Analysis of minority ranking w.r.t. homophily and RL recommenders

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Agenda

1. Motivation
2. Research Questions
3. Methods
4. Results
5. Conclusion

Motivation

Analysis of minority ranking w.r.t. homophily and RL recommenders

Motivation

“Birds of a feather flock together” - proverb

“Similarity begets friendship” - Plato (Phaederus)

Analysis of minority ranking w.r.t. **homophily** and RL recommenders

Human tendency to bond with people sharing same attributes or similar interests.

Motivation

Analysis of minority ranking w.r.t. homophily and RL recommenders

Motivation


OPINION › COLUMNISTS

On media: Social networks will be the death of all of us

By **ARIEL CARMONA** | arielcarmona@record-bee.com |
February 11, 2020 at 6:33 a.m.

As the editor of a small area newspaper and as a member of the print media, I have always been keenly interested in how people gather and share information and in how consumers attain their news in the wake of the internet explosion of the mid 1990s and the current proliferation of social media platforms and I have come to the conclusion that social media, although helpful to news delivery and informing the overall public in some respects, actually does more harm than good and continues to play a major role in the political and cultural polarization we currently find ourselves stuck in here in America.

[2]

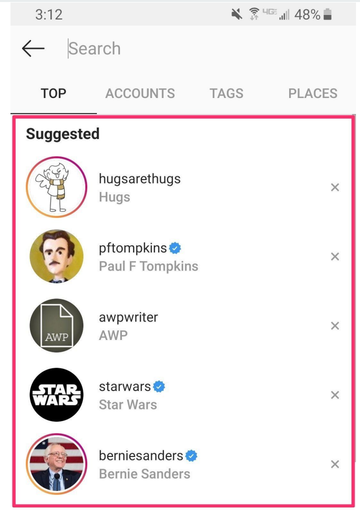
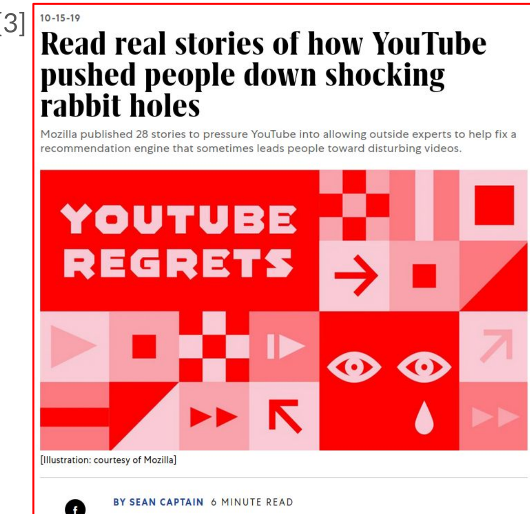


Image Source : https://www.pulse.com.gh/bi/tech/how-to-clear-suggested-searches-on-instagram-on-your-android-device/b7kfqvt

[3]


10-15-19

Read real stories of how YouTube pushed people down shocking rabbit holes

Mozilla published 28 stories to pressure YouTube into allowing outside experts to help fix a recommendation engine that sometimes leads people toward disturbing videos.

[Illustration: courtesy of Mozilla]

BY SEAN CAPTAIN 6 MINUTE READ

nking w.r.t. homophily and RL recommenders


From self-harm to terrorism, online recommendations cast a deadly shadow

John Naughton

The tragic case of Molly Russell has highlighted their malign influence

'The sad truth about the internet is that it holds up a mirror to human nature.' Photograph: Westend61/Getty Images/Westend61

My eye was caught by a headline in *Wired* magazine: "When algorithms think you want to die". Below it was an article by two academic researchers, Ysabel Gerrard and Tarleton Gillespie, about the "recommendation engines" that are a central feature of social media and e-commerce sites.

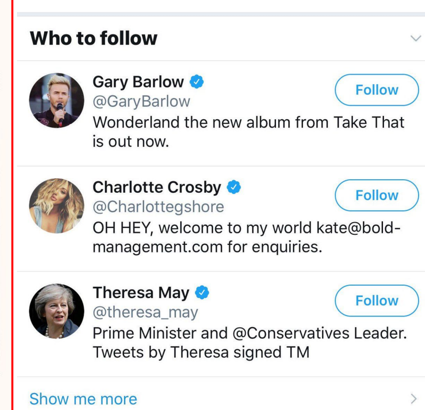


Image Source : https://twitter.com/bobbyllew/status/881608345282646016

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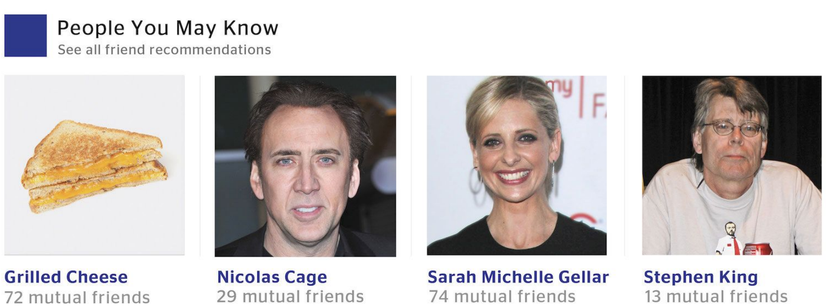


Image Source : https://lasvegasweekly.com/ae/2015/apr/29/cultural-attachment-facebook-people-you-may-know/

Motivation

AI = RL + DL [9]

David Silver, lead researcher
AlphaGO

"Reinforcement Learning might be considered to encompass all of AI: an agent is placed in an environment and must learn to behave successfully therein and reinforcement learning can be viewed as a microcosm for the entire AI problem." [8]

Russell & Norvig, author of Artificial Intelligence

Analysis of minority ranking w.r.t. homophily and **RL recommenders**

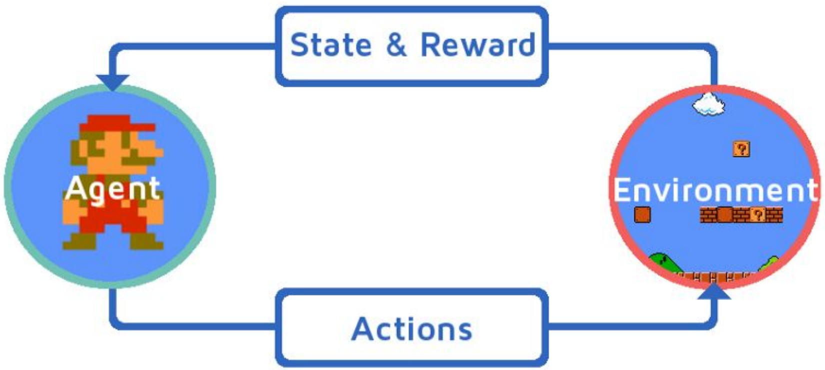


Image Source : https://www.freecodecamp.org/news/a-brief-introduction-to-reinforcement-learning-7799af5840db/

Motivation

Analysis of minority ranking w.r.t. homophily and RL recommenders

Motivation

Analysis of **minority ranking** w.r.t. homophily and RL recommenders

Visibility in network

Influence over network

Spreading Information over network

Research Questions

1. How minorities fare in recommender suggestions on Fixed Synthetic Network.

2. How the degree growth, distribution, node ranking develop when growing synthetic network using recommendations -
    a. from Adamic-Adar or Random-Walk (commonly used recommender strategies)
    b. from Reinforcement Learning Agent.

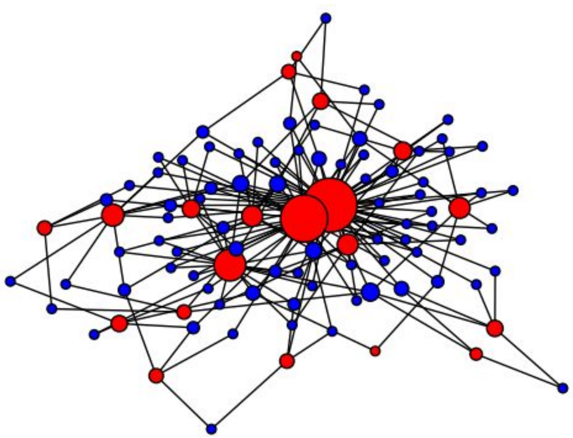
3. What strategies can be used to mitigate learnt bias in recommender nodes ranking.

Case Study:

Rank suggested nodes in selected networks from Facebook100 dataset [11].

Methods - Generating synthetic network

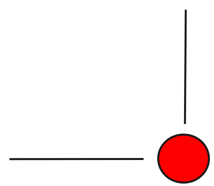
Synthetic Network



minority

majority

$G_t(V_t, E_t)$



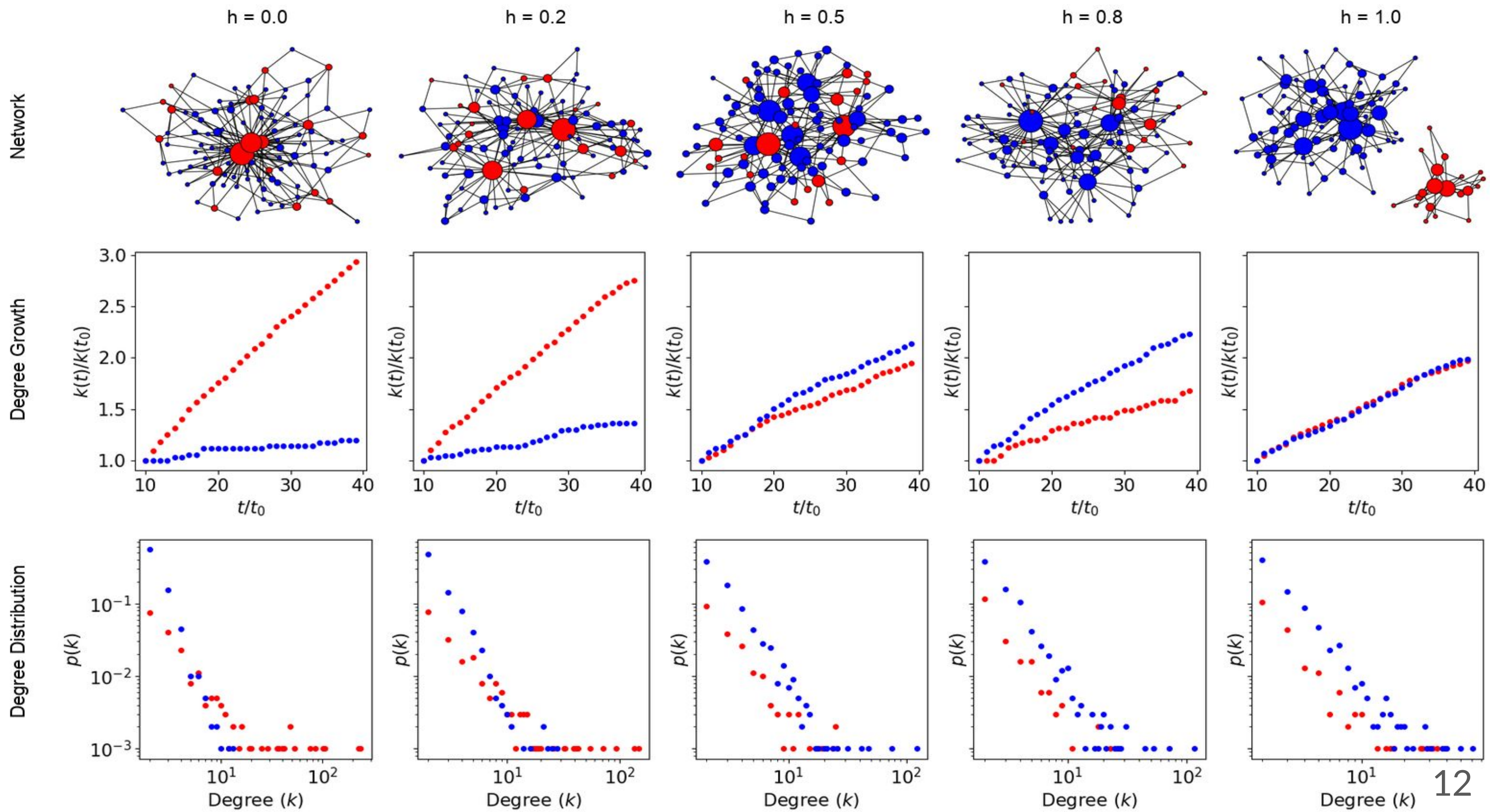
v

degree homophily

$$\alpha(u) = \frac{\delta(u)\times h(u,v)}{\sum_{w\in V^t}(\delta(w)\times h(w,v))}$$ [5]

Probability of existing vertex *u* to be selected by New node *v*

Methods - Synthetic Network properties



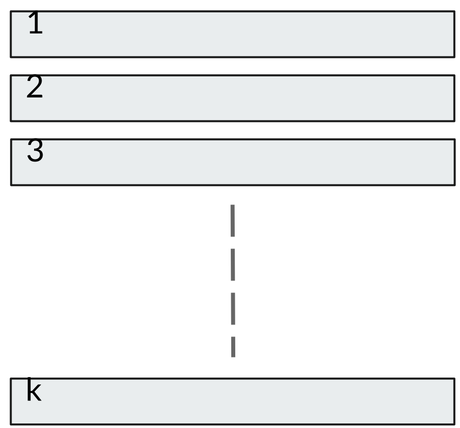
minority

majority

Methods - Link predictions

Adamic-Adar Index

[4]



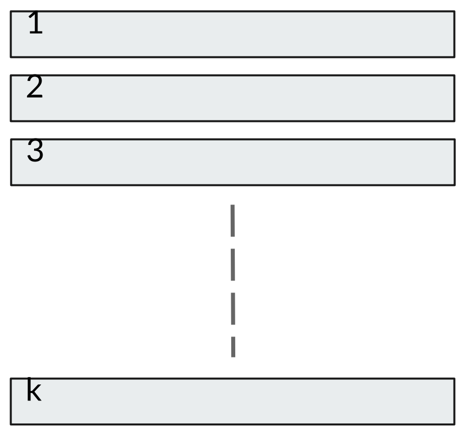
Index value for link between nodes *x* and *y*

$$A(x,y) = \sum_{u \in N(x) \cap N(y)} \frac{1}{log|N(u)|}$$

Neighbors of node *x*

Methods - Link predictions

Random Walk



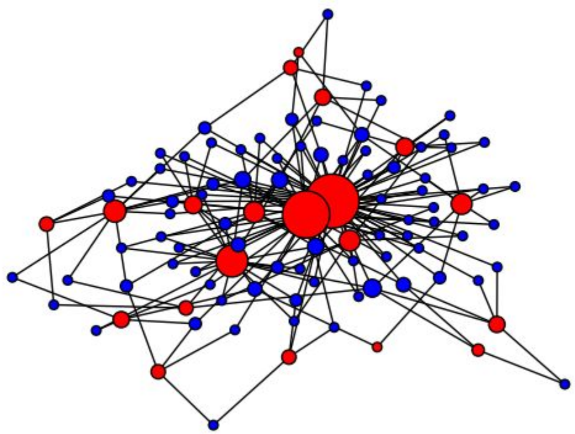
Walk of X0 -> X1 -> X2

$$RW(x, y) = Pr(X2 = y | X0 = x)$$

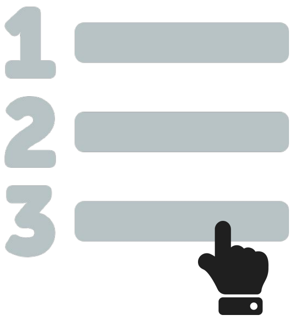
Probability for link between nodes *x* and *y*

Methods

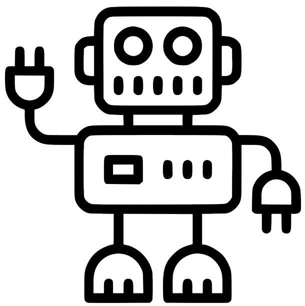
Synthetic Network



Click Model



Recommender Agent



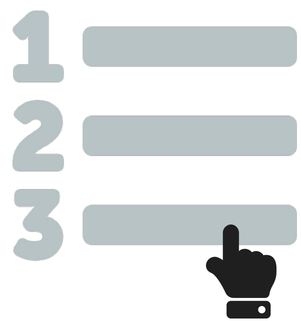
Learning to Rank

Methods

Click Model

$u_{i=1}$

$k = 3$



v

degree

homophily

$$\alpha_v(u_i) = \frac{\delta(u_i)\times h(u_i,v)\times e^{-(i-1)}}{\sum_{j=1}^{k}(\delta(u_j)\times h(u_j,v)\times e^{-(j-1)})}$$

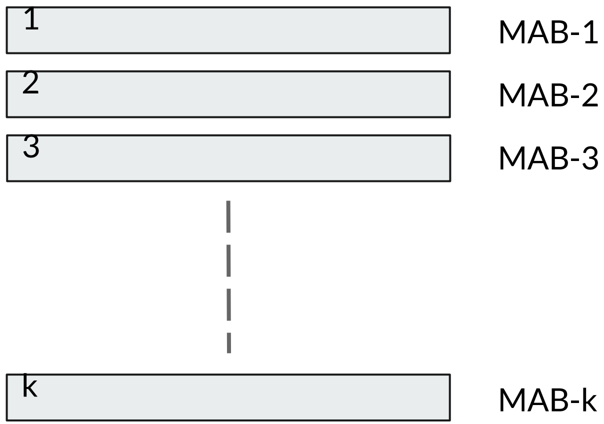
Probability of vertex v choosing u

Rank Priority

Methods - Learning to Rank

Ranked Bandits

[7]



$\epsilon - Greedy$

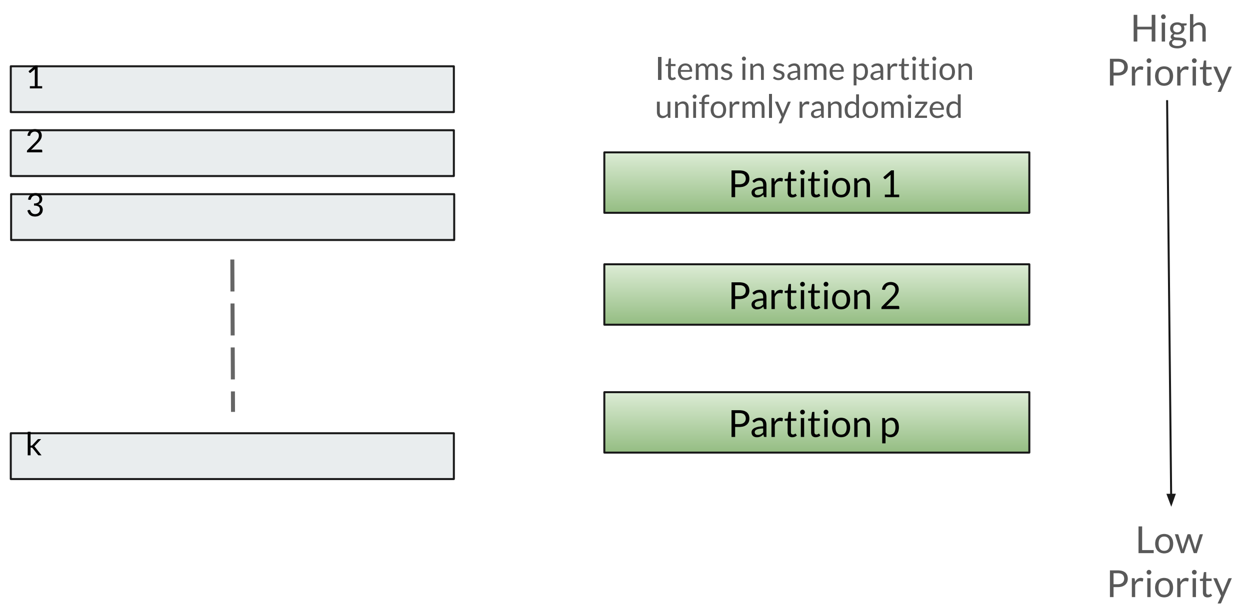
$\epsilon = 0.1$

Sample-average Action Value method

Methods - Learning to Rank

Top Rank

[6]



Results

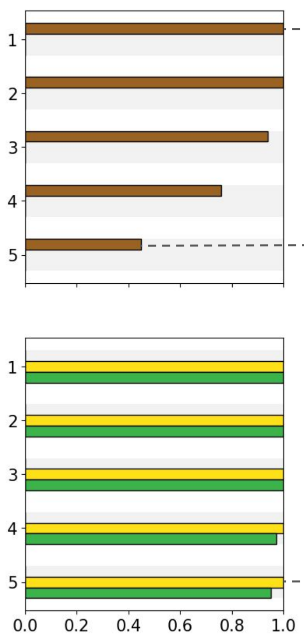
Network Properties -

Total Nodes : 1000
Homophily : 0.0

Adamic-Adar
Ranked bandits
Top Rank

Minority fraction (m)

1000 x 0.2 = 200



1000 x 0.8 = 800

Minority Nodes Plots Row

Majority Nodes Plots Row

At **Rank 1**,
for **100%(200) minority nodes**,
other minorities have been recommended according to **Adamic-Adar Index**

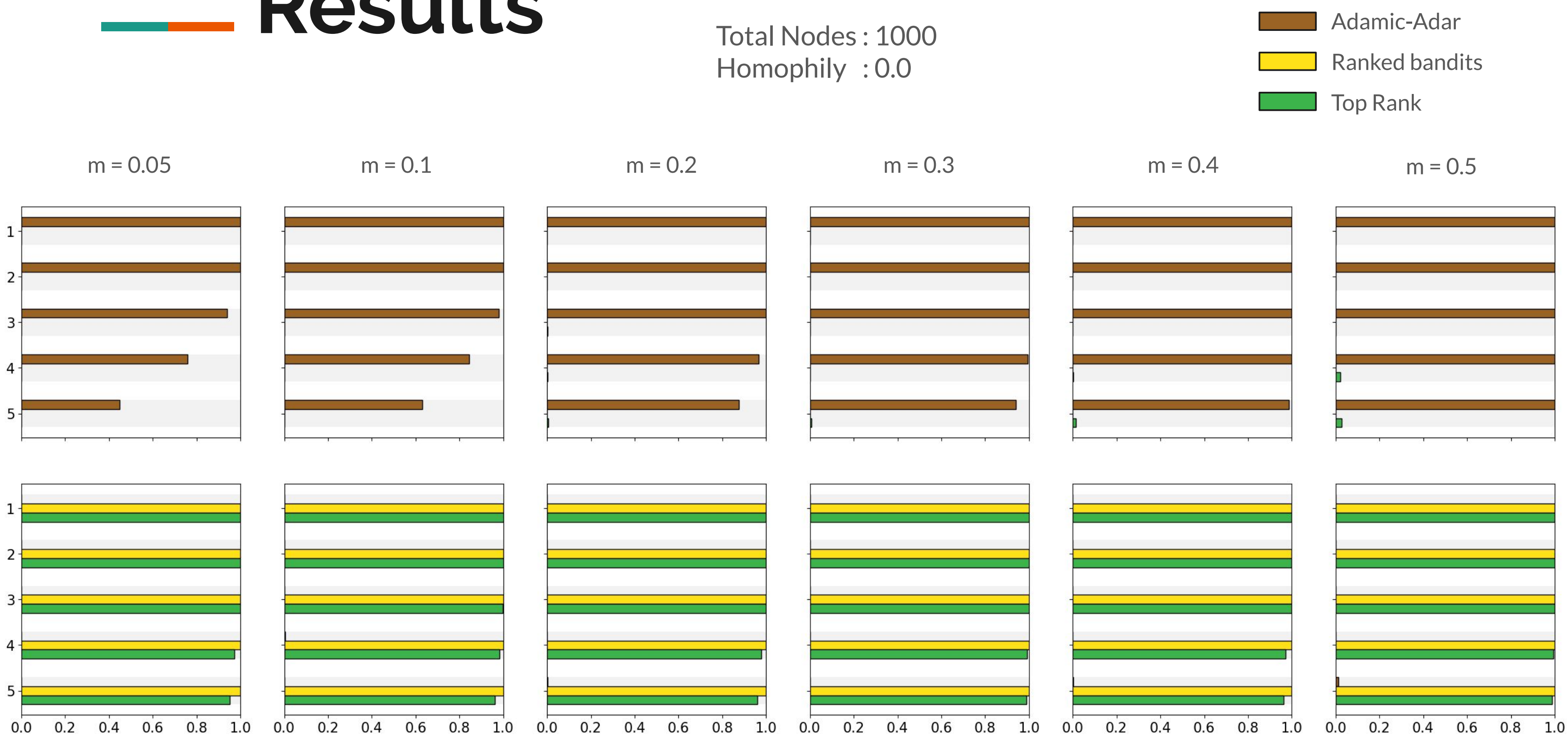
At **Rank 5**,
for **~42%(~84) minority nodes**,
other minorities have been recommended according to **Adamic-Adar index**

At **Rank 5**,
for **100%(800) majority nodes**,
other minorities have been recommended according to **Ranked-Bandits**

Results

Network Properties -

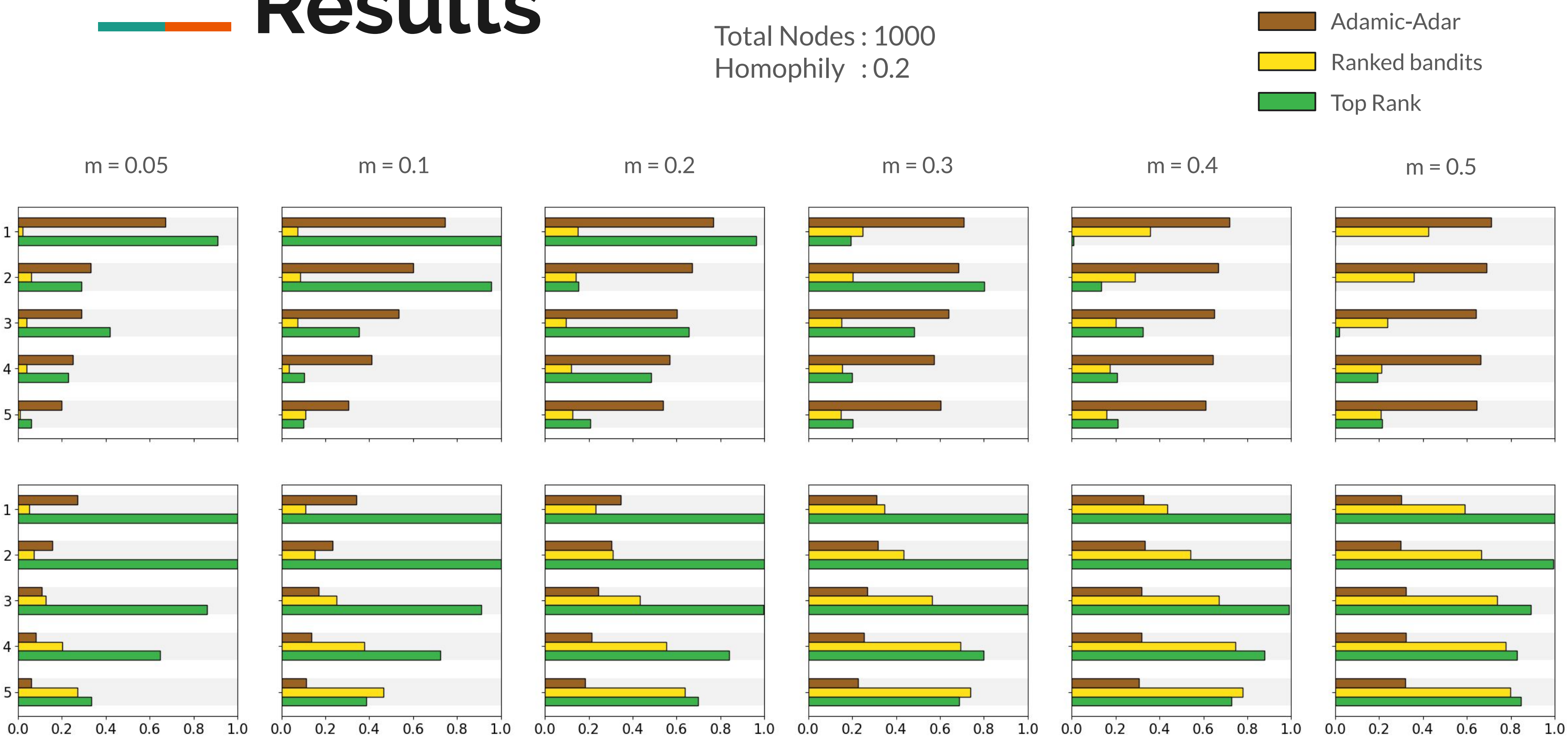
Total Nodes : 1000
Homophily : 0.0



Results

Network Properties -

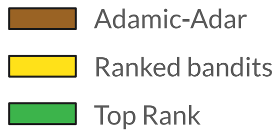
Total Nodes : 1000
Homophily : 0.2

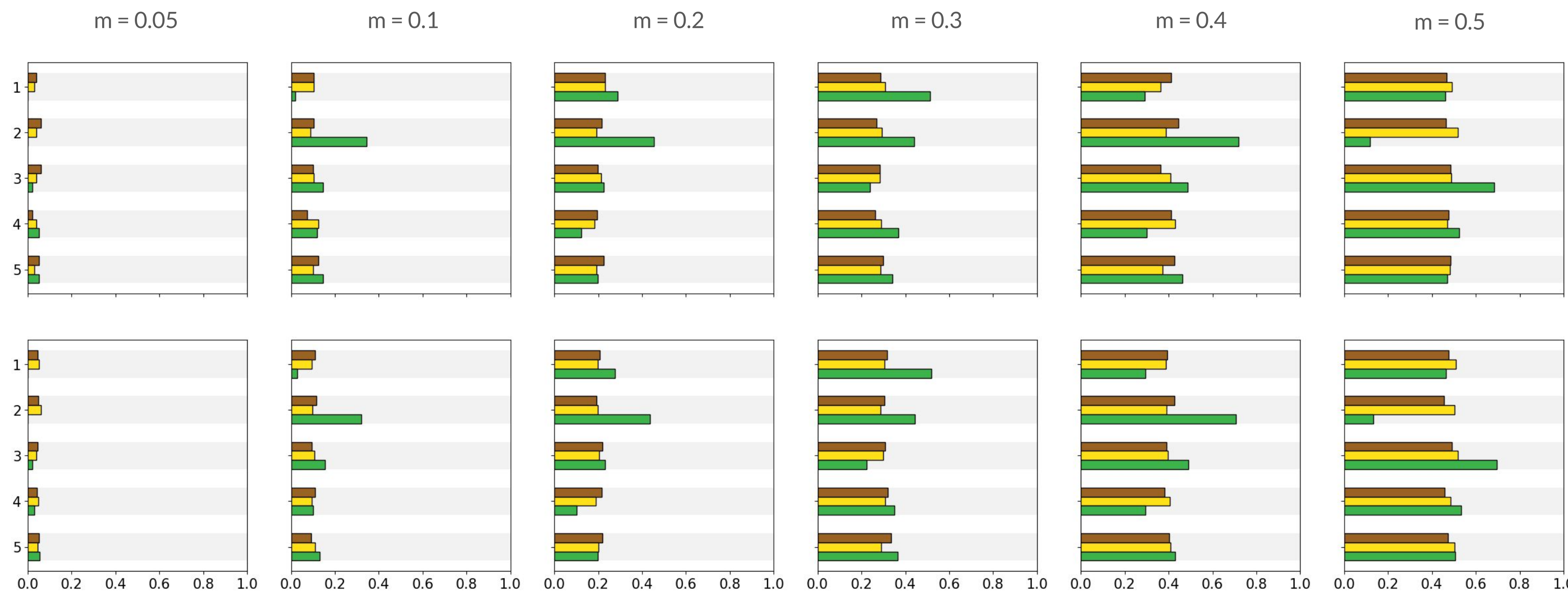


Results

Network Properties -

Total Nodes : 1000
Homophily : 0.5



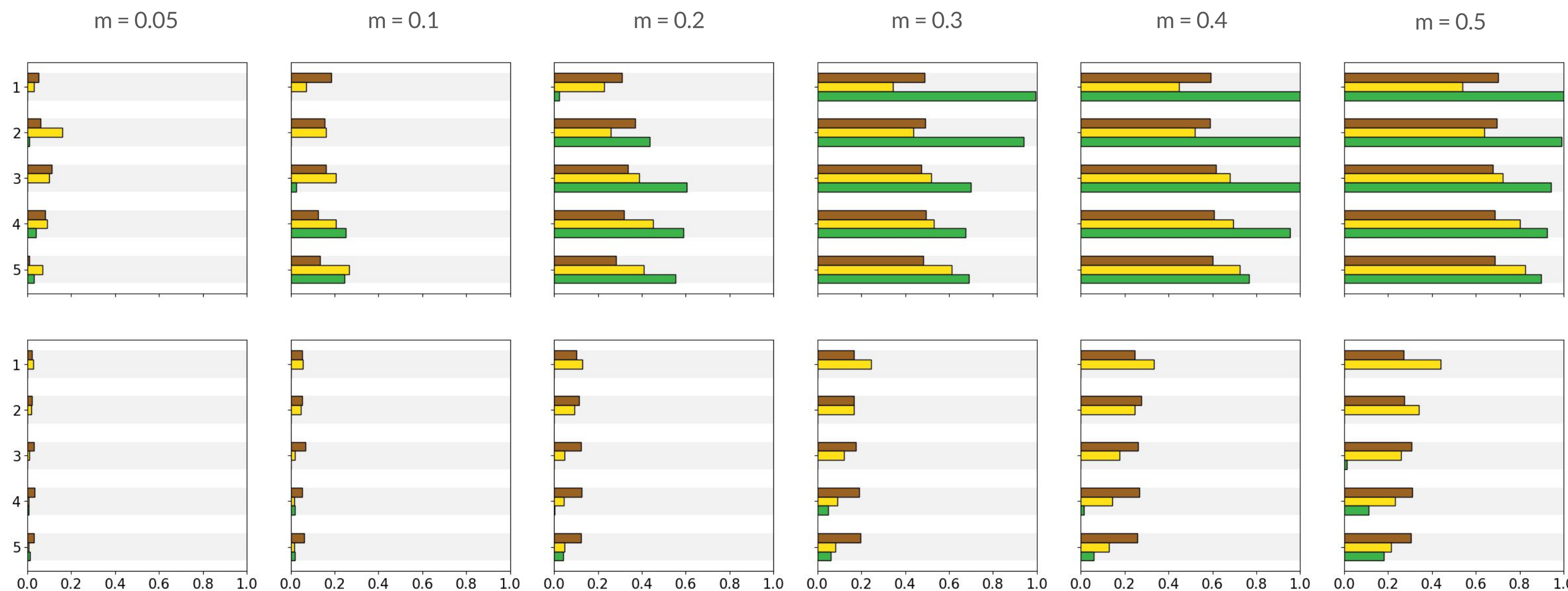


Results

Network Properties -

Total Nodes : 1000
Homophily : 0.8

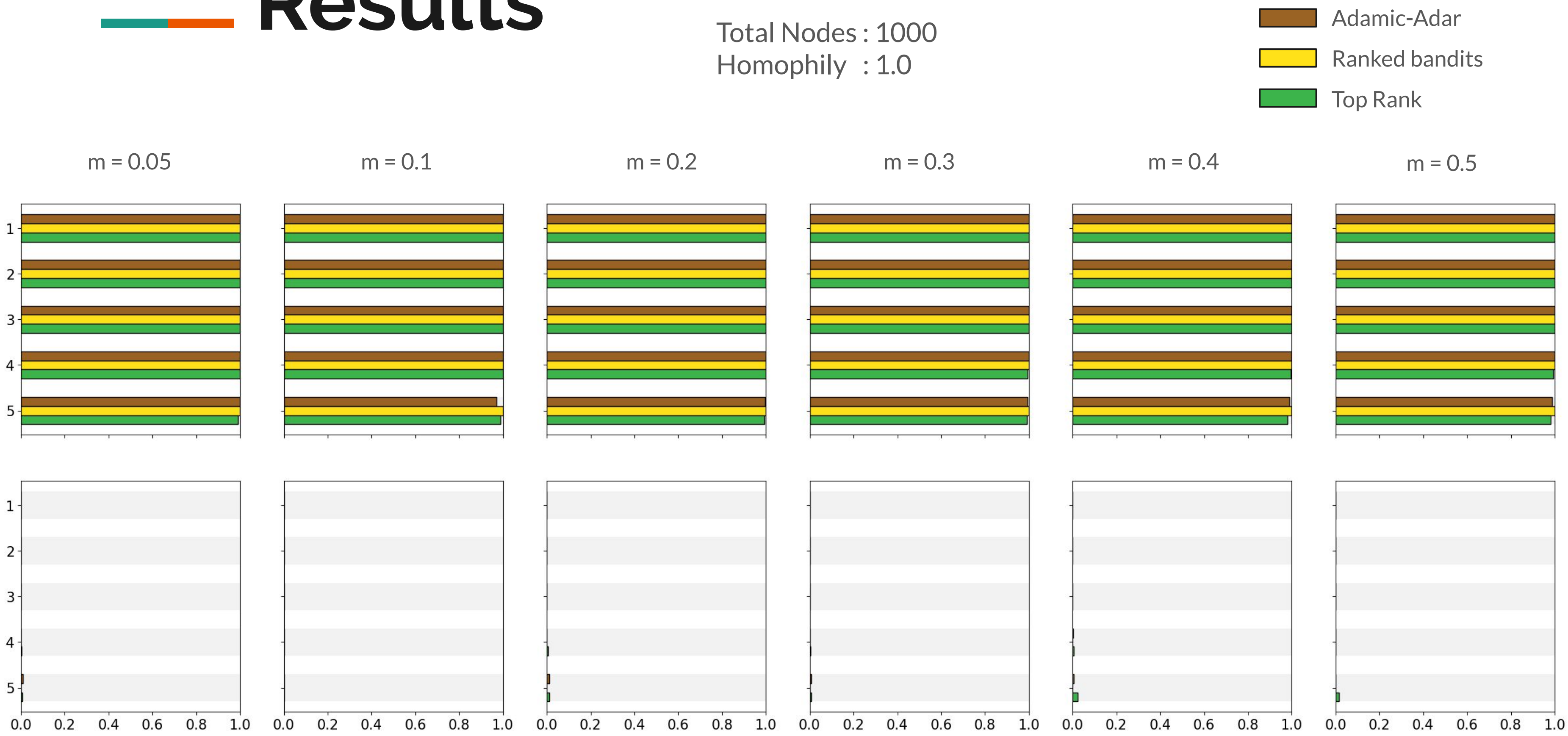
Adamic-Adar
Ranked bandits
Top Rank



Results

Network Properties -

Total Nodes : 1000
Homophily : 1.0



The way forward

For RQ2,
Grow a network systematically via organic and algorithmic growth as by Stoica et. al. [10].
Challenge - Reducing the re-training time for the RL models.
Possible Solution - Not train for each individual node, but only node categories.

For RQ3,
Possible ways to mitigate bias by using different reward mechanisms for different group selection.

For Case Study,
Challenge - Clicking Model behavior for the real world networks is unknown and difficult to collect.

Conclusion

Reinforcement Learning learns behaviors by observation and reward.

The homophilic behavior is imbibed in Social Networks.

Reinforcement Learning learns this homophilic behavior and reinforces the bias.

Try to mitigate this bias learnt in RL recommendation methods.

Q & A

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