Algorithmic Fairness on Graphs

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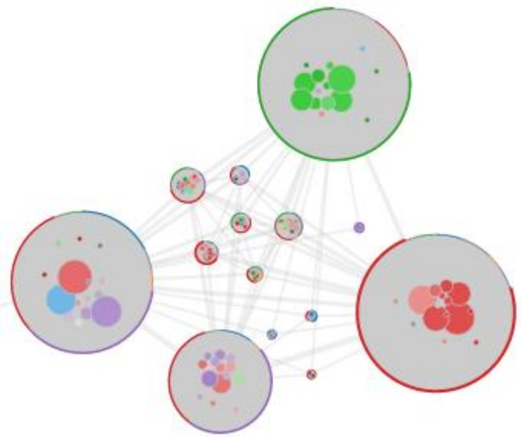
Acknowledgements

Many thanks to Jian Kang and Hanghang Tong for generously sharing their tutorial slides

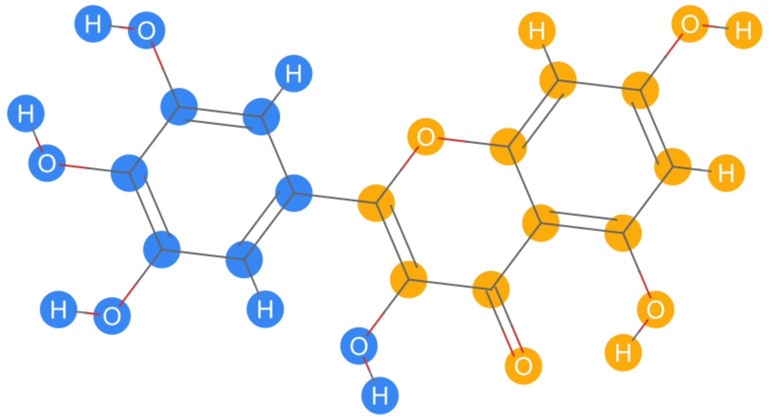
Jian Kang **Hanghang Tong**

University of Illinois Urbana Champaign

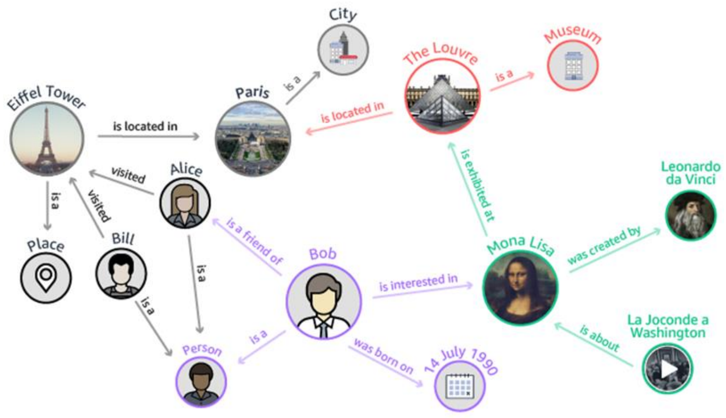
The Ubiquity of Graphs



Social network

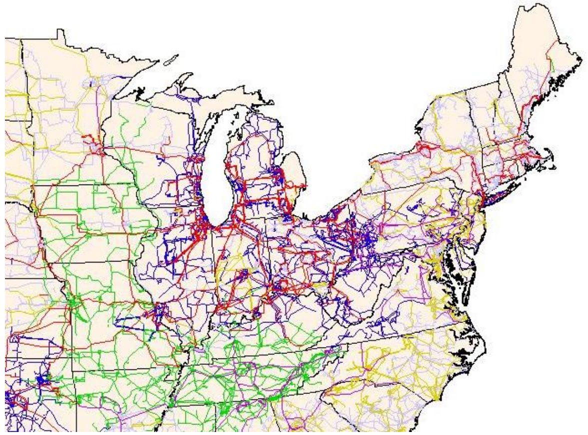


Molecular graph

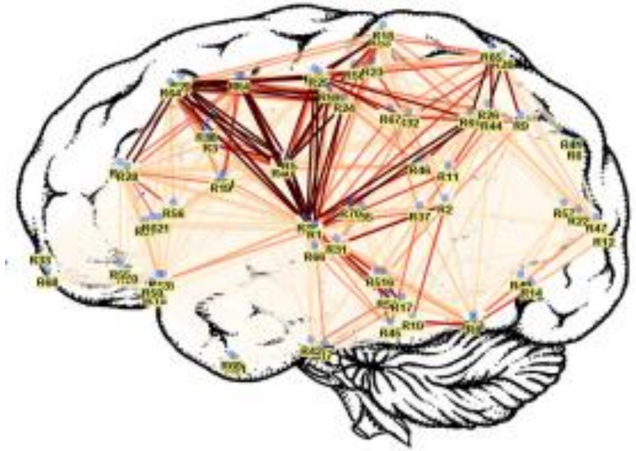


Knowledge graph

Road network



Power grid



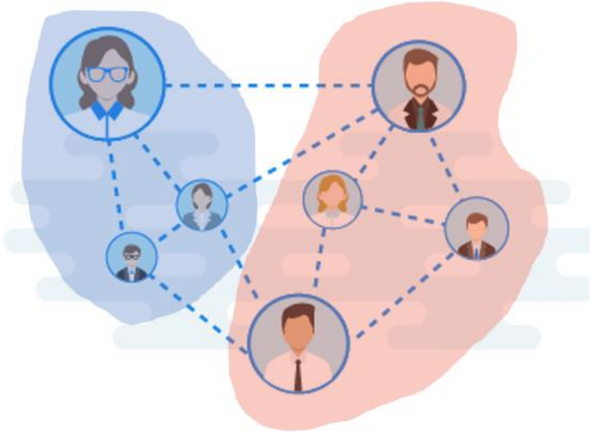
Brain network

This talk: Graphs = Networks

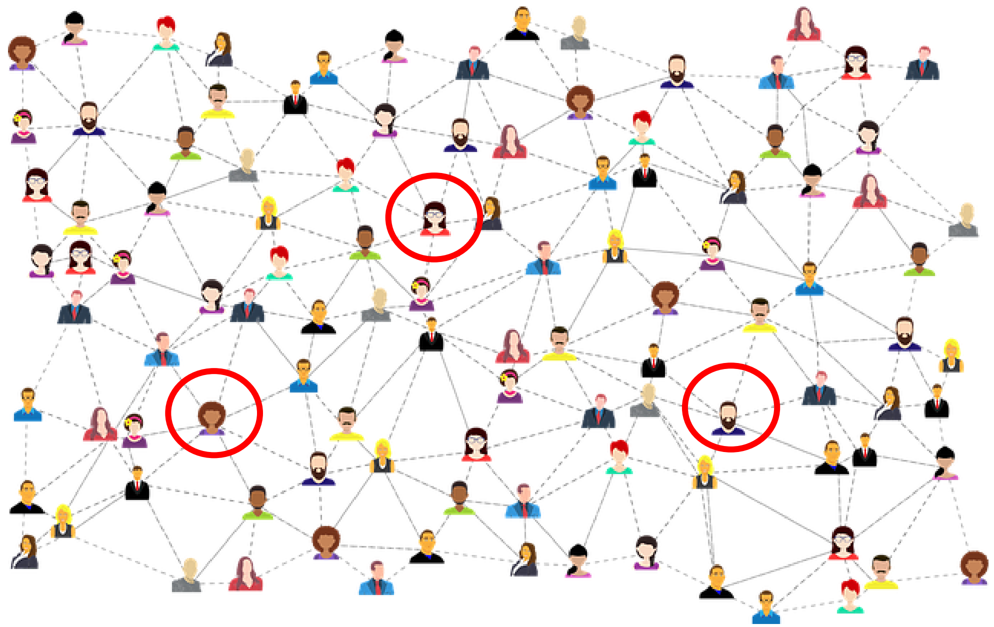
Graph Mining: Applications

Credit scoring

Financial fraud detection



User community detection

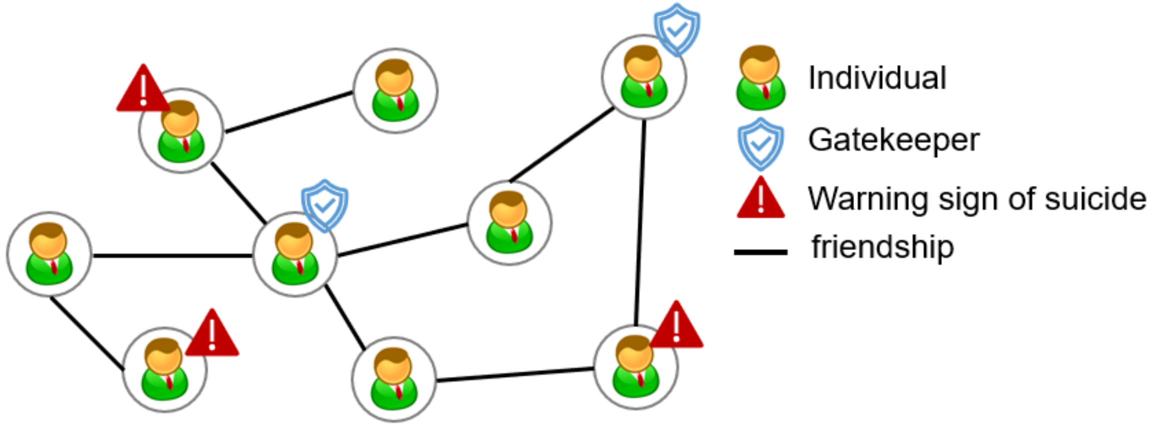


Identifying influencers

Algorithmic Fairness on Graphs: Suicide Prevention

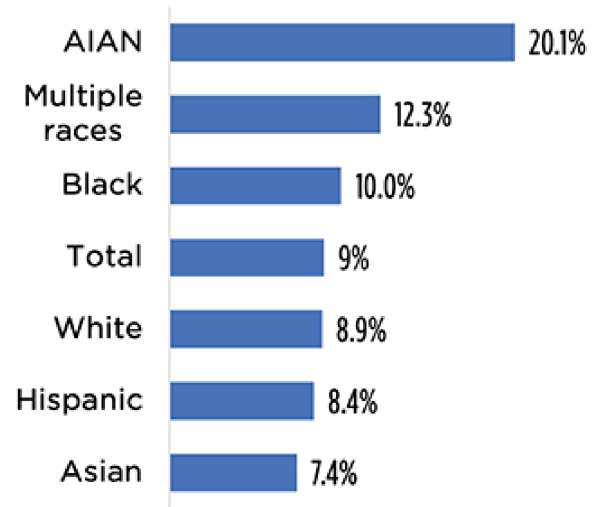
- Suicide is one of the leading causes of death in US

Gatekeeper training programs



Toy example of a gatekeeper training program

Percentage of high schoolers reporting a suicide attempt in the past 12 months, by race/ethnicity



Suicide attempts by race/ethnicity

- **Observation:** existing suicide prevention efforts disproportionately affect individuals of different demographics

[1] https://www.cdc.gov/nchs/data/vsrr/vsrr024.pdf
[2] https://988lifeline.org/
[3] https://www.childtrends.org/publications/addressing-discrimination-supports-youth-suicide-prevention-efforts

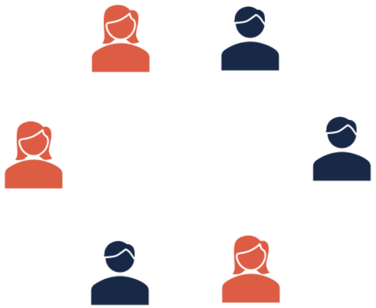
Challenge

- **Assumption**

	Classic machine learning	Graph mining
Data	IID samples	Non-IID graph

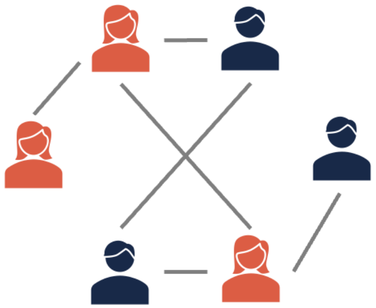
  – **IID:** independent and identically distributed

- **Example**



- Individuals are independent
- Cannot affect others

Classic machine learning



- Individuals are connected
- Can affect others through connection(s)

Graph mining

- **Challenges:** implication of non-IID nature on
  – Measuring bias
    - Dyadic fairness, degree-related fairness
  – Mitigating unfairness
    - Enforce fairness by graph structure imputation

Roadmap

- Network Centrality Fairness
- Spectral Clustering Fairness
- Fair Graph Embeddings
- Graph Neural Network Fairness

Roadmap

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The Pagerank Algorithm

- The best-known algorithm for measuring the centrality/importance of nodes in a graph, introduced by Google
- **Assumption:** important webpage → linked by many others

- Pagerank performs a random walk with restarts:
- At each step of the random walk:
  - With probability c perform a transition according to the transition probability matrix $\boldsymbol{A}$
  - With probability $1 - c$ restart to a randomly selected node according to teleportation (jump) vector $\boldsymbol{e}$
- The Pagerank vector is the stationary distribution $\boldsymbol{r}$ of this random walk

Preliminary: PageRank

- **Formulation**
  - Iterative method for the following linear system
    $$\mathbf{r} = c\mathbf{A}^T\mathbf{r} + (1-c)\mathbf{e}$$
    - $\boldsymbol{A}$: transition matrix
    - $\mathbf{r}$: PageRank vector
    - c: damping factor
    - $\mathbf{e}$: teleportation vector
  - Closed-form solution
    $$\mathbf{r} = (1-c)\left(\mathbf{I} - c\mathbf{A}^T\right)^{-\mathbf{1}}\mathbf{e}$$
- **Variants**
  - Personalized PageRank (PPR)

[1] Page, L., Brin, S., Motwani, R., & Winograd, T. (1999). The PageRank Citation Ranking: Bringing Order to the Web. Stanford InfoLab 1999.
[2] Haveliwala, T. H. (2003). Topic-sensitive PageRank: A Context-Sensitive Ranking Algorithm for Web Search. TKDE 2003.
[3] Tong, H., Faloutsos, C., & Pan, J. Y. (2006). Fast Random Walk with Restart and Its Applications. ICDM 2006.

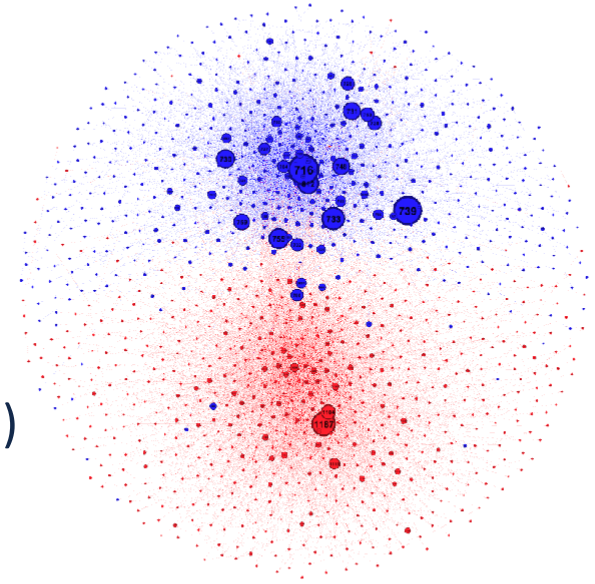
Unfairness in PageRank

- Pagerank distributes the importance values to the nodes in the network
  - But is it fair?
- **Example**
  - **Network:** 1222 nodes of political blogs
  - **Groups:** red (left-leaning) and blue (right-leaning)

Unfair ranking

Similar number of red nodes vs. blue nodes (48% red vs. 52% blue)

Much less PageRank mass of red nodes (33% red vs. 67% blue)



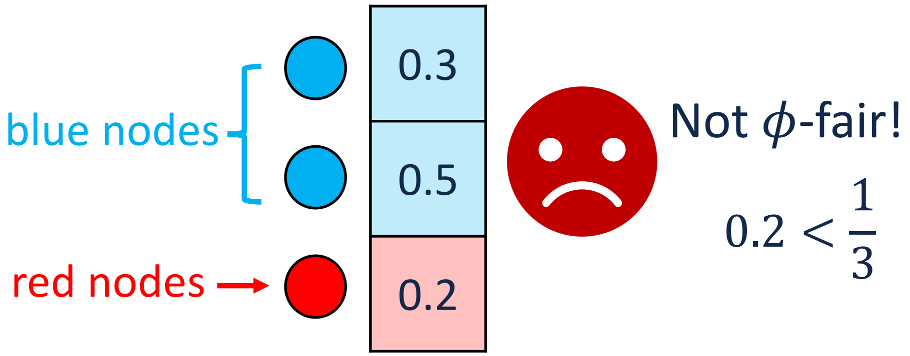
- How can we define Pagerank fairness?
- How do we make Pagerank fair?

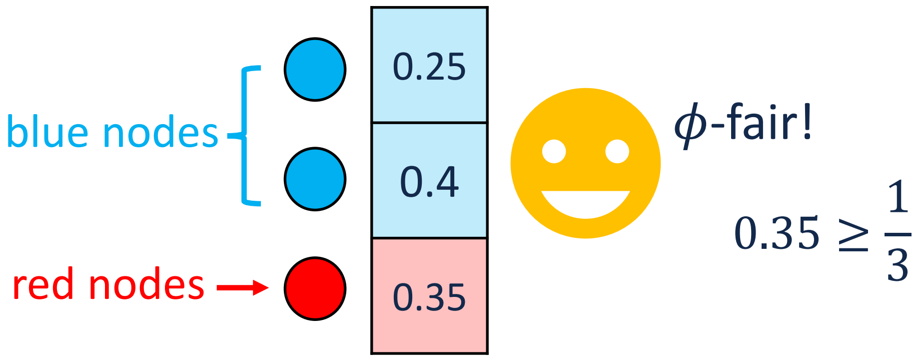
[1] Tsioutsiouliklis, S., Pitoura, E., Tsaparas, P., Kleftakis, I., & Mamoulis, N. (2021). Fairness-Aware PageRank. WWW 2021.

[2] Tsioutsiouliklis, S., Pitoura, E., Semertzidis, K., & Tsaparas, P. (2022). Link Recommendations for PageRank Fairness. WWW 2022.

Fairness Measure: ϕ-Fairness

- **Given:** (1) a graph G; (2) a parameter ϕ
- **Definition:** a PageRank vector is ϕ-fair if at least ϕ fraction of total PageRank mass is allocated to the protected group
- **Variants and generalizations**
  - Statistical parity → ϕ = fraction of protected group
  - Affirmative action → ϕ = a desired ratio (e.g., 20%)
- **Example**
  - Protected group = red nodes
  - $\phi = 1/3$





[1] Tsioutsiouliklis, S., Pitoura, E., Tsaparas, P., Kleftakis, I., & Mamoulis, N. (2021). Fairness-Aware PageRank. WWW 2021.
[2] Tsioutsiouliklis, S., Pitoura, E., Semertzidis, K., & Tsaparas, P. (2022). Link Recommendations for PageRank Fairness. WWW 2022.

Problem Definition: Fair PageRank

- **Given**
  - A graph with transition matrix $\mathbf{A}$
  - Partitions of nodes
    - Red nodes ($\mathcal{R}$): protected group
    - Blue nodes ($\mathcal{B}$): unprotected group
- **Produce:** a fair PageRank vector $\tilde{\mathbf{r}}$ that is
  - ϕ-fair
  - Close to the original PageRank vector $\mathbf{r}$ (minimizes the utility loss)

[1] Tsioutsiouliklis, S., Pitoura, E., Tsaparas, P., Kleftakis, I., & Mamoulis, N. (2021). Fairness-Aware PageRank. WWW 2021.
[2] Tsioutsiouliklis, S., Pitoura, E., Semertzidis, K., & Tsaparas, P. (2022). Link Recommendations for PageRank Fairness. WWW 2022.

Fair PageRank: Solutions

- **Recap:** closed-form solution for PageRank

$$\mathbf{r} = (1 - c)\left(\mathbf{I} - c\mathbf{A}^T\right)^{-1}\mathbf{e}$$

- **Parameters in PageRank**
  - **Damping factor** c avoids sinks in the random walk (i.e., nodes without outgoing links)
  - **Teleportation vector e** controls the starting node where a random walker restarts
    - Can we control where the walker teleports to? ← Solution #1: fairness-sensitive PageRank
  - **Transition matrix** $\mathbf{A}$ controls the next step where the walker goes to
    - Can we modify the transition probabilities?
    - Can we modify the graph structure?

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[2] Tsioutsiouliklis, S., Pitoura, E., Semertzidis, K., & Tsaparas, P. (2022). Link Recommendations for PageRank Fairness. WWW 2022.

Solution #1: Fairness-sensitive PageRank

- **Intuition**
  - Find a teleportation vector $\mathbf{e}$ to make PageRank vector ϕ-fair

$$\mathbf{r} = \mathbf{Q}^T\mathbf{e}, \quad \mathbf{Q}^T = (1-c)\left(\mathbf{I} - c\mathbf{A}^T\right)^{-1}$$

  - Keep transition matrix $\mathbf{A}$ and $\mathbf{Q}^T$ fixed
- **Observation:** mass of PageRank $\mathbf{r}$ w.r.t. red nodes $\mathcal{R}$

$$\mathbf{r}(\mathcal{R}) = \mathbf{Q}^T[\mathcal{R}, :]\mathbf{e}$$

  - $\mathbf{Q}^T[\mathcal{R}, :]$: rows of $\mathbf{Q}^T$ w.r.t. nodes in set $\mathcal{R}$
- **(Convex) optimization problem**

$$\begin{aligned} \min_{\mathbf{e}} \quad & \boxed{\|\mathbf{Q}^T\mathbf{e} - \mathbf{r}\|^2} \\ \text{s.t.} \quad & \boxed{\begin{aligned}&\mathbf{e}[i] \in [0,1], \forall i \\ &\|\mathbf{e}\|_1 = 1\end{aligned}} \\ & \boxed{\|\mathbf{Q}^T[\mathcal{R}, :]\mathbf{e}\|_1 = \phi} \end{aligned}$$

The fair PageRank $\mathbf{Q}^T\mathbf{e}$ is as close as possible to the original PageRank $\mathbf{r}$

The teleportation vector $\mathbf{e}$ is a probability distribution

The fair PageRank $\mathbf{Q}^T\mathbf{e}$ is ϕ-fair

  - Can be solved by any convex optimization solvers

[1] Tsioutsiouliklis, S., Pitoura, E., Tsaparas, P., Kleftakis, I., & Mamoulis, N. (2021). Fairness-Aware PageRank. WWW 2021.

Fairness-sensitive PageRank: Example

- **Settings:** $\phi = 1/3$ and protected node = red node
- **Original PageRank**

rows w.r.t. blue nodes

row w.r.t. red nodes

$$\underbrace{\begin{bmatrix} 0.55 & 0.3 & 0.2 \\ 0.4 & 0.6 & 0.2 \\ 0.05 & 0.1 & 0.6 \end{bmatrix}}_{\mathbf{Q}^T} \quad \underbrace{\begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}}_{\mathbf{e}} \qquad \mathbf{r} = \mathbf{Q}^T\mathbf{e} = \begin{bmatrix} 0.35 \\ 0.4 \\ 0.25 \end{bmatrix}$$

Not ϕ-fair!

$$0.25 < \frac{1}{3}$$

- **Fairness-sensitive PageRank**

rows w.r.t. blue nodes

row w.r.t. red nodes

$$\underbrace{\begin{bmatrix} 0.55 & 0.3 & 0.2 \\ 0.4 & 0.6 & 0.2 \\ 0.05 & 0.1 & 0.6 \end{bmatrix}}_{\mathbf{Q}^T} \quad \underbrace{\begin{bmatrix} 1/4 \\ 1/4 \\ 1/2 \end{bmatrix}}_{\tilde{\mathbf{e}}} \qquad \tilde{\mathbf{r}} = \mathbf{Q}^T\tilde{\mathbf{e}} = \begin{bmatrix} 0.31 \\ 0.35 \\ 0.34 \end{bmatrix}$$

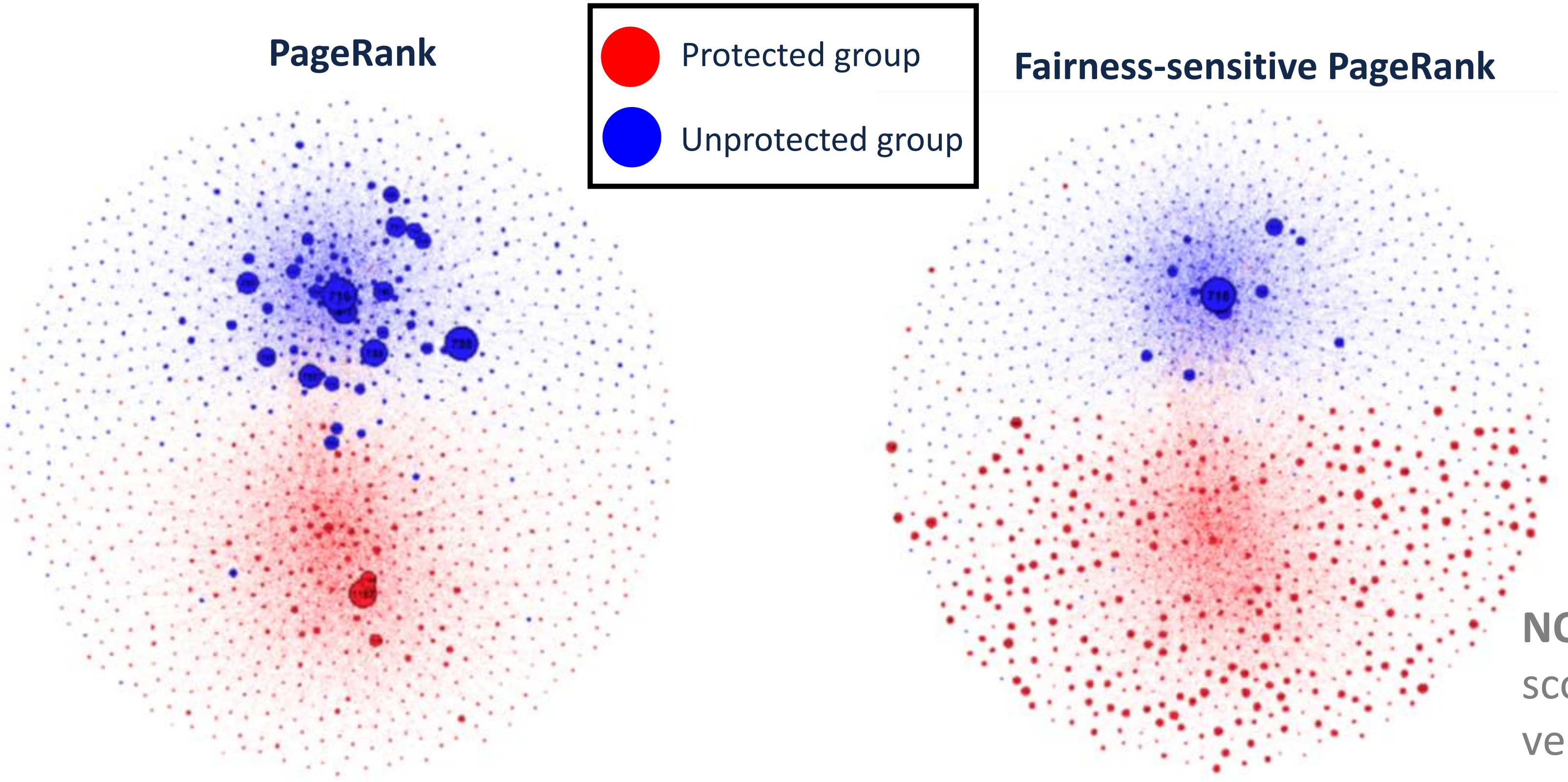
ϕ-fair!

$$0.34 \geq \frac{1}{3}$$

[1] Tsioutsiouliklis, S., Pitoura, E., Tsaparas, P., Kleftakis, I., & Mamoulis, N. (2021). Fairness-Aware PageRank. WWW 2021.

Fairness-sensitive PageRank: Experiment

- **Observation:** the teleportation vector allocates more weight to the red nodes, especially nodes at the periphery of the network
  - More likely to (1) restart at red nodes and (2) walk to other red nodes more often



NOTE: size is proportional to score in the teleportation vector

[1] Tsioutsiouliklis, S., Pitoura, E., Tsaparas, P., Kleftakis, I., & Mamoulis, N. (2021). Fairness-Aware PageRank. WWW 2021.

Fair PageRank: Solutions

- **Recap:** closed-form solution for PageRank

$$\mathbf{r} = (1 - c)\left(\mathbf{I} - c\mathbf{A}^T\right)^{-\mathbf{1}}\mathbf{e}$$

- **Parameters in PageRank**
  - **Damping factor** c avoids sinks in the random walk (i.e., nodes without outgoing links)
  - **Teleportation vector e** controls the starting node where a random walker restarts
    - Can we control where the walker teleports to?
  - **Transition matrix** $\boldsymbol{A}$ controls the next step where the walker goes to
    - Can we modify the transition probabilities? ← Solution #2: locally fair PageRank
    - Can we modify the graph structure?

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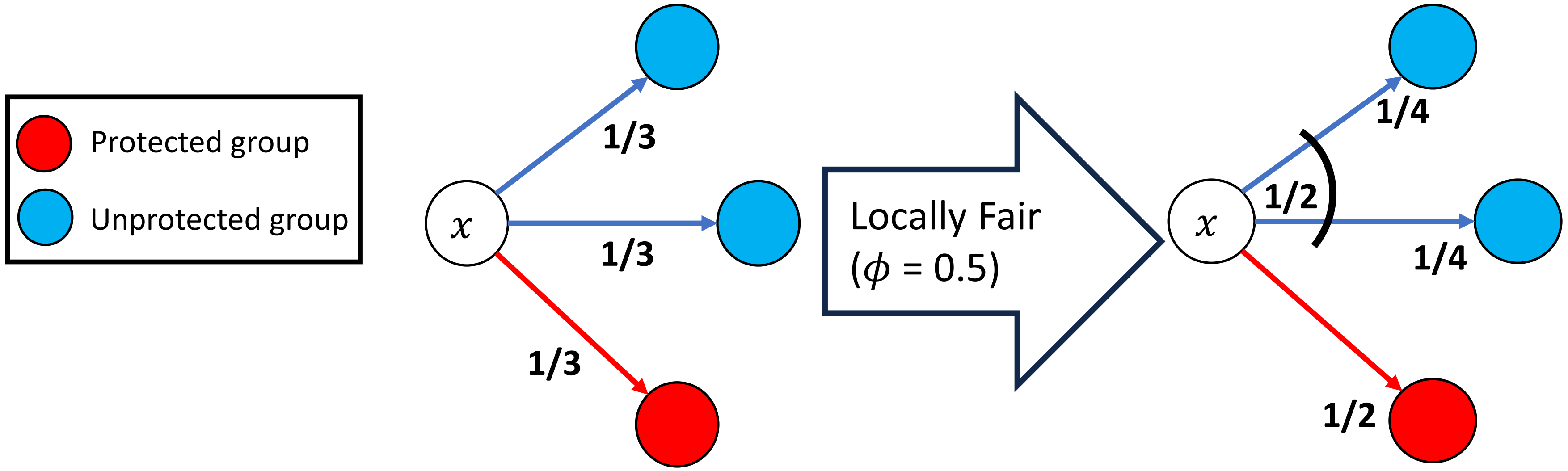
[2] Tsioutsiouliklis, S., Pitoura, E., Semertzidis, K., & Tsaparas, P. (2022). Link Recommendations for PageRank Fairness. WWW 2022.

Solution #2: Locally Fair PageRank

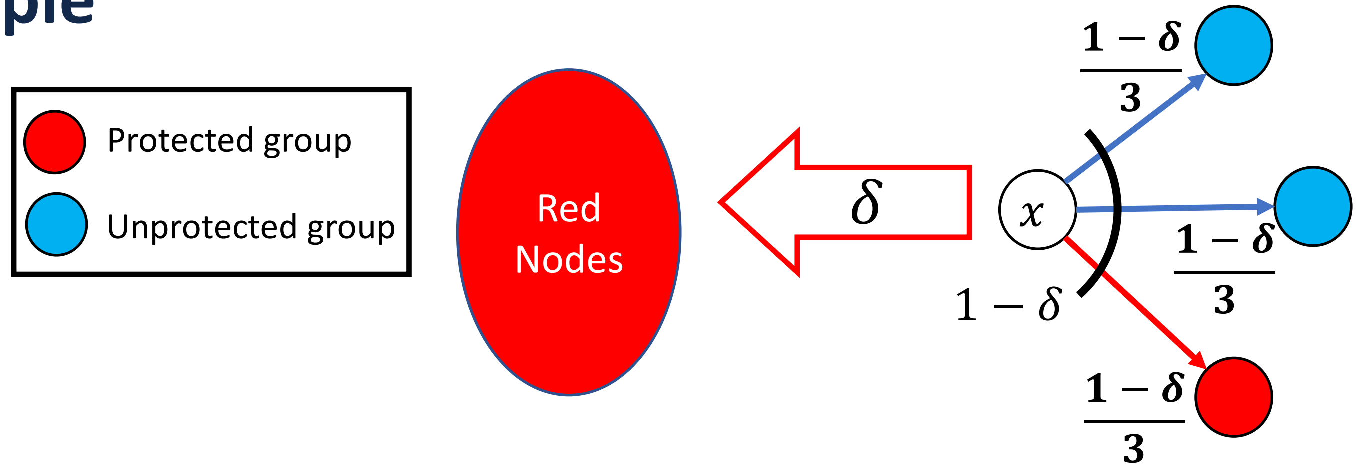
- **Intuition:** adjust the transition matrix A to obtain a fair random walk
- **Neighborhood locally fair PageRank**
  - **Key idea:** jump with probability ϕ to red nodes and (1- ϕ) to blue nodes
  - **Example**



[1] Tsioutsiouliklis, S., Pitoura, E., Tsaparas, P., Kleftakis, I., & Mamoulis, N. (2021). Fairness-Aware PageRank. WWW 2021.

Solution #2: Locally Fair PageRank

- **Residual locally fair PageRank**
  - **Key idea:** jump with
    - Equal probability to 1-hop neighbors
    - A residual probability δ to the other red nodes
  - **Example**



$$\delta + \frac{1-\delta}{3} = \phi$$

- **Residual allocation policies:** neighborhood allocation, uniform allocation, proportional allocation, optimized allocation

- **Neighborhood allocation:** allocate the residual to protected neighbors, equivalent to neighborhood locally fair PageRank
- **Uniform allocation:** uniformly allocate the residual to all protected nodes
- **Proportional allocation:** allocated the residual to all protected nodes proportionally to their PageRank score
- **Optimized allocation:** allocate the residual to all protected nodes while minimizing the difference with original PageRank score

[1] Tsioutsiouliklis, S., Pitoura, E., Tsaparas, P., Kleftakis, I., & Mamoulis, N. (2021). Fairness-Aware PageRank. WWW 2021.

Locally Fair PageRank: Experiment

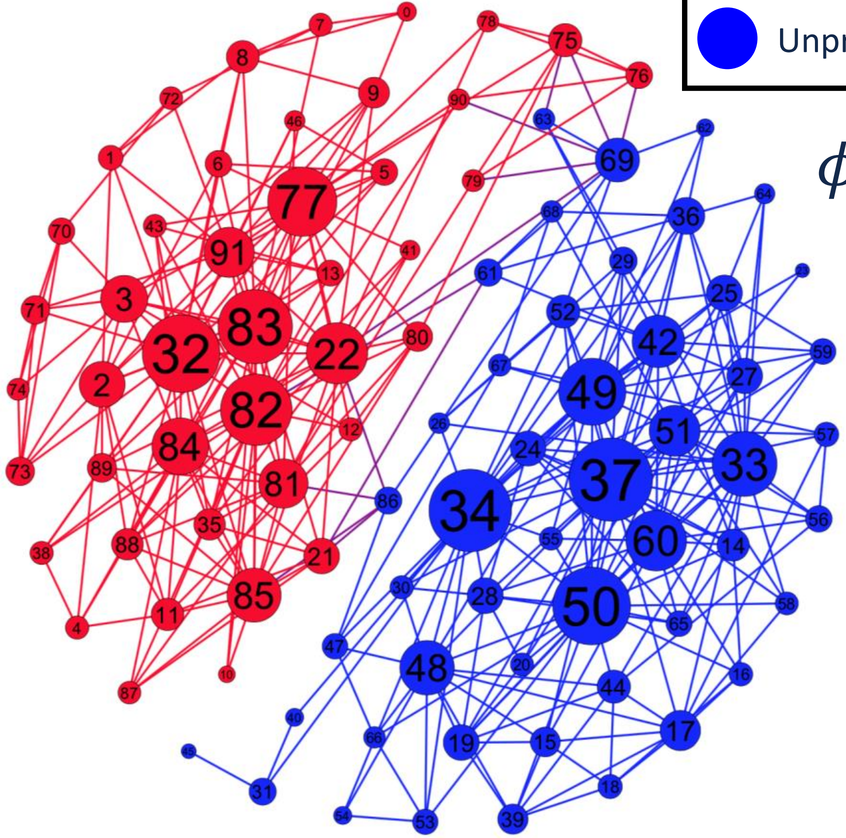
- **Observation:** PageRank weight is shifted to the blue nodes at boundary

Protected group

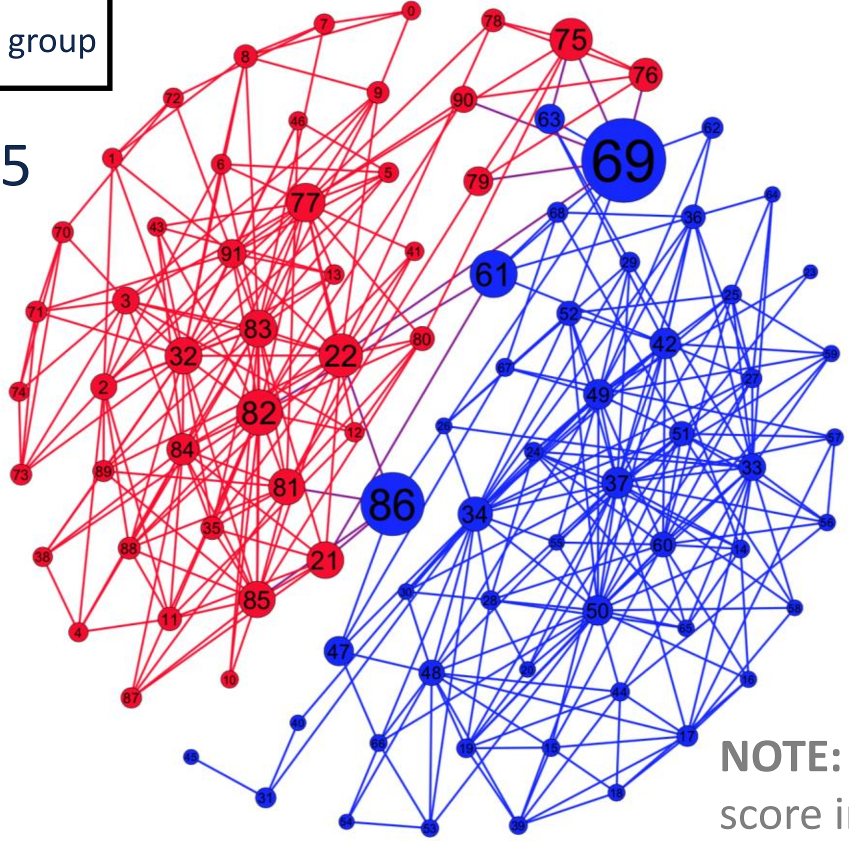
Unprotected group

$\phi = 0.5$

PageRank



Neighborhood Locally Fair PageRank



NOTE: size is proportional to score in the PageRank vector

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Fair PageRank: Solutions

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    - Can we modify the graph structure? ← Solution #3: best fair edge identification

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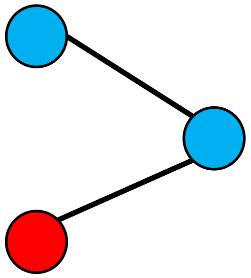
Solution #3: Best Fair Edge Identification

- **Intuition:** add edges that can improve the PageRank fairness to the graph
- **Example**
  - 🔴 = protected node
  - $\phi = 1/3$

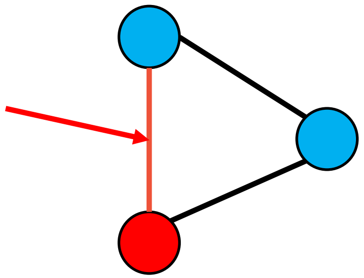


$$\mathbf{r} = \mathbf{Q}^T\mathbf{e} = \begin{bmatrix} 0.257 \\ 0.486 \\ 0.257 \end{bmatrix}$$

Not ϕ-fair!

$$\frac{0.257}{0.257 + 0.486 + 0.257} < \frac{1}{3}$$

New edge to add



$$\tilde{\mathbf{r}} = \tilde{\mathbf{Q}}^T\mathbf{e} = \begin{bmatrix} 0.333 \\ 0.333 \\ 0.333 \end{bmatrix}$$

ϕ-fair!

$$\frac{0.333}{0.333 + 0.333 + 0.333} = \frac{1}{3}$$

- **Question:** how to find the edges with the highest improvement?

[1] Tsioutsiouliklis, S., Pitoura, E., Semertzidis, K., & Tsaparas, P. (2022). Link Recommendations for PageRank Fairness. WWW 2022.

Best Fair Edge Identification: Problem Definition

- **Given**
  - $G = (\mathcal{V}, \mathcal{E})$
  - $\mathcal{S} \subseteq \mathcal{V}$: protected node set
  - $r_{\mathcal{E}}(\mathcal{S}) = \sum_{i \in \mathcal{V}} r_{\mathcal{E}}(i)$: total PageRank mass of nodes in $\mathcal{S}$ on graph with edge set $\mathcal{E}$
- **Fairness gain of edge addition**

$$\text{gain}(x, y) = \boxed{r_{\mathcal{E} \cup (x,y)}(\mathcal{S}) - r_{\mathcal{E}}(\mathcal{S})}$$

Naive method
Exhaustively recompute PageRank with the addition of **each** node pair

- **Goal:** find the edge $(x, y), \forall x, y \in \mathcal{V}$, such that

$$\underset{(x,y)}{\text{argmax}} \quad \text{gain}(x, y)$$

- **Question:** how to efficiently compute the gain?

[1] Tsioutsiouliklis, S., Pitoura, E., Semertzidis, K., & Tsaparas, P. (2022). Link Recommendations for PageRank Fairness. WWW 2022.

Best Fair Edge Identification: Fairness Gain

- **Main result:** Adding an edge to the graph is a **rank-1 perturbation** of the transition matrix
- We can estimate the gain as:

Closeness of target node y to $\mathcal{S}$

The average 'closeness' of neighbors of x to $\mathcal{S}$

$$\text{gain}(x, y) = r_{\mathcal{E}}(x) \frac{\frac{c}{1-c}\left(r_{\mathcal{E}}(\mathcal{S}|y) - \frac{1}{d_x}\sum_{u \in \mathcal{N}_x} r_{\mathcal{E}}(\mathcal{S}|u)\right)}{d_x + \frac{c}{1-c}\left(\frac{1}{d_x}\sum_{u \in \mathcal{N}_x} r_{\mathcal{E}}(x|u) - r_{\mathcal{E}}(x|y)\right) + 1}$$

degree of source node

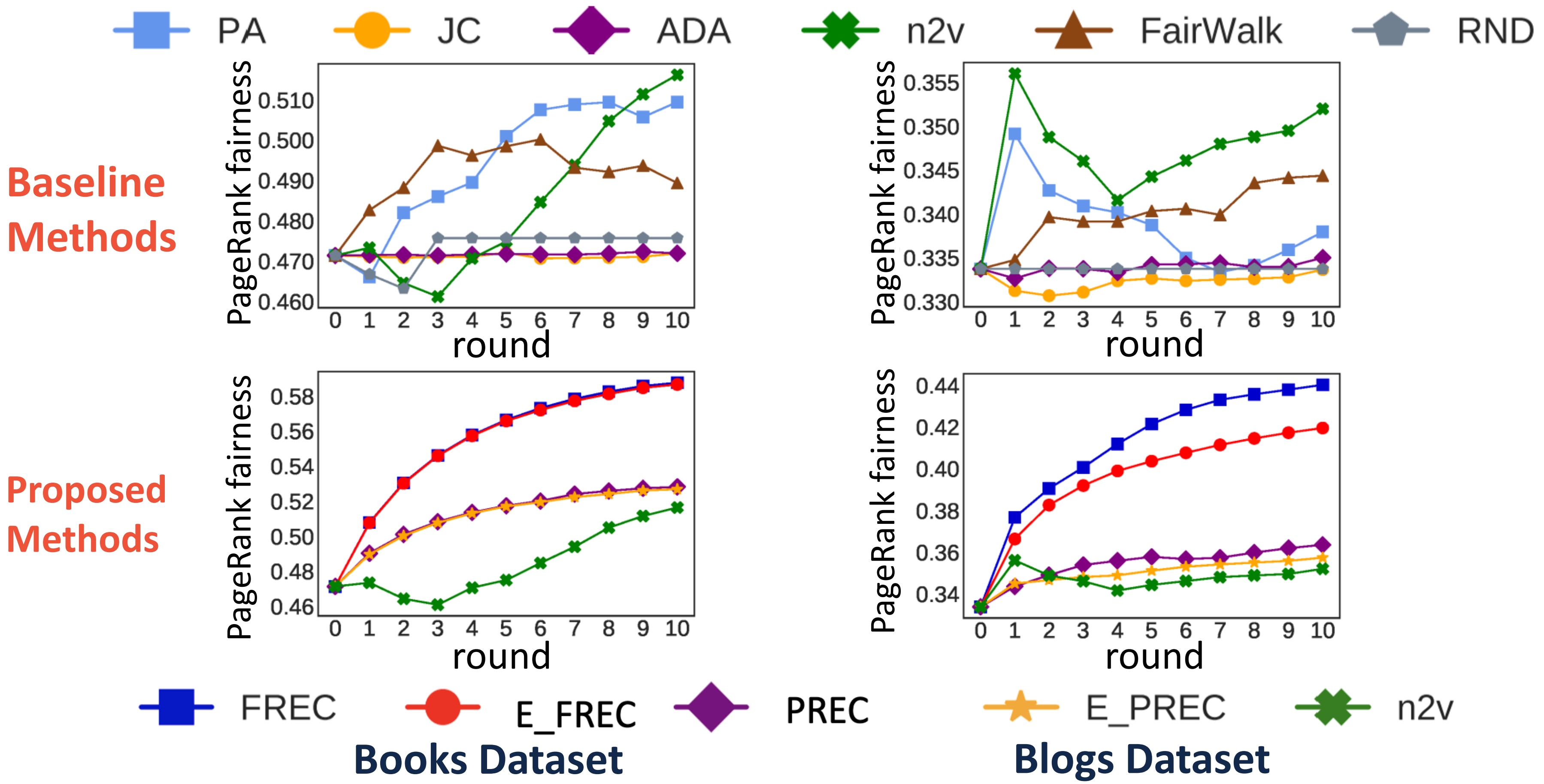
Average proximity of node x's neighbors to x

  - $r_{\mathcal{E}}(x|y)$: personalized PageRank (PPR) score of node x, with query node y, based on edge set $\mathcal{E}$
  - $r_{\mathcal{E}}(\mathcal{S}|y) = \sum_{i \in \mathcal{S}} r_{\mathcal{E}}(i|y)$: total PPR mass of nodes in $\mathcal{S}$, with query node y, based on edge set $\mathcal{E}$
- $r_{\mathcal{E}}(x)$: node x should have high PageRank score
- d_x: node x should have small degree
- $r_{\mathcal{E}}(x|y) - \frac{1}{d_x}\sum_{u \in \mathcal{N}_x} r_{\mathcal{E}}(x|u)$: node y is close to node x
- $r_{\mathcal{E}}(\mathcal{S}|y) - \frac{1}{d_x}\sum_{u \in \mathcal{N}_x} r_{\mathcal{E}}(\mathcal{S}|u)$: node y is closer to $\mathcal{S}$ than the neighborhood of x

[1] Tsioutsiouliklis, S., Pitoura, E., Semertzidis, K., & Tsaparas, P. (2022). Link Recommendations for PageRank Fairness. WWW 2022.

Best Fair Edge Identification: Experiment

- **Observation:** the proposed method find the best edges to improve PageRank fairness



- FREC: select edge (x, y) with highest $\text{gain}(x, y) = \Lambda(x, y) p_{\mathcal{E}}(x)$
- PREC: select edge (x, y) with highest $\text{gain}(x, y \mid x) = \Lambda(x, y) p_{\mathcal{E}}(x|x)$
- E_FREC: select edge (x, y) with highest $\text{gain}(x, y) p_{\text{acc}}(x, y)$
- E_PREC: select edge (x, y) with highest $\text{gain}(x, y \mid x) p_{\text{acc}}(x, y)$

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Roadmap

- Network Centrality Fairness
- Spectral Clustering Fairness
- Fair Graph Embeddings
- Graph Neural Network Fairness

Preliminary: Spectral Clustering (SC)

- **Goal:** partition the nodes into k subsets such that $\begin{cases} \text{maximize intra-connectivity} \\ \text{minimize inter-connectivity} \end{cases}$

- **Ratio cut**

$$RatioCut(C_1, C_2, \dots, C_k) = \sum_{i=1}^{k} \frac{Cut(C_i, V \setminus C_i)}{|C_i|}$$

- **Spectral Clustering**

$$\min_{\mathbf{U}} \quad \underbrace{\boxed{\mathrm{Tr}\left(\mathbf{U}^T \mathbf{L} \mathbf{U}\right)}}_{\text{Ratio cut}} \qquad \text{s.t.} \quad \mathbf{U}^T\mathbf{U} = \mathbf{I}$$

  where $\mathbf{L}$ is Laplacian matrix of $\mathbf{A}$, $\boldsymbol{L} = \boldsymbol{D} - \boldsymbol{A}$

  $\mathbf{U}$ is a matrix with k orthonormal column vectors

- **Solution:** rank-k eigen-decomposition
  - $\mathbf{U}$ = eigenvectors with k smallest eigenvalues

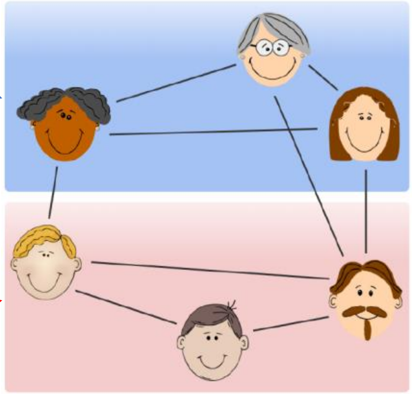
[1] Ng, A. Y., Jordan, M. I., & Weiss, Y. (2002). On Spectral Clustering: Analysis and an Algorithm. NeurIPS 2002.
[2] Shi, J., & Malik, J. (2000). Normalized Cuts and Image Segmentation. TPAMI 2000.

Preliminary: Spectral Clustering (SC)

- **Example:** Nodes are partitioned into groups based on a sensitive attribute (gender)

All female individuals are grouped together

All male individuals are grouped together



Unfair clustering
The clustering results are perfectly aligned with gender

- We would like groups to have proportional representation in the clusters

[1] Ng, A. Y., Jordan, M. I., & Weiss, Y. (2002). On Spectral Clustering: Analysis and an Algorithm. NeurIPS 2002.
[2] Shi, J., & Malik, J. (2000). Normalized Cuts and Image Segmentation. TPAMI 2000.

Fairness Measure: Balance Score

- **Intuition:** fairness as balance among clusters
- **Given:** a node set V with
  - h demographic groups: $V = V_1 \cup V_2 \ldots \cup V_h$
  - k clusters: $V = C_1 \cup C_2 \ldots \cup C_k$
- **Definition**

$$\text{balance}(C_l) = \min_{s \neq s' \in [h]} \frac{|V_s \cap C_l|}{|V_{s'} \cap C_l|} \in [0, 1], \qquad \forall l \in [1,2, \ldots, k]$$

$$\text{balance}(C_1, C_2, \ldots, C_k) = \min_{\ell} \text{balance}(C_l)\,,$$

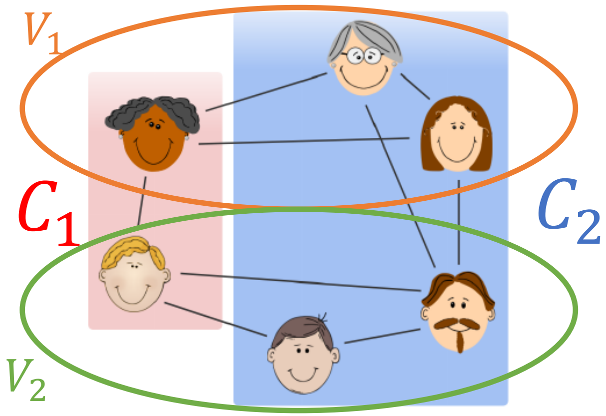
- **Intuition:** higher balance → fairer
  - Each demographic group is presented with similar fractions as in the whole dataset for every cluster

[1] Kleindessner, M., Samadi, S., Awasthi, P., & Morgenstern, J. (2019). Guarantees for Spectral Clustering with Fairness Constraints. ICML 2019.

Fairness Measure: Balance Score

- **Example**

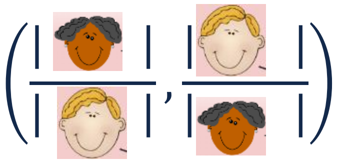
V_1: female group



V_2: male group

$$\text{balance}(C_1) = \min\left(\frac{|V_1 \cap C_1|}{|V_2 \cap C_1|}, \frac{|V_2 \cap C_1|}{|V_1 \cap C_1|}\right)$$

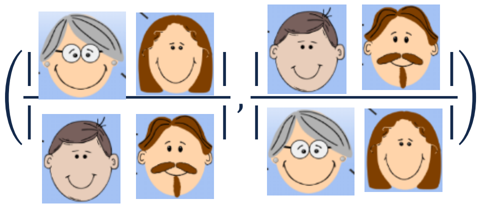
$= \min$



$= 1$

$$\text{balance}(C_2) = \min\left(\frac{|V_1 \cap C_2|}{|V_2 \cap C_2|}, \frac{|V_2 \cap C_2|}{|V_2 \cap C_2|}\right)$$

$= \min$



$= 1$

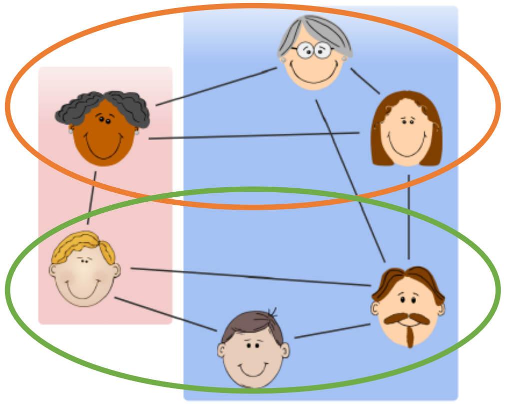
[1] Kleindessner, M., Samadi, S., Awasthi, P., & Morgenstern, J. (2019). Guarantees for Spectral Clustering with Fairness Constraints. ICML 2019.

Fair Spectral Clustering: Formulation

- **Key idea:** fairness as linear constraint
  - **Given**
    - The spectral embedding $\mathbf{U}$ of n nodes in l clusters $(C_1, \dots, C_l)$
    - h demographic groups $(V_1, \dots, V_s)$
  - **Define**
    - $\mathbf{f}^{(s)}[i] = 1$ if $i \in V_s$ and 0 otherwise
    - $\mathbf{F} =$ a matrix with $\mathbf{f}^{(s)} - \left(\frac{|V_s|}{n}\right)\mathbf{1}_n$ $(s \in [1, \dots, h-1])$ as column vectors
  - **Observation:** $\mathbf{F}^T\mathbf{U} = \mathbf{0}$ $\Leftrightarrow$ balanced clusters (i.e., fair clusters)
- **Example**

V_1: female group

V_2: male group



$\mathbf{f}^{(1)}$	$\mathbf{f}^{(2)}$
1	0
1	0
1	0
0	1
0	1
0	1

Fair fraction

0.5	0.5
0.5	0.5
0.5	0.5
0.5	0.5
0.5	0.5
0.5	0.5

$$\mathbf{F} = \begin{bmatrix} 0.5 & -0.5 \\ 0.5 & -0.5 \\ 0.5 & -0.5 \\ -0.5 & 0.5 \\ -0.5 & 0.5 \\ -0.5 & 0.5 \end{bmatrix}$$

[1] Kleindessner, M., Samadi, S., Awasthi, P., & Morgenstern, J. (2019). Guarantees for Spectral Clustering with Fairness Constraints. ICML 2019.

Fair Spectral Clustering: Solution

- **Optimization problem**

$$\min_{\mathbf{U}} \quad \mathrm{Tr}\left(\mathbf{U}^T\mathbf{L}\mathbf{U}\right) \qquad \text{s.t.} \quad \mathbf{U}^T\mathbf{U} = \mathbf{I}, \boxed{\mathbf{F}^T\mathbf{U} = \mathbf{0}}$$

How to solve?

- **Solution**
  - **Observation:** $\mathbf{F}^T\mathbf{U} = \mathbf{0}$ → $\mathbf{U}$ is in the null space of $\mathbf{F}^T$
  - **Steps**
    - Define $\mathbf{Z}$ = orthonormal basis of null space of $\mathbf{F}^T$
    - Rewrite $\mathbf{U} = \mathbf{Z}\mathbf{Y}$

$$\min_{\mathbf{Y}} \quad \mathrm{Tr}\left(\mathbf{Y}^T\mathbf{Z}^T\mathbf{L}\mathbf{Z}\mathbf{Y}\right) \qquad \text{s.t.} \quad \mathbf{Y}^T\mathbf{Y} = \mathbf{I}$$

  - **Method:** rank-k eigen-decomposition on $\mathbf{Z}^T\mathbf{L}\mathbf{Z}$

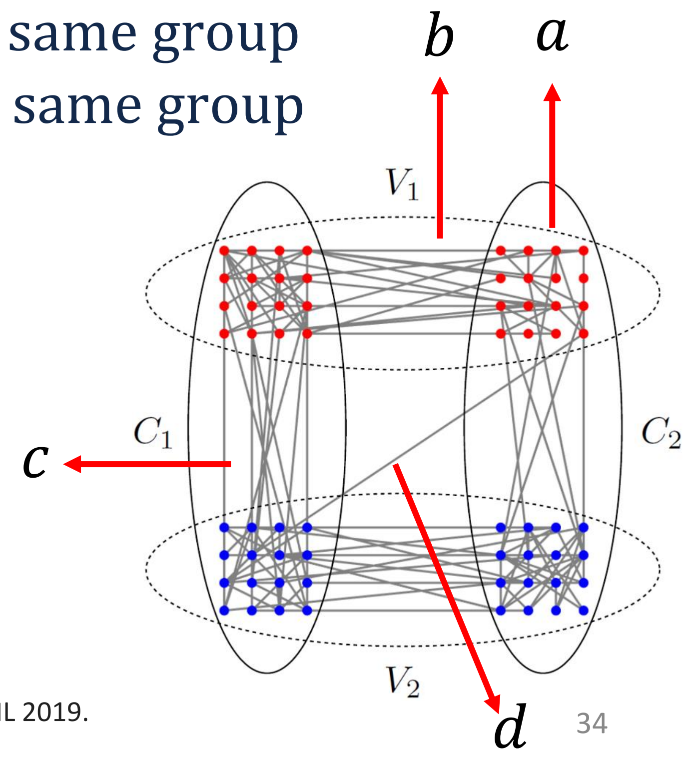
[1] Kleindessner, M., Samadi, S., Awasthi, P., & Morgenstern, J. (2019). Guarantees for Spectral Clustering with Fairness Constraints. ICML 2019.

Fair Spectral Clustering: Correctness

- **Given**
  - A random graph with nodes V by a variant of the Stochastic Block Model (SBM)
  - Edge probability between two nodes i and j

$$\mathrm{P}(i,j) = \begin{cases} a, & i \text{ and } j \text{ in same cluster and in same group} \\ b, & i \text{ and } j \text{ not in same cluster but in same group} \\ c, & i \text{ and } j \text{ in same cluster but not in same group} \\ d, & i \text{ and } j \text{ not in same cluster and not in same group} \end{cases}$$

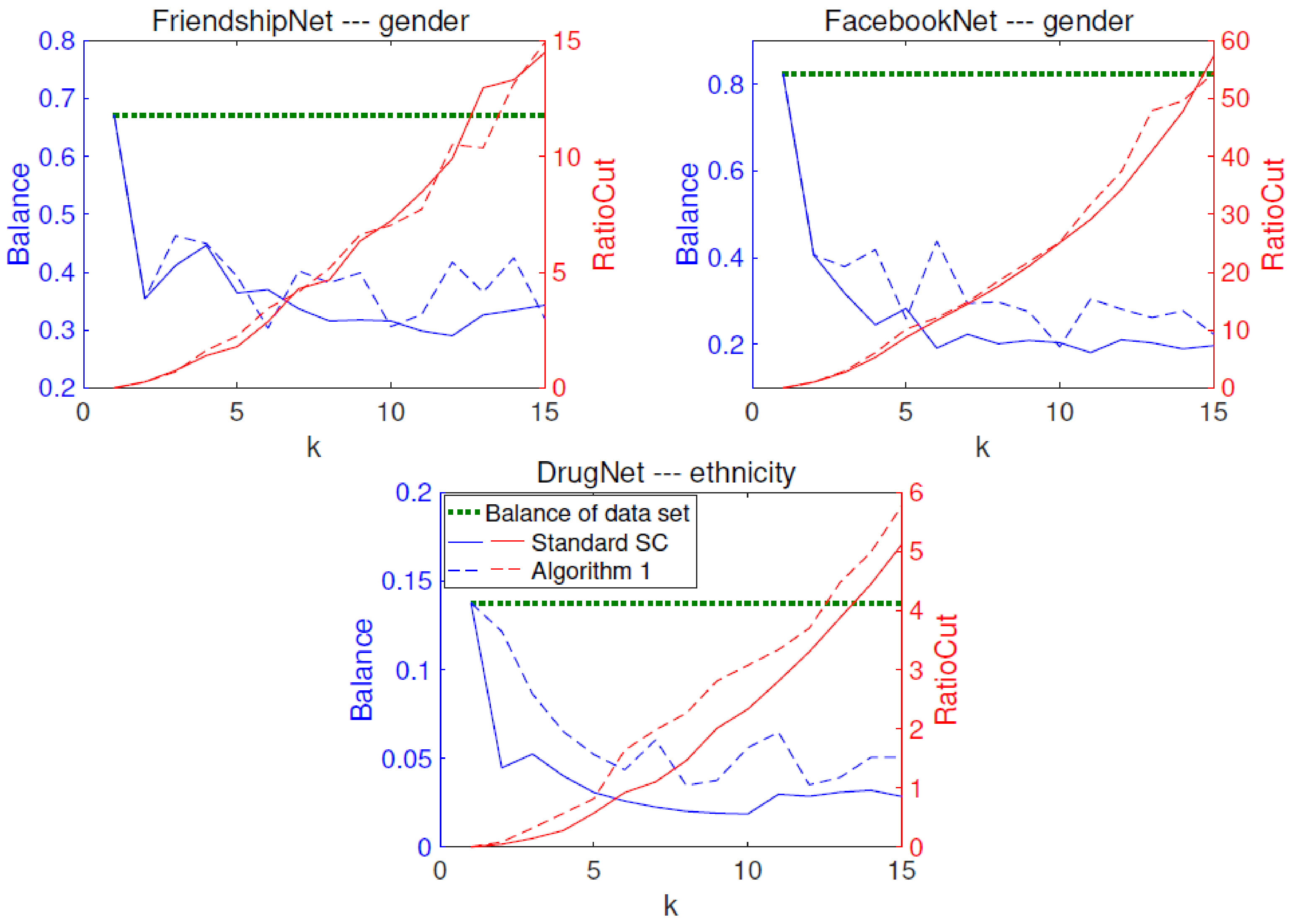
  for some $a > b > c > d$
  - A fair ground-truth clustering $V = C_1 \cup C_2$
- **Theorem:** Fair SC recovers the ground-truth clustering $C_1 \cup C_2$
- **Example**
  - Standard SC is likely to return $V_1 \cup V_2$
  - Fair SC will return $C_1 \cup C_2$



[1] Kleindessner, M., Samadi, S., Awasthi, P., & Morgenstern, J. (2019). Guarantees for Spectral Clustering with Fairness Constraints. ICML 2019.

Fair Spectral Clustering: Experiment

- **Observation:** Fairer (higher balance score) with similar ratio cut values for the proposed method (Algorithm 1 in the figure)



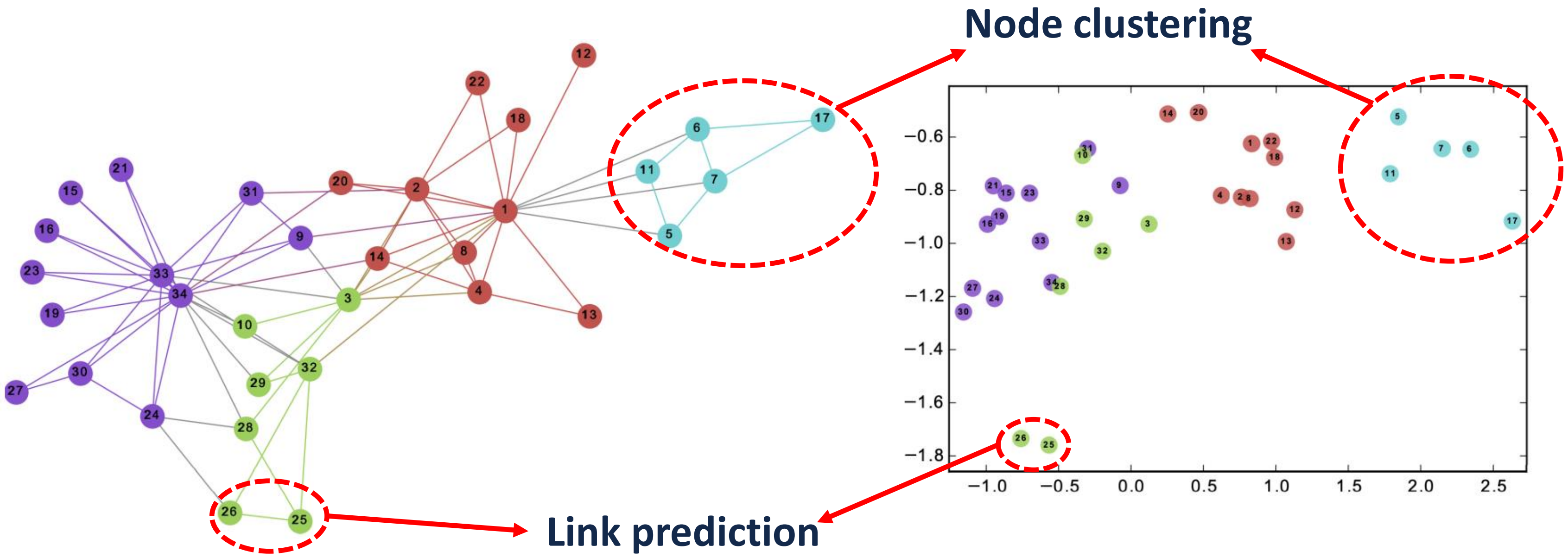
[1] Kleindessner, M., Samadi, S., Awasthi, P., & Morgenstern, J. (2019). Guarantees for Spectral Clustering with Fairness Constraints. ICML 2019.

Roadmap

- Network Centrality Fairness
- Spectral Clustering Fairness
- Fair Graph Embeddings
- Graph Neural Network Fairness

Preliminary: Node Embedding

- **Motivation:** learn low-dimensional node representations that preserve structural/attributive information
- **Applications**
  - Node classification
  - Link prediction
  - Node visualization



(a) Input: Karate Graph (b) Output: Representation

Visualization of Node Embedding

[1] Perozzi, B., Al-Rfou, R., & Skiena, S. (2014). Deepwalk: Online Learning of Social Representations. KDD 2014.
[2] Grover, A., & Leskovec, J. (2016). node2vec: Scalable Feature Learning for Networks. KDD 2016.
[3] Bordes, A., Usunier, N., Garcia-Duran, A., Weston, J., & Yakhnenko, O. (2013). Translating Embeddings for Modeling Multi-relational Data. NeurIPS 2013.

Graph embeddings

- Graph embeddings utilize only the graph structure to derive the node representation
- In broad terms, the embedding of a node depends on the embeddings of the k-hop neighborhood of the node
- Since neighboring nodes tend to have similar (sensitive) attributes, the embeddings are likely to encode information about the sensitive attributes
  - Therefore, they are **biased**

- How can we remove these biases?

Graph unfairness

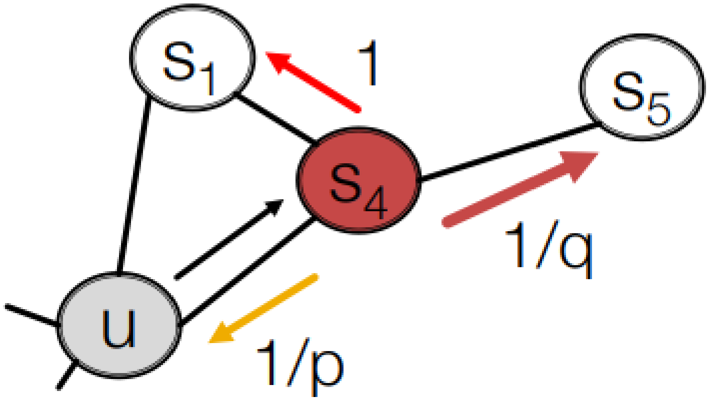
- Homophily-based metrics:
  - E.g., the fraction of edges that link nodes with the same sensitive attribute value

- Neighborhood metrics:
  - The entropy of the label distribution of the neighborhood of a node.

- Preprocessing approach:
  - Change the graph (e.g., via edge rewiring or edge additions) to improve fairness

Preliminary: Random Walk-based Node Embedding

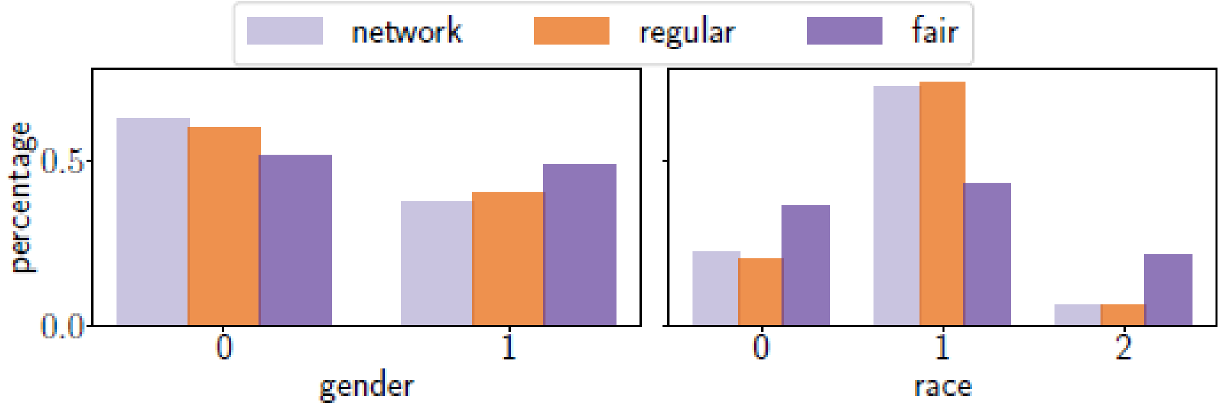
- **Goal:** learn node embeddings that are predictive of nodes in its neighborhood
- **Key idea**
  - Simulate random walk as a sequence of nodes
  - Apply skip-gram technique to predict the context node
- **Example**
  - **DeepWalk:** random walk for sequence generation
  - **Node2vec:** biased random walk for sequence generation
    - **Return parameter** p: how fast the walk **explores** the neighborhood of the starting node
    - **In-out parameter** q: how fast the walk **leaves** the neighborhood of the starting node



[1] Perozzi, B., Al-Rfou, R., & Skiena, S. (2014). Deepwalk: Online Learning of Social Representations. KDD 2014.
[2] Grover, A., & Leskovec, J. (2016). node2vec: Scalable Feature Learning for Networks. KDD 2016.

Fairwalk: Solution

- **Key idea:** modify the random walk procedure in node2vec
- **Steps of Fairwalk**
  - Partition neighbors into demographic groups
  - Uniformly sample a demographic group to walk to
  - Randomly select a neighboring node within the chosen demographic group
- **Example:** ratio of each demographic group
  - Original network vs. regular random walk vs. fair random walk



[1] Rahman, T., Surma, B., Backes, M., & Zhang, Y. (2019). Fairwalk: Towards Fair Graph Embedding. IJCAI 2019.

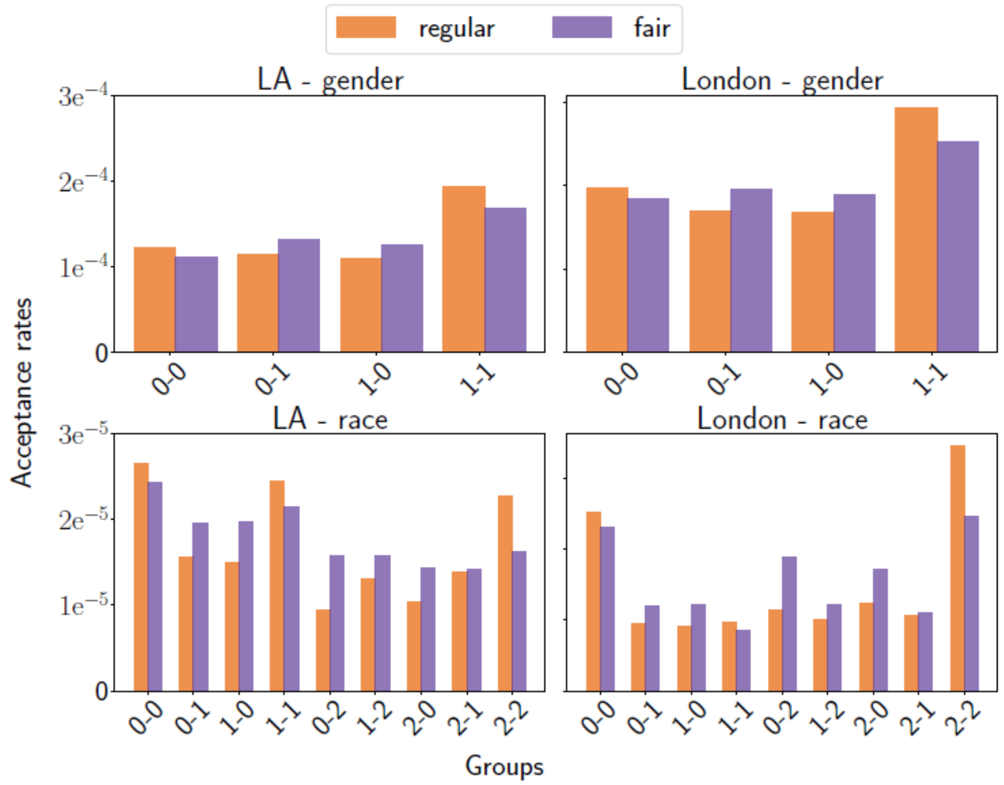
Fairwalk vs. Existing Works

- **Fairwalk vs. node2vec**
  - **Node2vec:** skip-gram model + walk sequences by original random walk
  - **Fairwalk:** skip-gram model + walk sequences by fair random walk
- **Fairwalk vs. fairness-aware PageRank**
  - **Fairness-aware PageRank:** the minority group should have a certain proportion of PageRank probability mass
  - **Fairwalk:** all demographic group have the same random walk transition probability mass

[1] Rahman, T., Surma, B., Backes, M., & Zhang, Y. (2019). Fairwalk: Towards Fair Graph Embedding. IJCAI 2019.
[2] Grover, A., & Leskovec, J. (2016). node2vec: Scalable Feature Learning for Networks. KDD 2016.
[3] Tsioutsiouliklis, S., Pitoura, E., Tsaparas, P., Kleftakis, I., & Mamoulis, N. (2021). Fairness-Aware PageRank. WWW 2021.

Fairwalk: Results on Statistical Parity

- **Observations**
  - Fairwalk achieves a more balanced acceptance rates among groups
  - Fairwalk increases the fraction of cross-group recommendations



[1] Rahman, T., Surma, B., Backes, M., & Zhang, Y. (2019). Fairwalk: Towards Fair Graph Embedding. IJCAI 2019.

Roadmap

- Network Centrality Fairness
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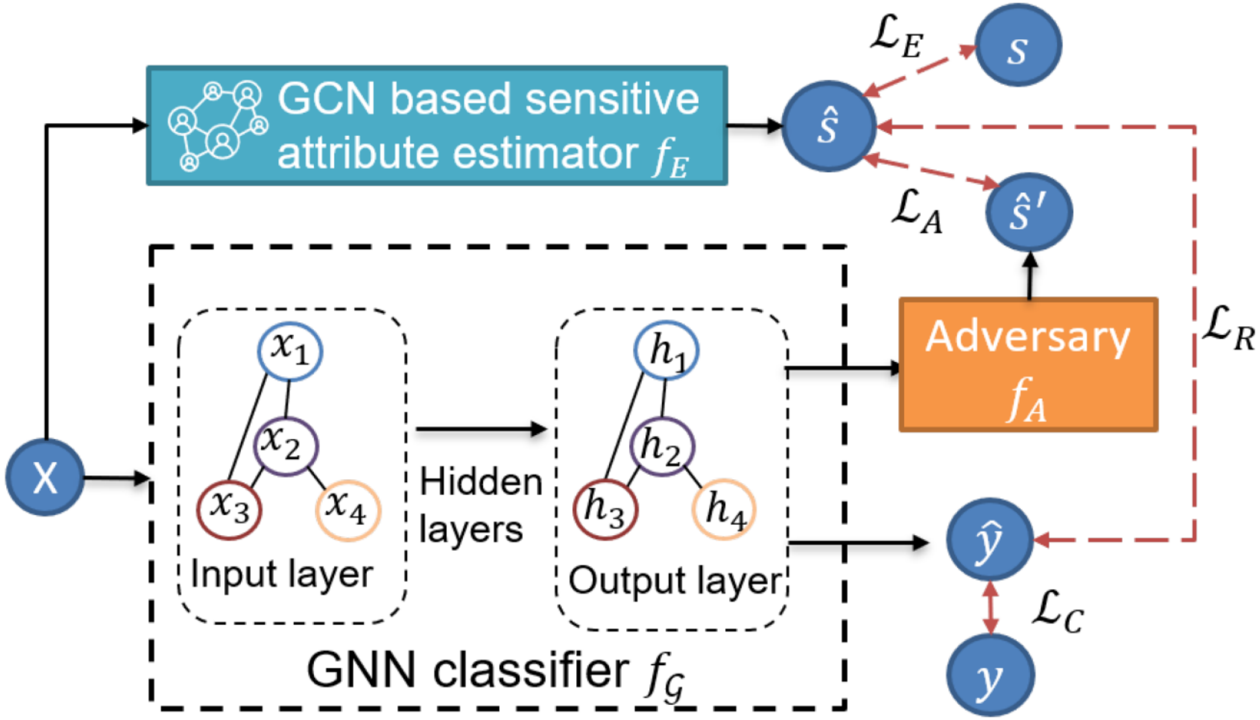
FairGNN: Fairness with Limited Sensitive Attribute Information

- **Key idea**
  - Train a sensitive attribute estimator to infer pseudo sensitive attribute
  - Train adversary to learn fair embedding using the pseudo sensitive attribute
- **FairGNN framework**
  - A backbone graph neural network (GNN)
    - Any GNN can be the backbone
  - Adversarial debiasing module
    - GCN-based sensitive attribute estimator
    - Adversary in the figure
  - Covariance minimizer

Main focus



[1] Dai, E., & Wang, S. (2021). Say No to the Discrimination: Learning Fair Graph Neural Networks with Limited Sensitive Attribute Information. WSDM 2021.

FairGNN: Adversarial Debiasing Module

- **Adversary**
  - **Intuition:** maximize the error of predicting pseudo sensitive attribute information
  - **Loss function**

$$\mathcal{L}_A = \mathbb{E}_{\mathbf{h}\sim p(\mathbf{h}|\tilde{s}=1)}[\log f_A(\mathbf{h})] + \mathbb{E}_{\mathbf{h}\sim p(\mathbf{h}|\tilde{s}=0)}\left[\log\left(1 - f_A(\mathbf{h})\right)\right]$$

    - $\tilde{s}$: pseudo sensitive attribute information
    - $\mathbf{h}$: node embedding extracted from a graph neural network
    - $\mathbf{h} \sim p(\mathbf{h}|\tilde{s} = 1)$: randomly sample a node embedding whose corresponding node has $\tilde{s} = 1$
    - $f_A(\mathbf{h})$: output of the adversary

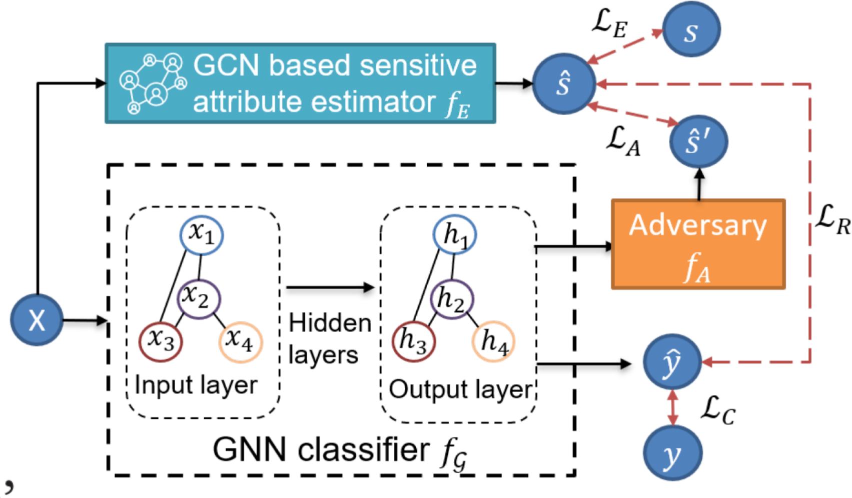
[1] Dai, E., & Wang, S. (2021). Say No to the Discrimination: Learning Fair Graph Neural Networks with Limited Sensitive Attribute Information. WSDM 2021.

FairGNN: Covariance Minimizer

- **Observation:** adversarial learning is notoriously unstable to train
  - Failure to converge may cause discrimination
- **Key idea:** additional prerequisite of independence is needed to provide additional supervision signal
- **Solution:** absolute covariance between model prediction $\hat{y}$ and pseudo sensitive attribute $\hat{s}$ should be minimized
  - **Why absolute:** covariance can be negative

$$\mathcal{L}_R = |\mathrm{cov}(\hat{s}, \hat{y})| = \left|\mathbb{E}[(\hat{s} - \mathbb{E}[\hat{s}])(\hat{y} - \mathbb{E}[\hat{y}])]\right|$$

FairGNN: Overall Loss Function



- **Regularized learning**

$$\min_{\theta_{\mathcal{G}},\theta_E} \max_{\theta_A} \mathcal{L}_C + \mathcal{L}_E + \alpha\mathcal{L}_R - \beta\mathcal{L}_A,$$

- **Intuition**
  - $\mathcal{L}_C$: classification loss (e.g., cross entropy) for learning representative node representation
  - $\mathcal{L}_E$: sensitive attribute estimation loss for generating accurate pseudo sensitive attribute information
  - $\mathcal{L}_A$: adversarial loss for debiasing the learned node representation
  - $\mathcal{L}_R$: covariance for stabilizing the training of adversary

FairGNN: Experiment

- **Observation:** FairGNN achieves comparable node classification accuracy with a much smaller bias

Dataset	Metrics	GCN	GAT	ALFR	ALFR-e	Debias	Debias-e	FCGE	FairGCN	FairGAT
Pokec-z	ACC (%)	70.2 ±0.1	70.4 ±0.1	65.4 ±0.3	68.0 ±0.6	65.2 ±0.7	67.5 ±0.7	65.9 ±0.2	**70.0 ±0.3**	**70.1 ±0.1**
	AUC (%)	77.2 ±0.1	76.7 ±0.1	71.3 ±0.3	74.0 ±0.7	71.4 ±0.6	74.2 ±0.7	71.0 ±0.2	**76.7 ±0.2**	**76.5 ±0.2**
	Δ_{SP} (%)	9.9 ±1.1	9.1 ±0.9	2.8 ±0.5	5.8 ±0.4	1.9 ±0.6	4.7 ±1.0	3.1 ±0.5	**0.9 ±0.5**	**0.5 ±0.3**
	Δ_{EO} (%)	9.1 ±0.6	8.4 ±0.6	1.1 ±0.4	2.8 ±0.8	1.9 ±0.4	3.0 ±1.4	1.7 ±0.6	**1.7 ±0.2**	**0.8 ±0.3**
Pokec-n	ACC (%)	70.5 ±0.2	70.3 ±0.1	63.1 ±0.6	66.2 ±0.5	62.6 ±0.9	65.6 ±0.8	64.8 ±0.5	**70.1 ±0.2**	**70.0 ±0.2**
	AUC (%)	75.1 ±0.2	75.1 ±0.2	67.7 ±0.5	71.9 ±0.3	67.9 ±0.7	71.7 ±0.7	69.5 ±0.4	**74.9 ±0.4**	**74.9 ±0.4**
	Δ_{SP} (%)	9.6 ±0.9	9.4 ±0.7	3.05 ±0.5	4.1 ±0.5	2.4 ±0.7	3.6 ±0.2	4.1 ±0.8	**0.8 ±0.2**	**0.6 ±0.3**
	Δ_{EO} (%)	12.8 ±1.3	12.0 ±1.5	3.9 ±0.6	4.6 ±1.6	2.6 ±1.0	4.4 ±1.2	5.5 ±0.9	**1.1 ±0.5**	**0.8 ±0.2**
NBA	ACC (%)	71.2 ±0.5	71.9 ±1.1	64.3 ±1.3	66.0 ±0.4	63.1 ±1.1	65.6 ±2.4	66.0 ±1.5	**71.1 ±1.0**	**71.5 ±0.8**
	AUC (%)	78.3 ±0.3	78.2 ±0.6	71.5 ±0.3	72.9 ±1.0	71.3 ±0.7	72.9 ±1.2	73.6 ±1.5	**77.0 ±0.3**	**77.5 ±0.7**
	Δ_{SP} (%)	7.9 ±1.3	10.2 ±2.5	2.3 ±0.9	4.7 ±1.8	2.5 ±1.5	5.3 ±0.9	2.9 ±1.0	**1.0 ±0.5**	**0.7 ±0.5**
	Δ_{EO} (%)	17.8 ±2.6	15.9 ±4.0	3.2 ±1.5	4.7 ±1.7	3.1 ±1.9	3.1 ±1.3	3.0 ±1.2	**1.2 ±0.4**	**0.7 ±0.3**

Resources

- **Datasets:** https://github.com/yushundong/Graph-Mining-Fairness-Data
- **Paper collection:** https://github.com/EdisonLeeeee/Awesome-Fair-Graph-Learning
- **Surveys**
  - Dong, Y., Ma, J., Chen, C., & Li, J. (2023). Fairness in Graph Mining: A Survey. TKDE 2023.
  - Zhang, W., Weiss, J. C., Zhou, S., & Walsh, T. (2022). Fairness Amidst Non-IID Graph Data: A Literature Review. arXiv preprint arXiv:2202.07170.
  - Zhang, H., Wu, B., Yuan, X., Pan, S., Tong, H., & Pei, J. (2022). Trustworthy Graph Neural Networks: Aspects, Methods and Trends. arXiv preprint arXiv:2205.07424.
  - Dai, E., Zhao, T., Zhu, H., Xu, J., Guo, Z., Liu, H., ... & Wang, S. (2022). A Comprehensive Survey on Trustworthy Graph Neural Networks: Privacy, Robustness, Fairness, and Explainability. arXiv preprint arXiv:2204.08570.
- **Related tutorials**
  - Algorithmic Fairness on Graphs: Methods and Trends
    - http://jiank2.web.illinois.edu/tutorial/kdd22/algofair_on_graphs.html
  - Fairness in Graph Mining: Metrics, Algorithms, and Applications
    - https://yushundong.github.io/icdm_tutorial_2022.pdf
  - Fair Graph Mining
    - http://jiank2.web.illinois.edu/tutorial/cikm21/fair_graph_mining.html
  - Fairness in Networks
    - https://algofairness.github.io/kdd-2021-network-fairness-tutorial/

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  - Xianfeng Tang (Amazon)
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References

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- Tsioutsiouliklis, S., Pitoura, E., Semertzidis, K., & Tsaparas, P. (2022). Link Recommendations for PageRank Fairness. WWW 2022.
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Thank you!