Designing **link recommendation algorithms** for **social good**

Fernando P. Santos

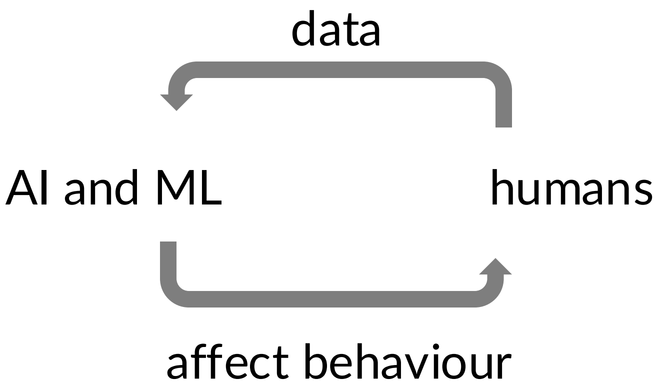
SIAS / Civic AI Lab / Prosocial Dynamics Lab

October 30, 2024

Human-Centred Machine Learning

*Human-centered artificial intelligence is a perspective on **AI and ML** that algorithms must be designed **with awareness that they are part of a larger system consisting of humans**.*

Mark O.Riedl



A loop hard to understand and control…
examples:

Strategic Classification
People strategically adapting to classifiers
(modelled as a Stackelberg Game)

Link-recommendation

Summary

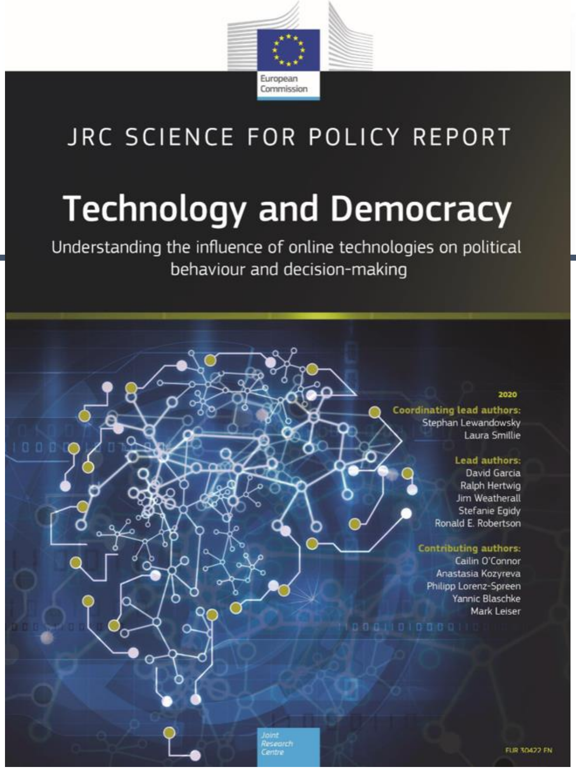
- Interactions in online social networks mediated by **link recommendation algorithms**
- **Part I:** Impact of link recommendation algorithms on **opinion polarization**
  - Model of opinion formation on dynamic social networks
- **Part II:** Impact of link recommendation algorithms on **fair network centrality**
  - Test previous fair embedding methods; correct unfair betweenness centrality

Online social networks: large system comprised of humans and AI

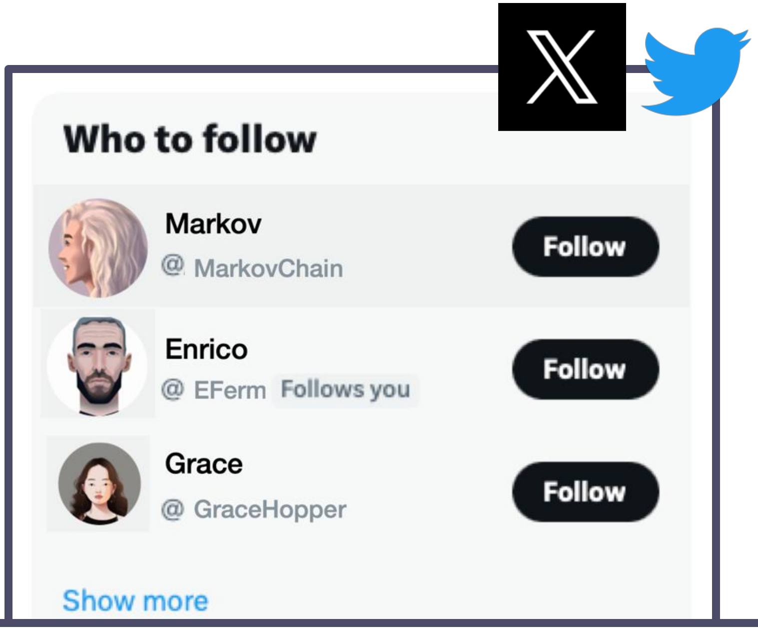
Social media influences our political behaviour and puts pressure on our democracies, new report finds

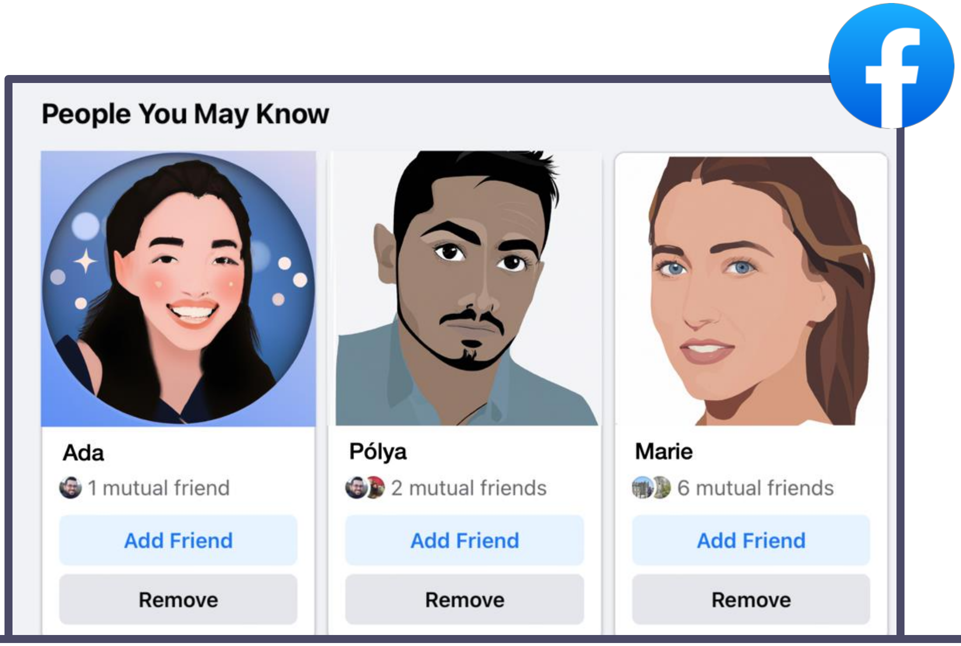
OCT 27 2020

The democratic foundations of our societies are under pressure from the influence that social media has on our political opinions and our



Human-AI systems: Networks shaped by link recommendation algorithms

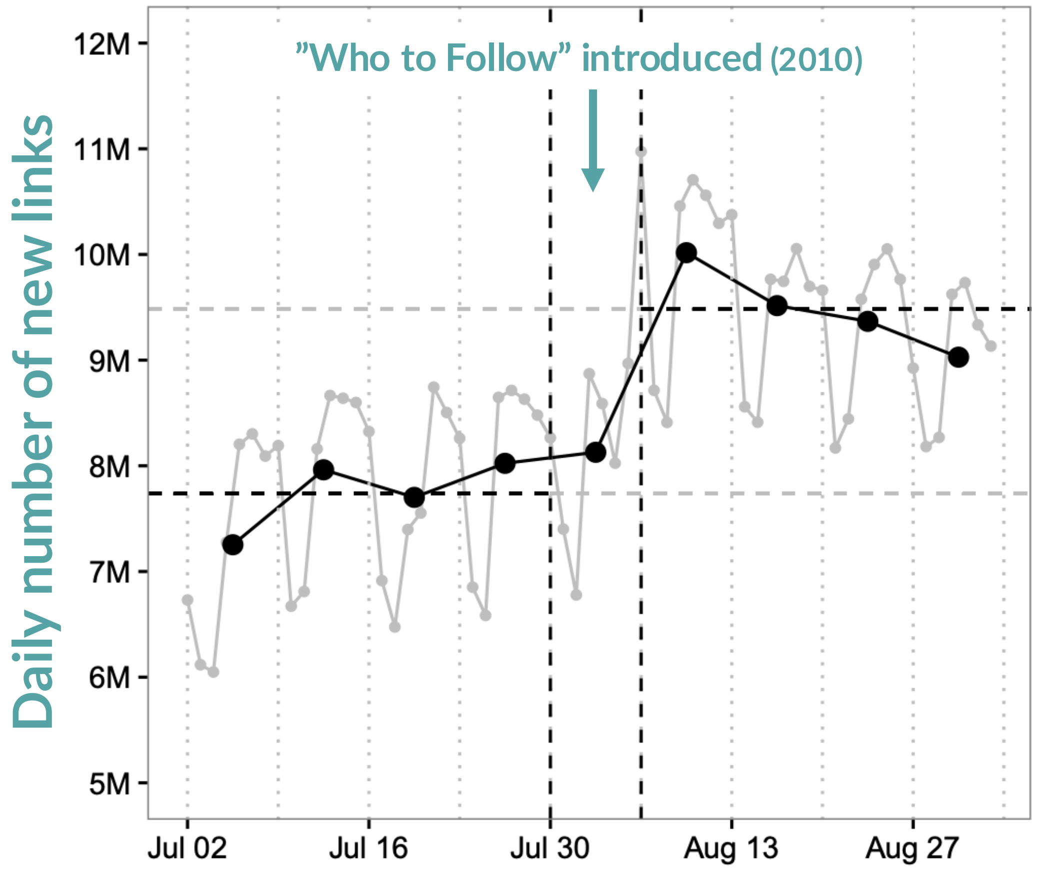




Link-recommendation algorithms

recommend new connections to users in online social networks

Link-recommendation algorithms impact network evolution



[Su et al., WWW'16]

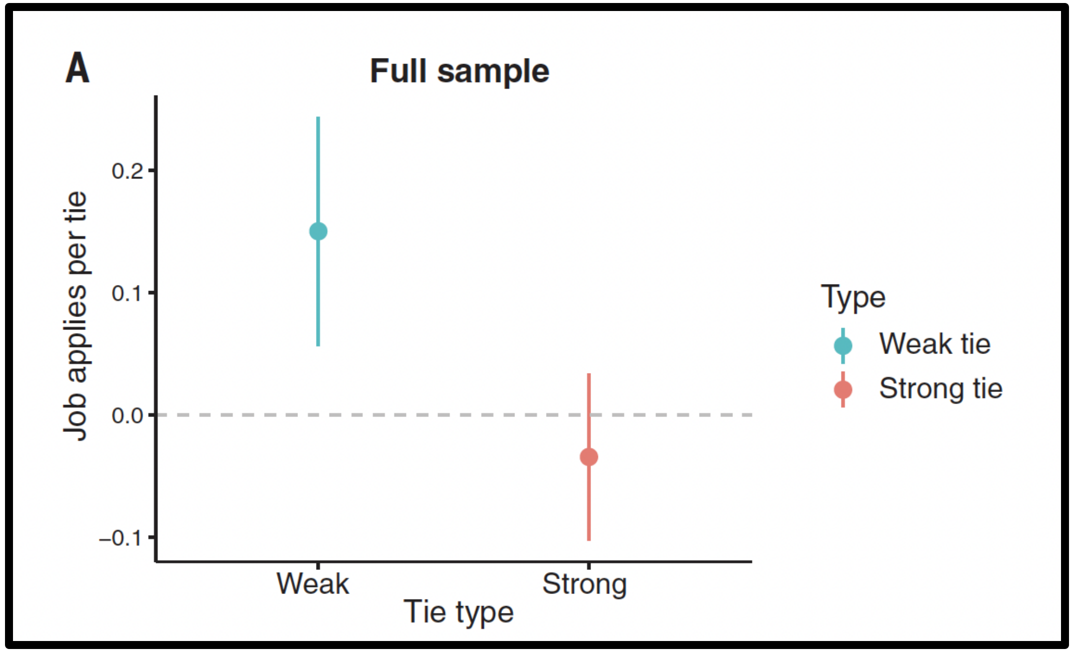
Link recommendation algorithms impact job applications & transmission

Science NETWORKS

A causal test of the strength of weak ties

KARTHIK RAJKUMAR, GUILLAUME SAINT-JACQUES, IAVOR BOJINOV, ERIK BRYNJOLFSSON, AND SINAN ARAL

Tuning the "*People You May Know*" algorithm on LinkedIn affects **job applications** and job **transmission**



[Rajkumar et al., *Science*, 2022]

WIRED on Algorithms

Why does Facebook recommend friends I've never even met?

By **AMELIA TAIT**

Wednesday 29 May 2019

Facebook's People You May Know algorithm is shrouded in mystery – even within the company itself. But its suggestions have often led to dark consequences

Structurally similar individuals recommended to each other

What information does Facebook use to show suggestions in People You May Know?

People You May Know suggests people you might be likely to add as a friend on Facebook. Friend suggestions come from things like:

- Having friends in common. This is the most common reason for suggestions
- Your profile information and networks (example: your school, university or work)
- Your Facebook activity (example: joining groups, being tagged in photos)

https://www.facebook.com/help/findingfriends

Part I

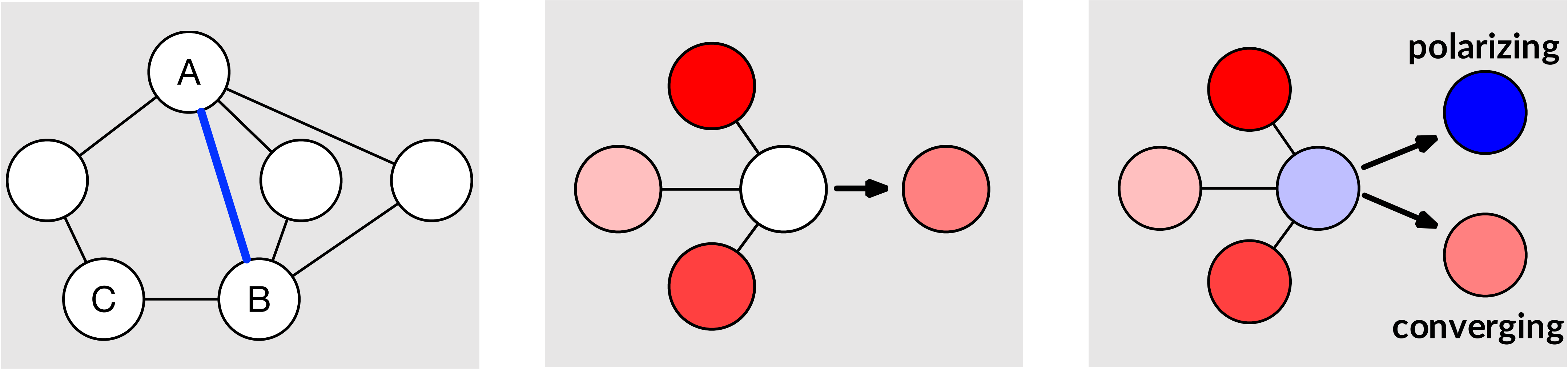
What is the impact of link recommendation algorithms on opinion dynamics, polarization and radicalization?

Part II

What is the impact of link recommendation algorithms on fair betweenness centrality?

Model of opinion formation on dynamic social networks

- Population with N individuals (nodes)
- Connected through dynamic network (adjacency matrix $A(t) \in \{0,1\}^{N \times N}$)
- Each individual (node) has opinion $x \in (-\infty, +\infty)$



1. Rewire based on structural similarity

2. Opinions vary through social influence

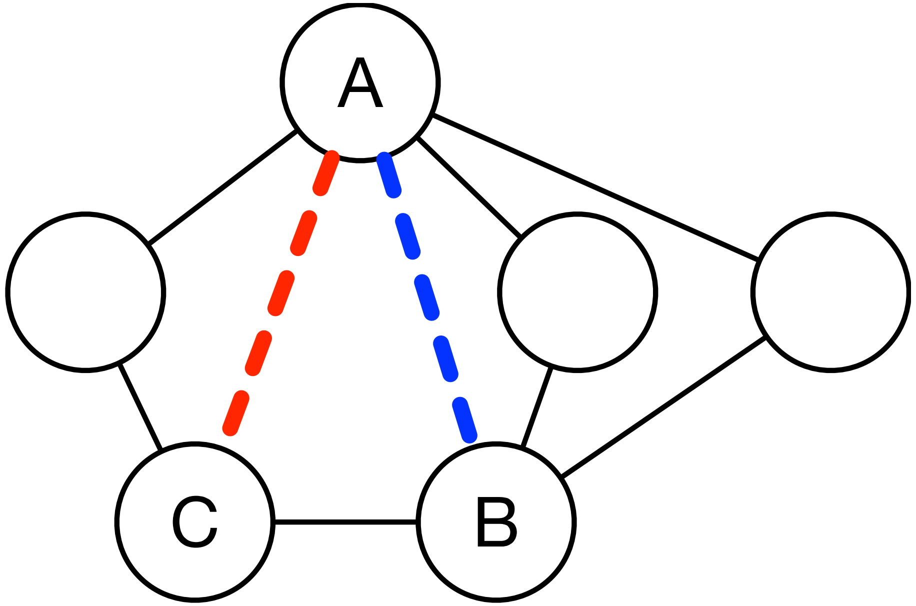
3. Two types of reaction to out-group: **converging** and **polarizing**

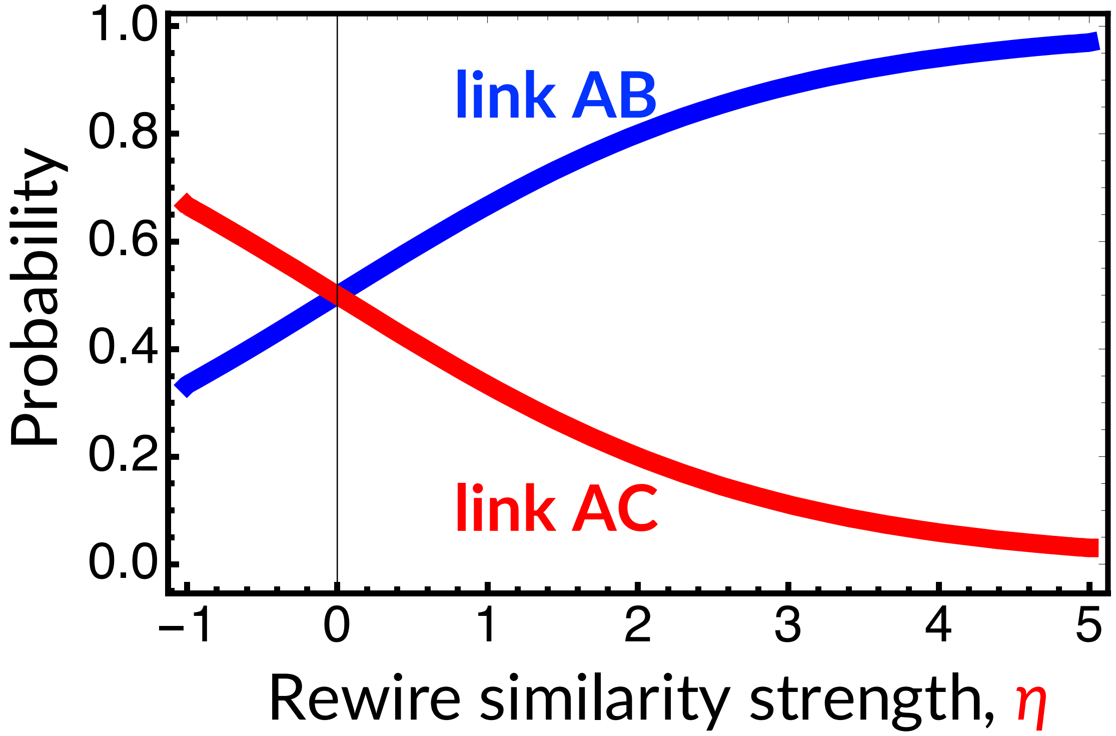
structural similarity:
$c(i,j) \rightarrow$ #common friends between *i* and *j*

$$s_{i,j} = \frac{c(i,j)^{\eta}}{\sum_k^N c(i,k)^{\eta}} \longrightarrow$$

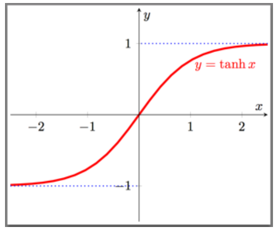
At each time-step, select random node *i* and rewire link of *i*:

1. Select random link with *i to break*
2. Add link between *i* and *j with probability* $s_{i,j}$





1. Rewire based on structural similarity



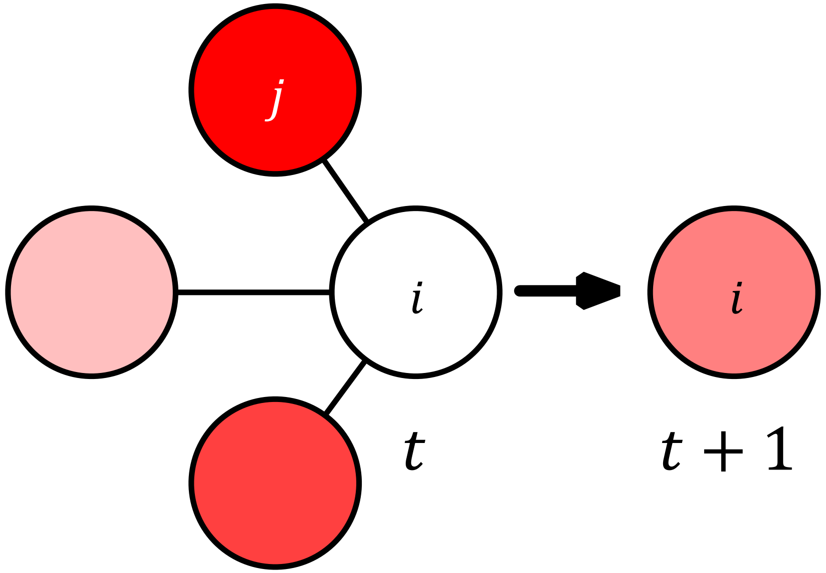
bounded; social influence of extreme opinions is capped

$$x_i(t+1) = \gamma x_i(t) + K \sum_{j}^{N} A_{i,j} \tanh\left(\alpha x_j(t)\right)/k_i$$

0<γ<1, stabilizing effect / decay

neighbors

social influence / issue controversy



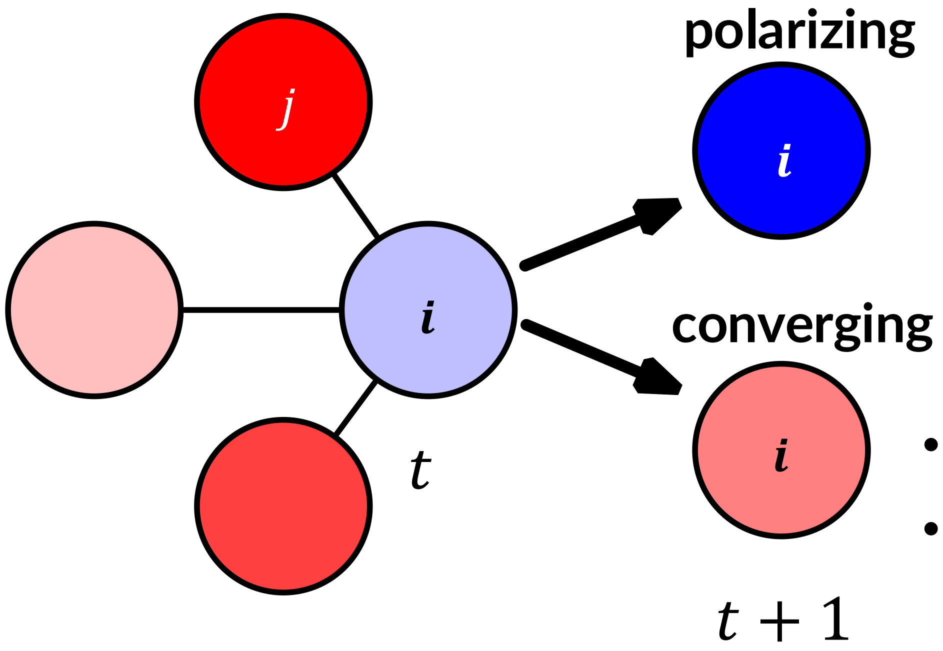
- Leonard, N. et al. (**2021**). The nonlinear feedback dynamics of asymmetric political polarization. PNAS
- Bizyaeva, A. et al. (**2021**). A general model of opinion dynamics with tunable sensitivity. IEEE Transactions on Automatic Control
- Baumann, F. et al. (**2020**). Modeling echo chambers and polarization dynamics in social networks. Physical Review Letters

- Intra-group contacts reinforce opinions: **group polarization**
- Inter-group contacts **moderate** opinions

2. Opinions vary through social influence

$\mathrm{sgn}(x)$ -> sign opinion x

$$x_i(t+1) = \gamma x_i(t) + K \sum_{j}^{N} A_{i,j} \tanh\left(\alpha.\,\mathrm{sgn}(x_j)\mathrm{sgn}(x_i).\,x_j\,(t)\right)/k_i$$



Exposure to opposing views on social media can increase political polarization

Christopher A. Bail[a,1], Lisa P. Argyle[b], Taylor W. Brown[a], John P. Bumpus[a], Haohan Chen[c], M. B. Fallin Hunzaker[d], Jaemin Lee[a], Marcus Mann[a], Friedolin Merhout[a], and Alexander Volfovsky[e]

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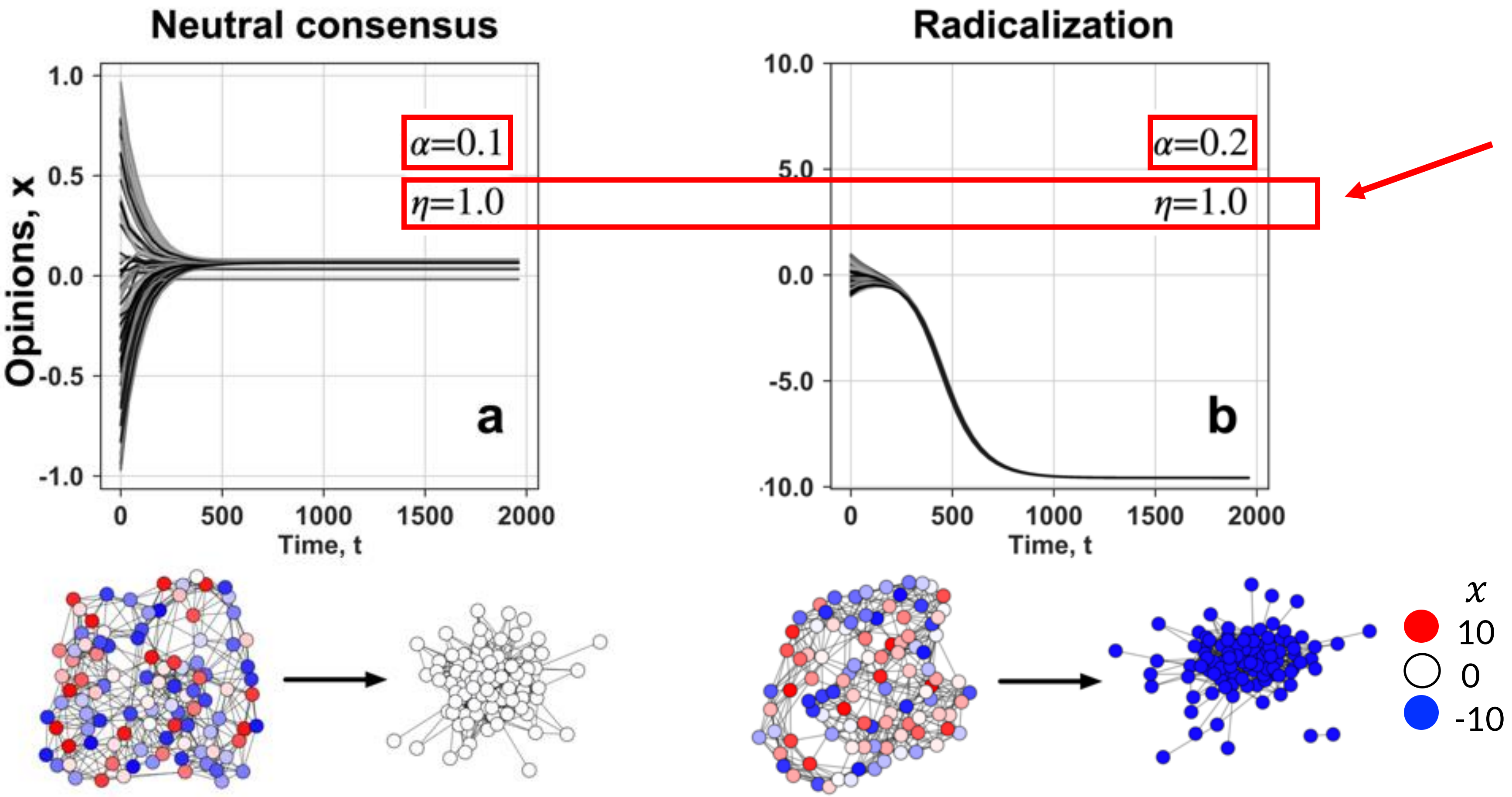
Edited by Peter S. Bearman, Columbia University, New York, NY, and approved August 9, 2018 (received for review March 20, 2018)

- **Intra**-group contacts reinforce opinions: group polarization
- **Inter**-group contacts **reinforce** ~~moderate~~ opinions

3. Two types of reaction to out-group: converging and polarizing

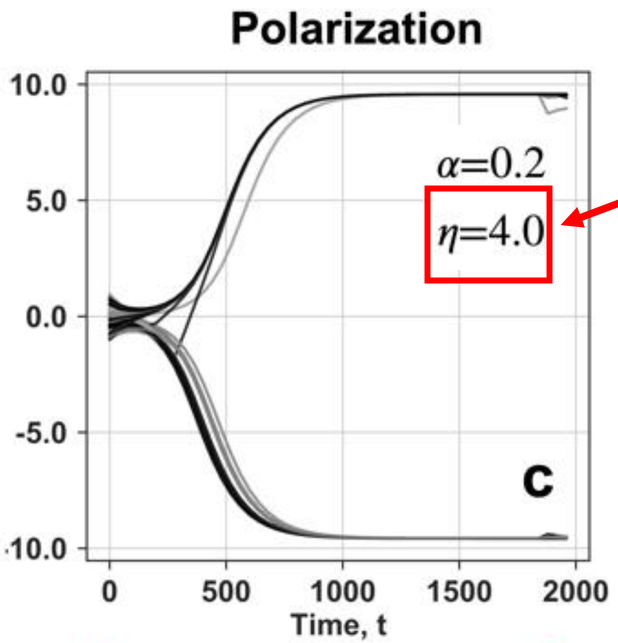
Results: baseline



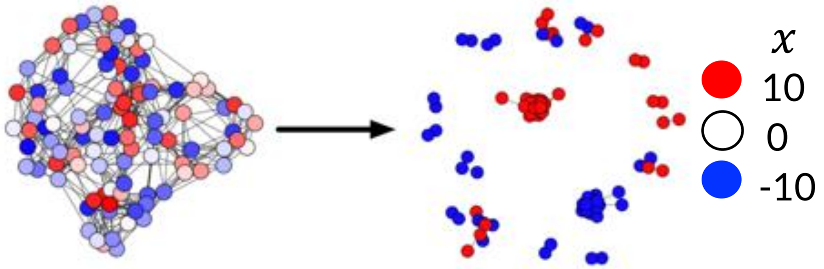
Low η
Rewire depends weakly on structural similarity

$N = 100, \langle k \rangle = 10, K = 0.1, \gamma = 0.99 \longrightarrow$ Parameters such that: $-10 < x < 10$

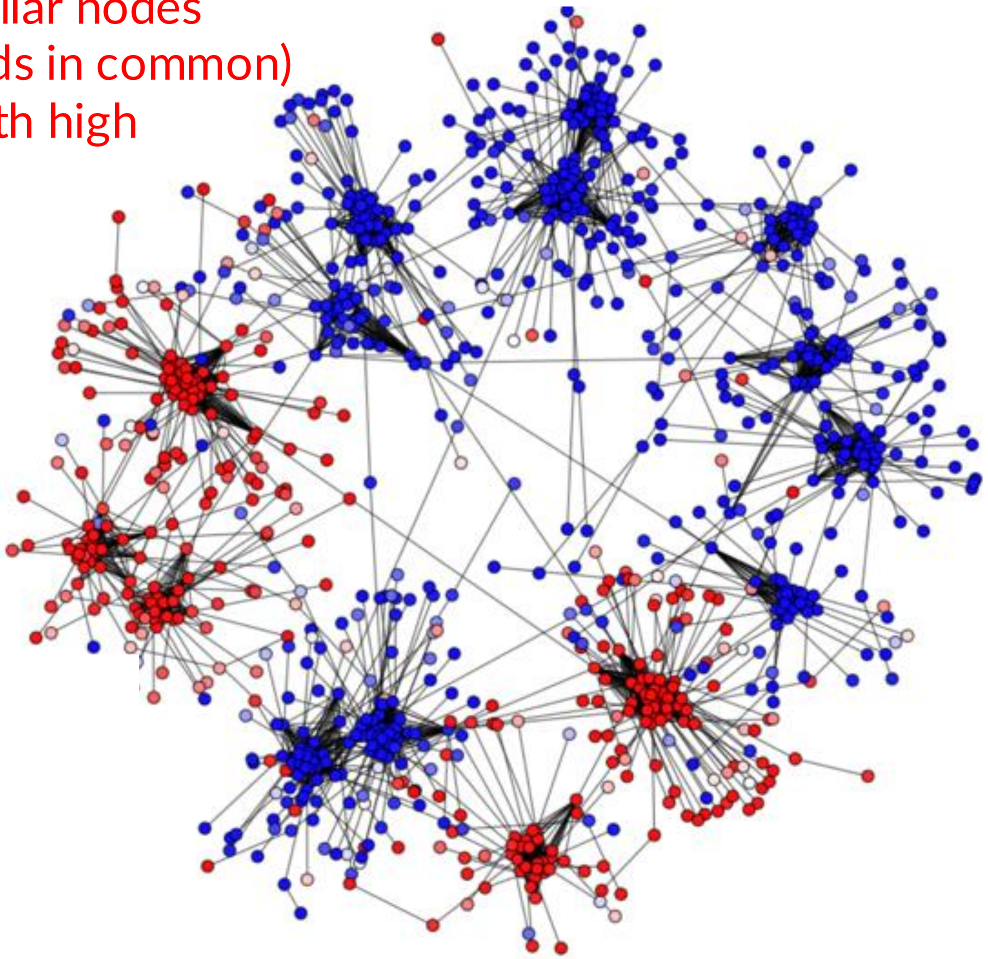
Results: Connect structural similar nodes → modules & polarization



Structural similar nodes
(if many friends in common)
connected with high
probability

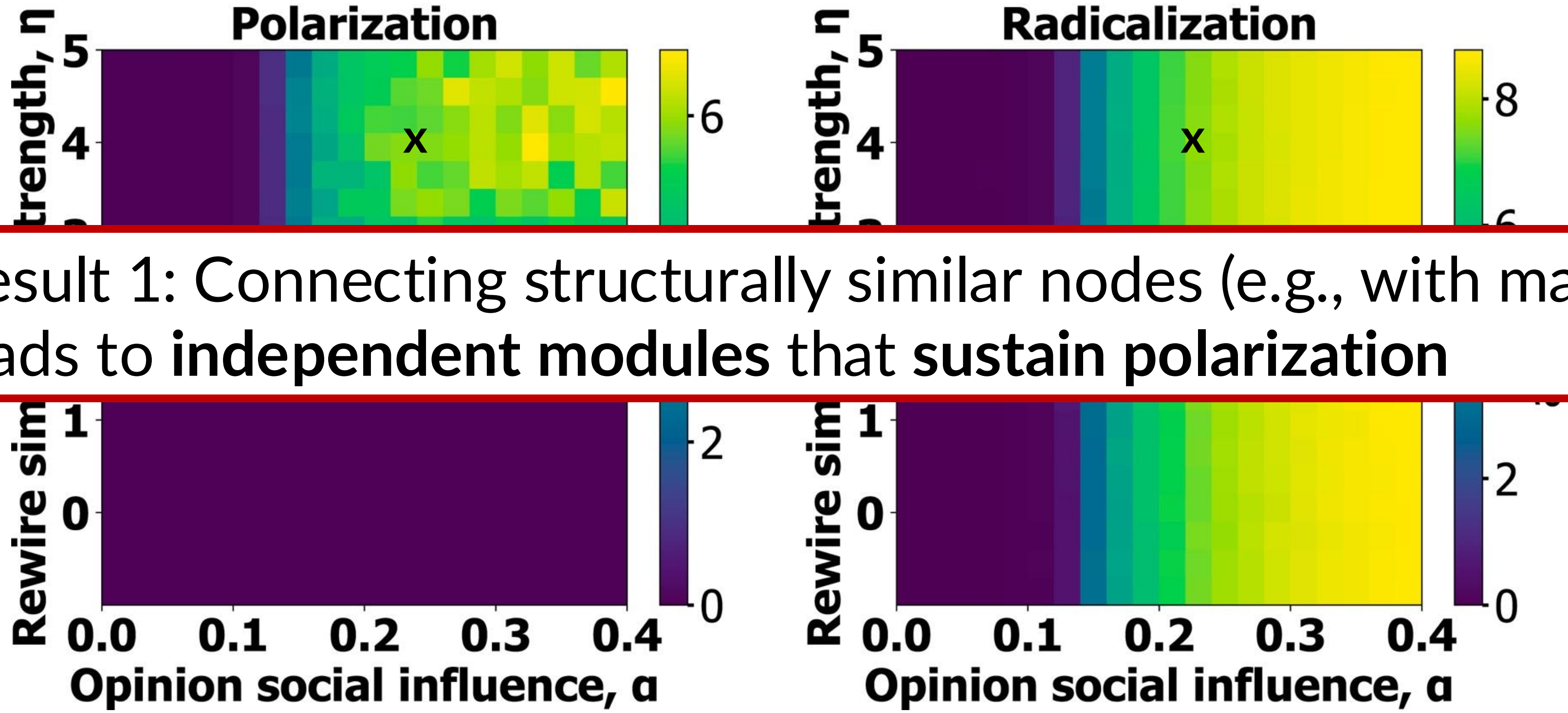


$N = 100, \langle k \rangle = 10, K = 0.1, \gamma = 0.99$



$N = 1000$

Results: Connect structural similar nodes → modules & polarization



Result 1: Connecting structurally similar nodes (e.g., with many common friends) leads to **independent modules** that **sustain polarization**

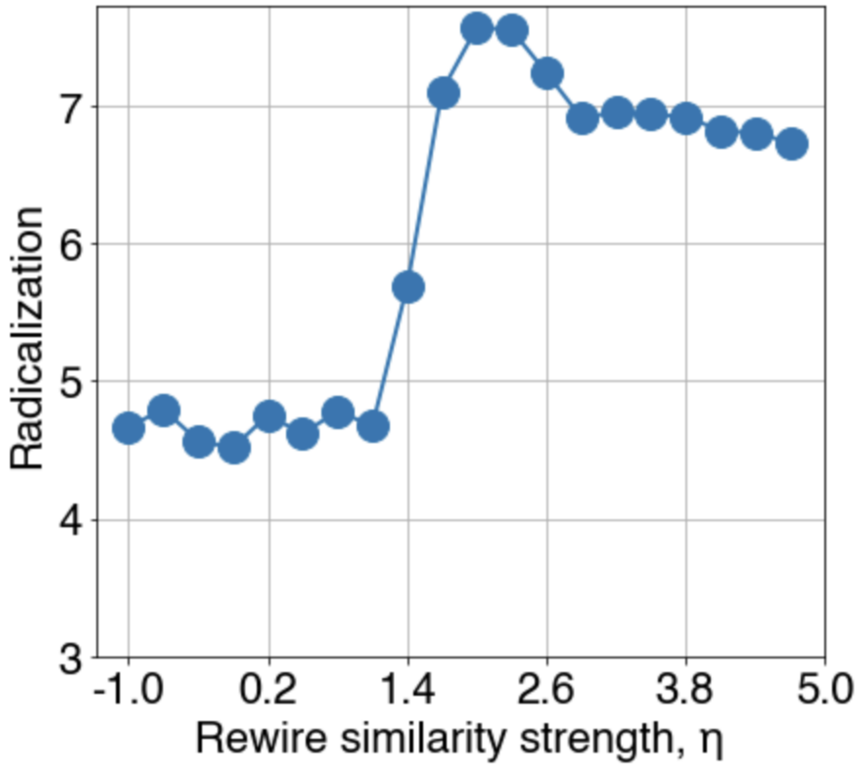
average 100 independent runs $N = 100, \langle k \rangle = 10, K = 0.1, \gamma = 0.99$

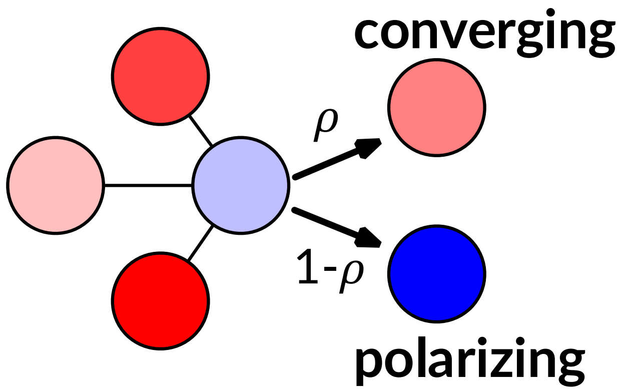
Polarization:
Standard deviation x

Radicalization:
Average absolute x

Results: Connect structural similar nodes → radicalization

50% polarizing
50% converging ($\rho = 0.5$)





Polarization:
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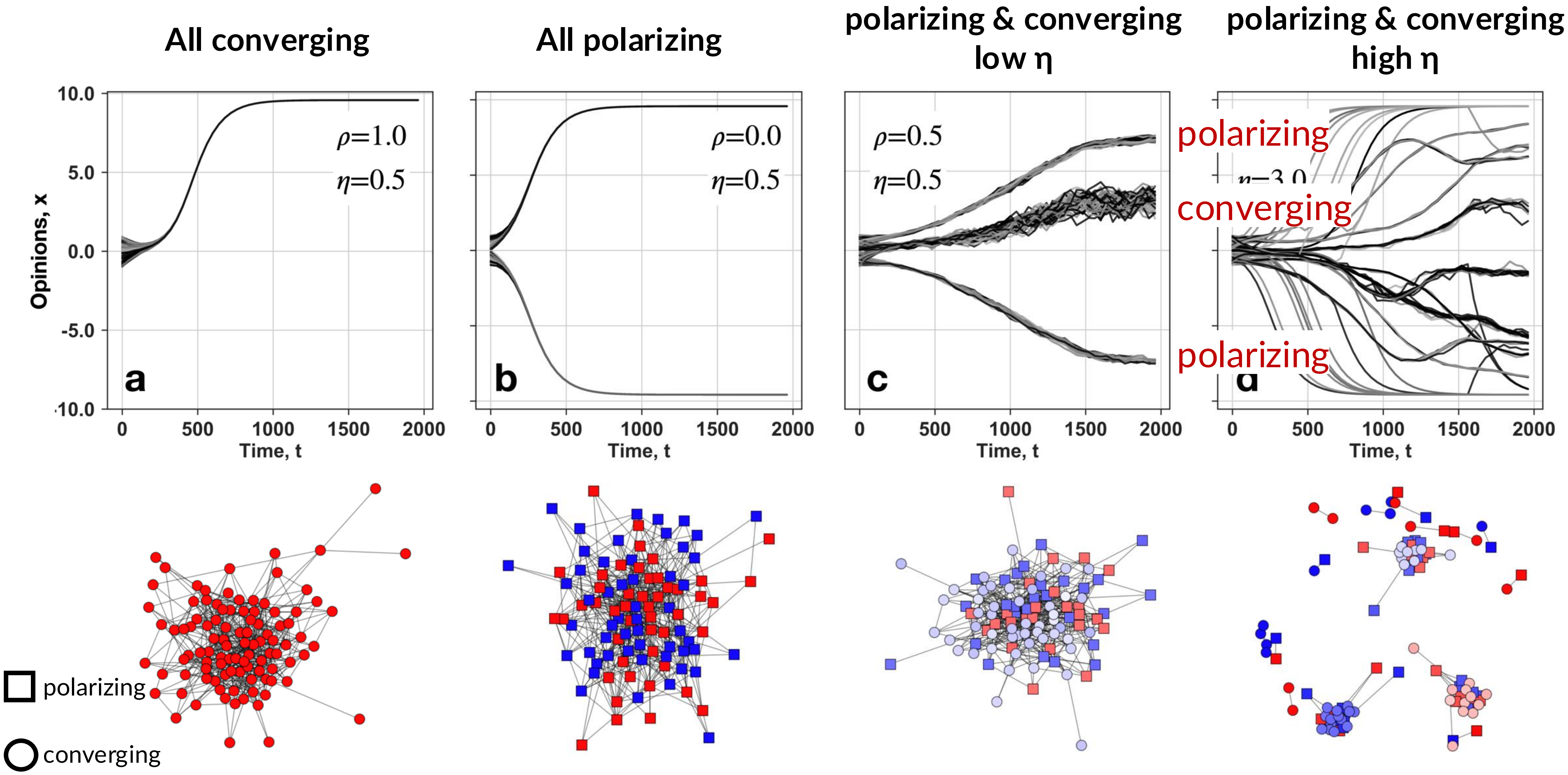
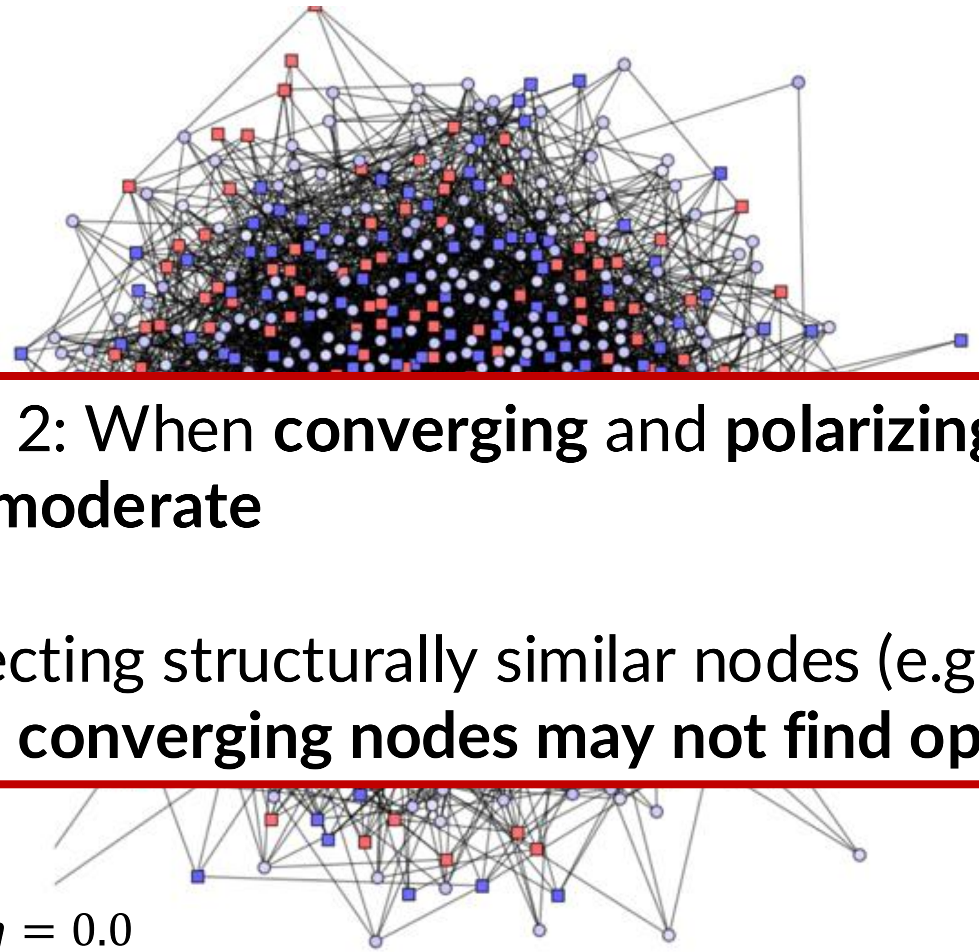
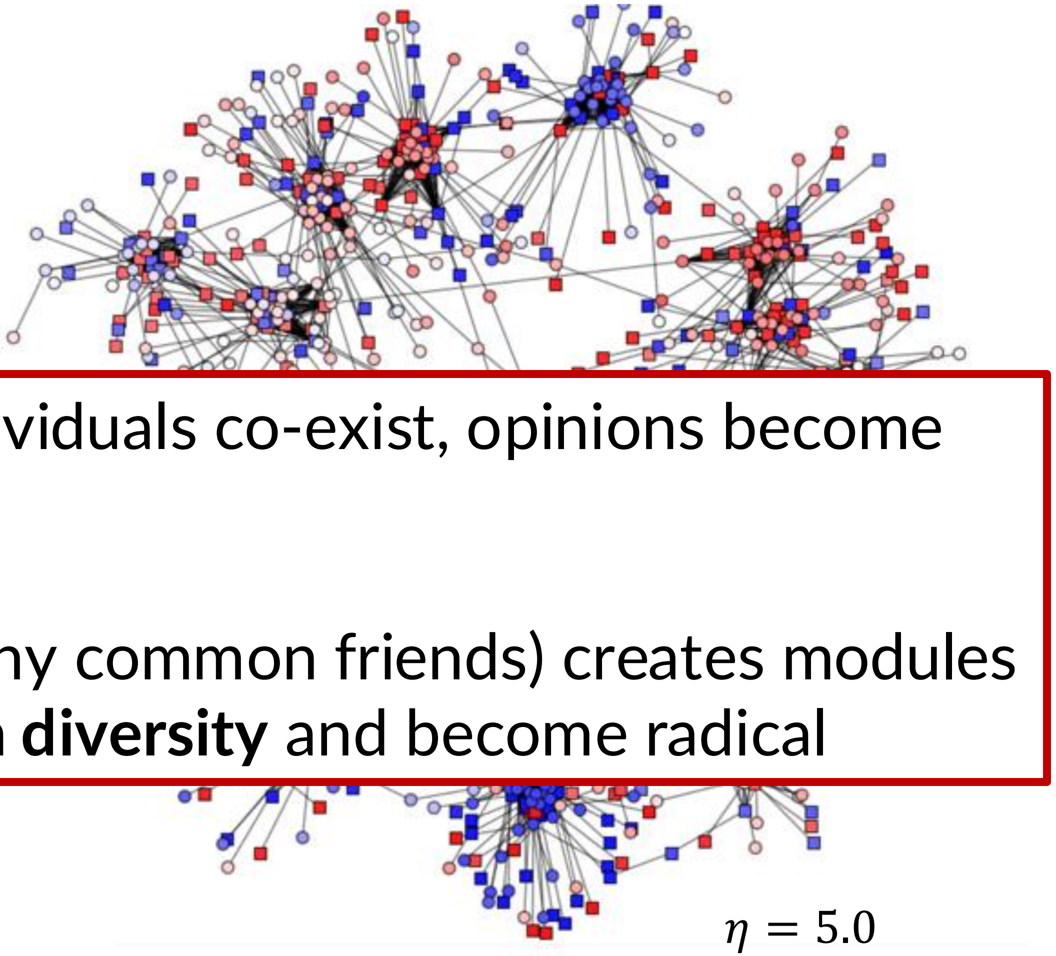




$\eta = 0.0$



$\eta = 5.0$

Result 2: When **converging** and **polarizing** individuals co-exist, opinions become more **moderate**

Connecting structurally similar nodes (e.g., many common friends) creates modules where **converging nodes may not find opinion diversity** and become radical

$N = 1000, K = 0.1, \langle k \rangle = 10, \gamma = 0.99, \alpha = 0.2, \rho = 0.5$

Part I

What is the impact of link recommendation algorithms on opinion dynamics, polarization and radicalization?

Connecting structurally similar nodes (e.g., with many common friends) leads to independent modules that sustain polarization & radicalization

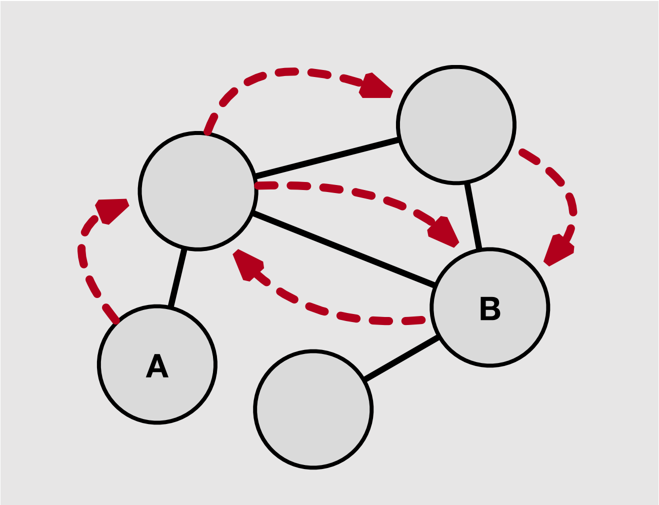
~~Part I~~

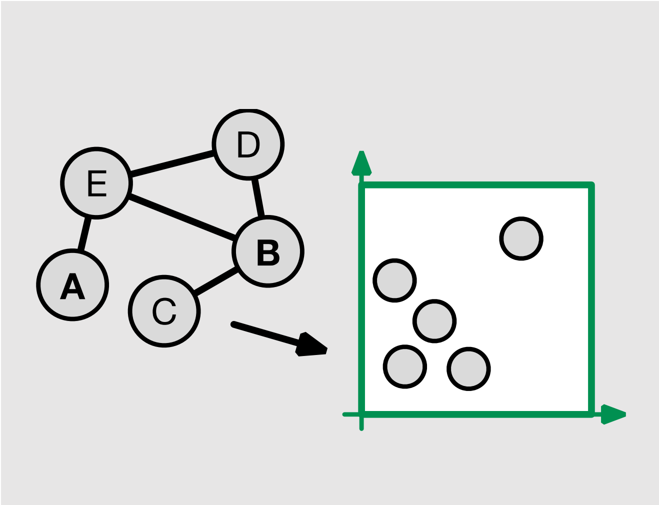
~~What is the impact of link recommendation algorithms on opinion dynamics, polarization and radicalization?~~

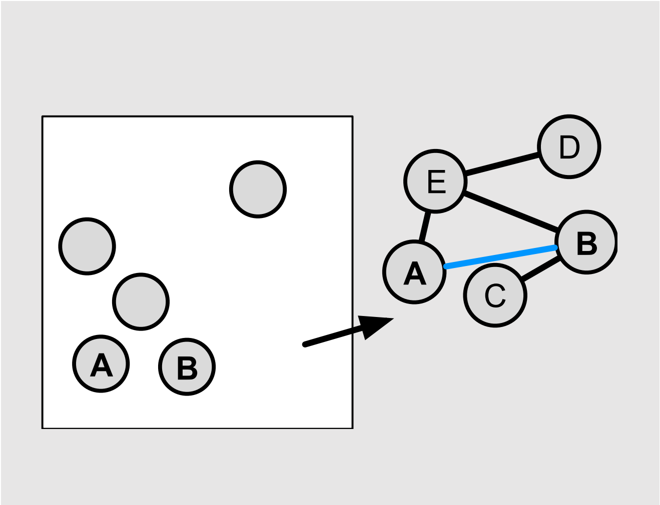
Part II

What is the impact of link recommendation algorithms on fair betweenness centrality?

Random-walk embedding based recommendations







1. Use **random-walks** to define similarity between node pairs

2. Learn low-dimensional **node embedding** such that proximity captures probability of co-occurring in random walks (e.g., **DeepWalk**, **node2vec**…)

3. **Recommend** based on node distance in the embedded space

Fairness in link-recommendation algorithms (any ideas?)

Algorithmic Glass Ceiling in Social Networks

The effects of social recommendations on network diversity

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link-recommendation algorithms can worsen pre-existing inequalities on the network and organic growth

when the majority group is homophilic, the minority group is underrepresented in recommendations

Article | Open access | Published: 07 February 2022

Inequality and inequity in network-based ranking and recommendation algorithms

Lisette Espín-Noboa, Claudia Wagner, Markus Strohmaier & Fariba Karimi

Scientific Reports **12**, Article number: 2012 (2022) | Cite this article

The Effect of Homophily on Disparate Visibility of Minorities in People Recommender Systems

Francesco Fabbri,[1,3] Francesco Bonchi,[2,3] Ludovico Boratto,[3] Carlos Castillo[1]
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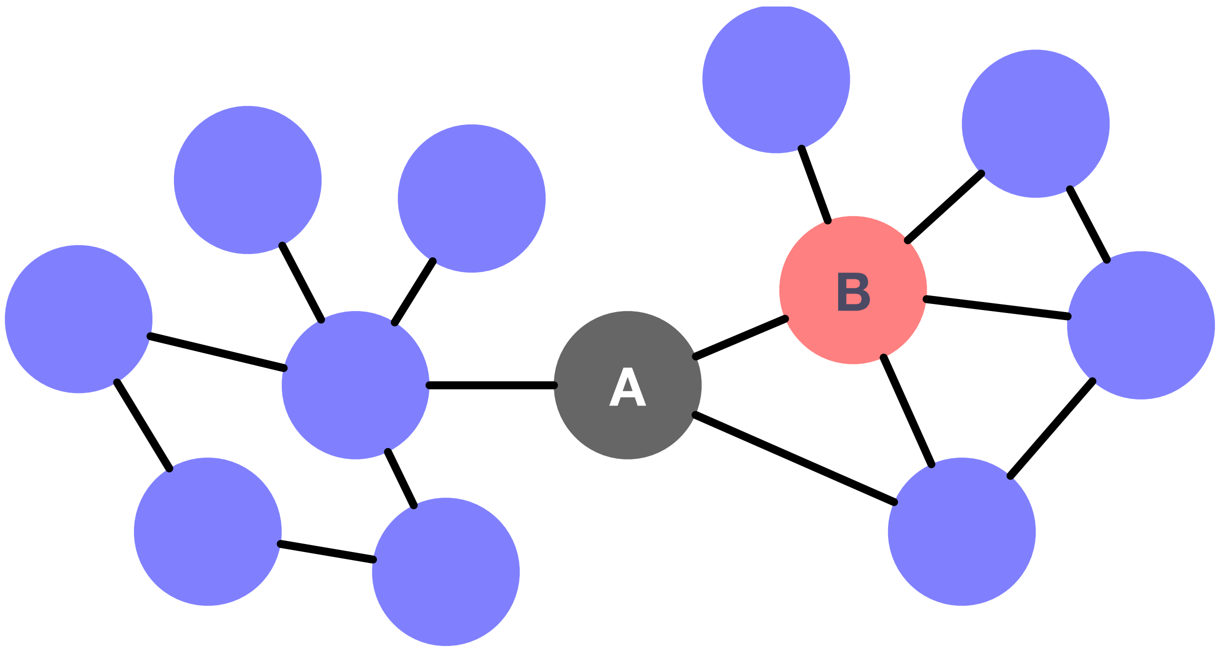
[2]ISI Foundation, Turin, Italy
[3]Eurecat, Barcelona, Spain

homophily plays a key role in the visibility that is given to a group, even if group is a minority

Fairness in link-recommendation algorithms

fairness beyond representation on recommendations?



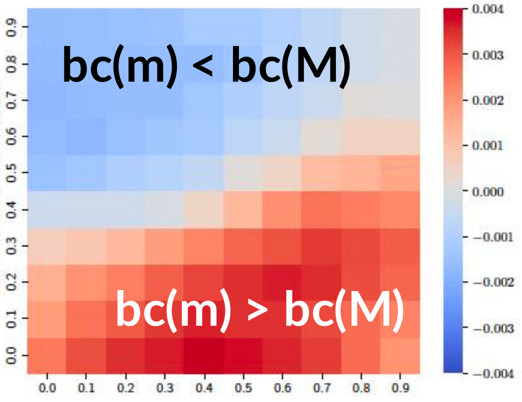
Fairness in link-recommendation algorithms: betweenness centrality

1. Generate networks with **DPAH**: directed networks, 2 groups, pref. attachment and homophily [Espín-Noboa et al, Sci Rep, 2022]
2. $\forall v \in V$: add top-1 recommendation based on cosine similarity in embedded space; repeat
3. Evaluate the group-average betweenness centrality of the resulting networks

M. Pawar
MSc AI thesis!

Before recommendations

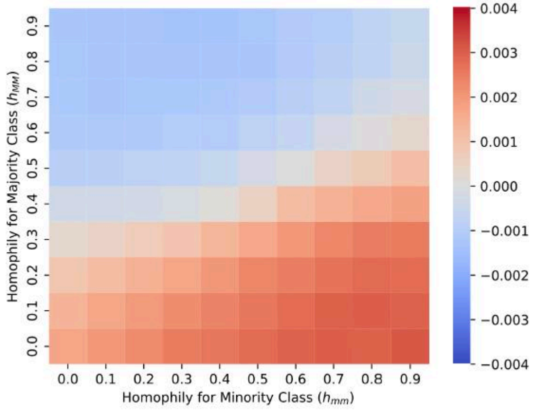
homophily majority



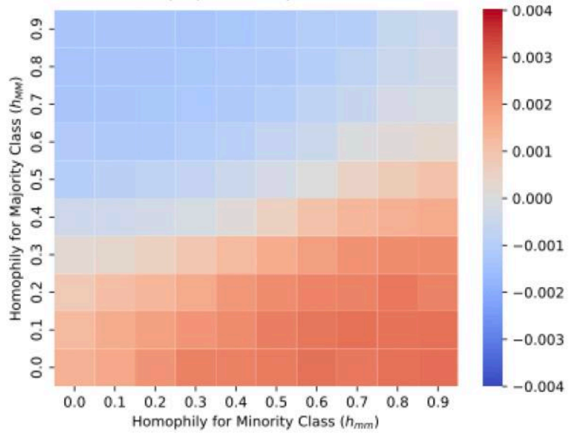
bc(m)-bc(M)

homophily minority

After ***n2v*** recommendations

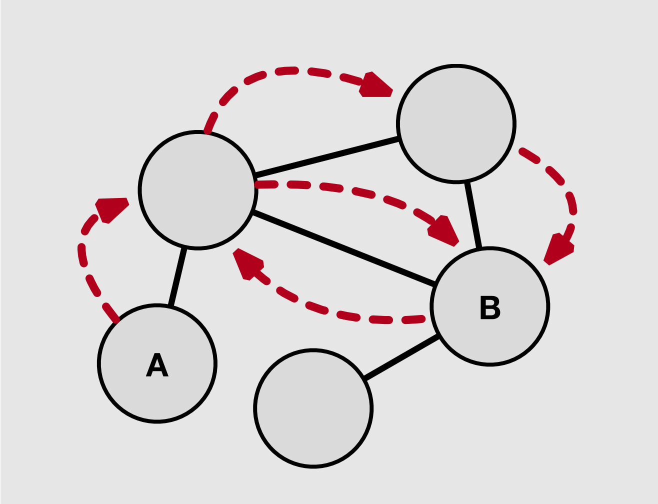


After ***Fairwalk*** recommendations



Betweenness centrality disparities remain even with fair embedded method algorithm

Random-walk embedding based recommendations: bias to sustain fairness



1. Use **random-walks** to define similarity between node pairs

Previous fair embedding methods (e.g., ***Fairwalk***): equalize transition probabilities between groups

Unable to improve fair betweenness centrality

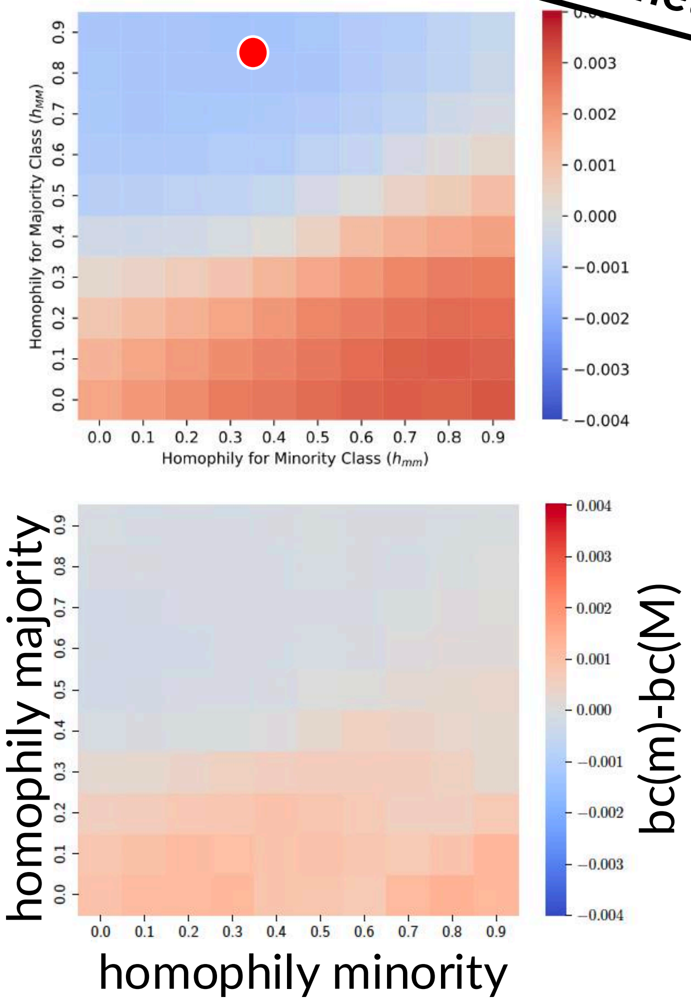
Our approach: bias based on in-degree:
Higher probability of jumping to high-indegree node (local jump with probability α; non-local otherwise)

Random-walk embedding based recommendations: in-degree based

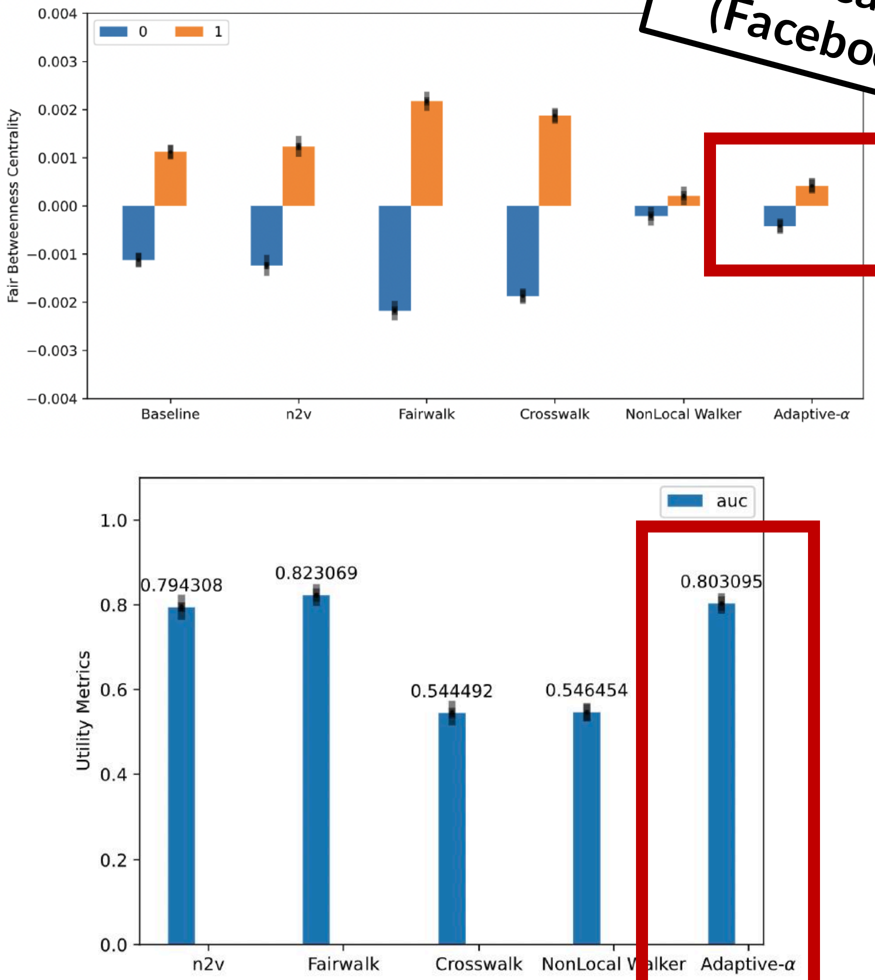
Synthetic networks

n2v / FairWalk

In-group-based Random walks



Empirical network (Facebook Rice)



Link recommendation algorithms can impact minority groups centrality

Result 1: Recommendations based on fair embedding methods do not avoid disparities in network centrality

Intuition: the group identity of nodes recommended is not the only important feature; degree also important

Result 2: In-degree based random walks can be engineered to improve fair betweenness centrality while keeping utility

Summary

- What is the impact of **link recommendation algorithms** on social dynamics?

Part I

- Model of **opinion formation on dynamic social networks**
    - **Result**: Connecting structurally similar nodes (e.g., with many common friends) leads to **independent modules** that **sustain polarization** and **radicalization**

Part II

- Link recommendation algorithms can impact minority groups centrality
    - **New algorithm:** In-degree based random walks can be engineered to improve fair betweenness centrality while keeping utility

thank you!

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Link recommendation algorithms and dynamics of polarization in online social networks

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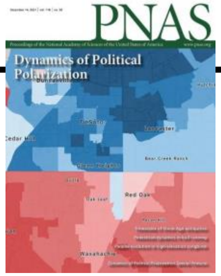

RE LINK

European Research Council





Humans-Algs-Society Workshop @ ICML

Improving Centrality Fairness in Algorithmic Link-Recommendations

Madhura Pawar[1] Fariba Karimi[2,3] Fernando P. Santos[1]

(in progress)

TA for FACT-AI?