 1} \cdot k(n)^{1-\beta(R)} + n \cdot (1 - \alpha) \cdot d \cdot \frac{\beta(B) - 2}{\beta(B) - 1} \cdot k(n)^{1-\beta(B)},$$

based on the network parameters. The condition from our corollary turns into solving for the roots of a function:

$$F(x) = \mathbb{E}(|\phi_V(S_{k^B(x)}^B \cup S_{k^R(x)}^R)|) - \mathbb{E}(|\phi_V(S_{k(n)})|)$$

Key take-aways:

- Seeding can mirror biases existing in the network:
  - In the people chosen as early-adopters,
  - In the population that receives information.
- We can ensure fairness without losing outreach in certain conditions that are achievable in real datasets.
- Our model allows us to compute such conditions analytically and to design better algorithms for information diffusion.