Fairness-Aware Selective Sampling on Attributed Graphs

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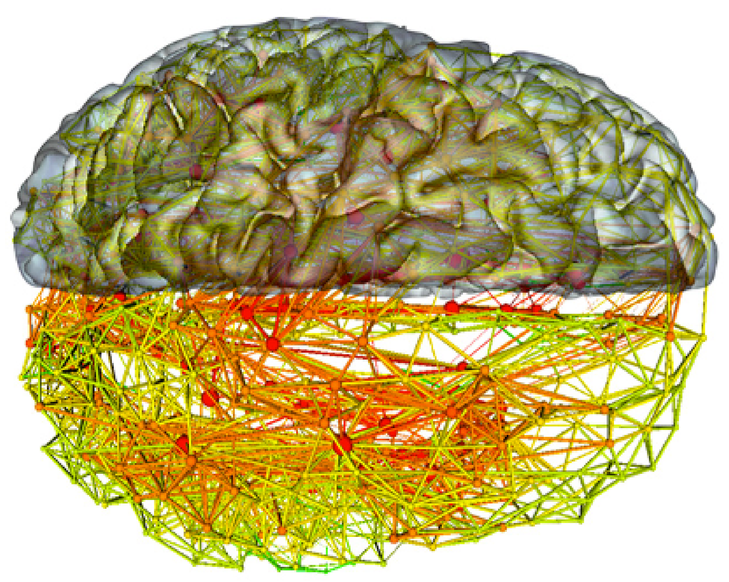
Motivation

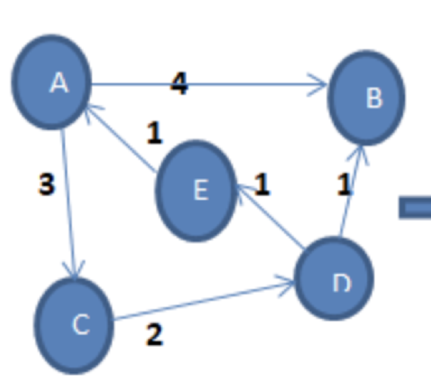
- Graphs model a number of real-world systems
  - Graph nodes: neurons in brain, users in social networks
  - Graph edges: neuron connections, friendship between users
  - Nodal features: types of neurons, education level of users
- Goal: Node classification
  - Disease detection, social network analysis



- Method: Online learning & Selective sampling over graphs
  - No need to store historical data
  - Not requires the availability of all labels
- Challenge 1: Efficient use of nodal features
  - Not considered in previous studies
  - Nodal features contain useful information for better utility
- Challenge 2: Increased bias resulted from the utilization of connectivity
  - Biased results affect critical real-life decisions
  - Bias not taken into consideration in previous works

Problem Statement

- Goal: Node classification over graphs for a given graph adjacency $\mathbf{A} \in \{0,1\}^{N\times N}$, nodal features $\mathbf{X} \in \mathbb{R}^{N\times F}$ and partially available labels $\mathbf{y}$
- Utilization of structural information: $\frac{1}{2}\sum_{i,j=1}^{n}\left(f_i - f_j\right)^2 \mathbf{A}_{ij} = \mathbf{f}^\top \mathbf{L}\mathbf{f}$

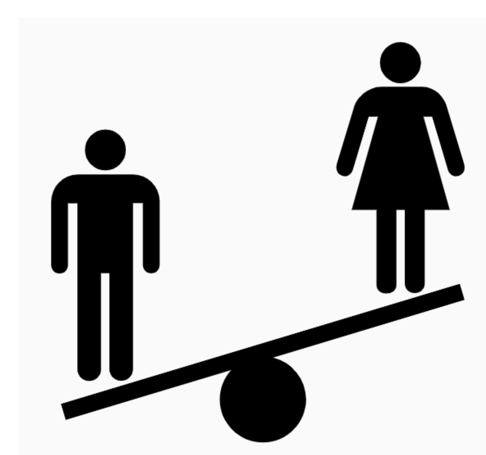


$$\begin{array}{c|ccccc} & A & B & C & D & E \\ \hline A & 0 & 4 & 3 & 0 & 0 \\ B & 0 & 0 & 0 & 0 & 0 \\ C & 0 & 0 & 0 & 2 & 0 \\ D & 0 & 1 & 0 & 0 & 1 \\ E & 1 & 0 & 0 & 0 & 0 \end{array}$$

- Problem formulation: $\min_{\mathbf{w}} \frac{1}{2}\left\|\mathbf{M}^\top\mathbf{w} - \mathbf{y}\right\|^2 + \frac{\mu}{2}\|\mathbf{w}\|^2$, where $\mathbf{L}^\dagger = \mathbf{M}^\top\mathbf{M}$
- Recursive solution in online setting: $\mathbf{w}_{t+1} = \mathbf{A}_t^{-1}\mathbf{b}_t$ where $\mathbf{A}_t = \mu\mathbf{I} + \sum_{i=1}^{t}\mathbf{m}_i\mathbf{m}_i^\top$, and $\mathbf{b}_t = \sum_{i=1}^{t} y_i\mathbf{m}_i$

Proposed Scheme

1. **Fusion of Nodal Features**
   - Nodal feature can benefit node classification
     - Gender of patients for disease detection
     - Age of users for community detection
   - Non-optimality of direct concatenation of nodal features and topology information
   - Proposed method:
     (a) Generate the similarity matrix $\mathbf{K}$ for nodal features based on cosine similarity:
     $$K_{i,j} = \frac{\mathrm{Sim}_{\cos}(\tilde{\mathbf{x}}_i, \tilde{\mathbf{x}}_j) + 1}{2}$$
     (b) Transform $\mathbf{K}$ into a laplacian-like matrix $\mathbf{L}_\mathbf{x}$:
     $$\mathbf{L}_x = \mathbf{I} - \mathbf{K}_D^{-\frac{1}{2}}\mathbf{K}\mathbf{K}_D^{-\frac{1}{2}}$$
     (c) Combine the information coming from graph topology and nodal features:
     $$(\mathbf{L} + \beta\mathbf{L}_x)^\dagger = \hat{\mathbf{M}}^\top\hat{\mathbf{M}}$$
   - Updated Problem Formulation: $\min_{\hat{\mathbf{w}}} \frac{1}{2}\left\|\hat{\mathbf{M}}^\top\hat{\mathbf{w}} - \mathbf{y}\right\|^2 + \frac{\mu}{2}\|\hat{\mathbf{w}}\|^2$
   - Recursive solution:
     $$\hat{\mathbf{w}}_{t+1} = \hat{\mathbf{A}}_t^{-1}\hat{\mathbf{b}}_t$$
     with $\hat{\mathbf{A}}_t = \mu\mathbf{I} + \sum_{i=1}^{t}\hat{\mathbf{m}}_i\hat{\mathbf{m}}_i^\top$, and $\hat{\mathbf{b}}_t = \sum_{i=1}^{t} y_i\hat{\mathbf{m}}_i$
2. **Fairness Enhancement**
   - Machine learning algorithms propagate bias
     - Impact of race in credit decision
     - Impact of gender in ad recommendation



   - Use of network connectivity amplifies existing bias
   - Dimensionality reduction is utilized to reduce computational complexity
     - $(\mathbf{L} + \beta\mathbf{L}_x)^\dagger = \hat{\mathbf{M}}^\top\hat{\mathbf{M}}$ creates N dimensional data vectors
     - Training of linear regressor $\hat{w}$: $\mathcal{O}(N^2)$
     - Create $\hat{\mathbf{M}}^d \in \mathbb{R}^{d\times N}$ such that $\hat{\mathbf{M}}^d = \mathrm{diag}\left(\frac{1}{\sqrt{\sigma_1}}, \ldots, \frac{1}{\sqrt{\sigma_d}}\right)[\mathbf{v}_1, \ldots, \mathbf{v}_d]^\top$ where $(\mathbf{L} + \beta\mathbf{L}_x) = \sum_{i=1}^{N}\sigma_i\mathbf{v}_i\mathbf{v}_i^\top$
   - Proposed method:
     (a) Measure correlation between the sensitive attribute and the $d + d_s$ smallest eigenvectors of $(\mathbf{L} + \beta\mathbf{L}_x)$
     (b) Create $\hat{\mathbf{V}} \in \mathbb{R}^{d\times N}$ consisting of the eigenvectors corresponding to d smallest correlation values as rows
     (c) $\hat{\mathbf{M}}^d_{fair} = \hat{\boldsymbol{\Sigma}}^{-\frac{1}{2}}\hat{\mathbf{V}}$
   - Intuition: Use bases less correlated with sensitive attributes

Results

- **Fusion of Nodal Features**
- Datasets: Real-world social networks where region information is sensitive attribute and working field is label
- Utility metric: Error rate (ER)
- Fairness metrics:
  - $\Delta_{SP} = |P(\hat{y} = 1 \mid s = 0) - P(\hat{y} = 1 \mid s = 1)|$
  - $\Delta_{EO} = |P(\hat{y} = 1 \mid y = 1, s = 0) - P(\hat{y} = 1 \mid y = 1, s = 1)|$
- Baselines:
  - Online learning with local and global consistency (OLLGC)[1]
  - Selective sampling with local and global consistency (SSLGC) [1]
  - Aggressive graph-based selective sampling (AGS) [2]

	Pokec-z				Pokec-n			
	ER (%)	Δ_{SP} (%)	Δ_{EO} (%)	Q_{num}	ER (%)	Δ_{SP} (%)	Δ_{EO} (%)	Q_{num}
OLLGC	41.69	4.33	6.84	-	42.11	6.49	6.57	-
SSLGC	39.91	10.00	4.65	2622	40.61	10.69	8.86	2173
AGS	38.67	11.67	14.53	3865	39.37	11.30	9.56	3077
OLLGC, Direct Fusion	39.77	5.59	6.98	-	41.63	4.99	4.39	-
SSLGC, Direct Fusion	38.65	3.74	4.87	5054	41.44	5.22	2.94	4189
AGS, Direct Fusion	35.64	8.72	9.67	2680	38.87	6.95	5.46	2309
OLLGC, Kernel Fusion	39.23	7.54	10.81	-	40.99	7.03	8.76	-
SSLGC, Kernel Fusion	37.12	5.75	8.20	2563	39.25	2.34	4.35	1849
AGS, Kernel Fusion	35.58	14.49	16.86	3617	37.05	10.70	12.67	2912

- Utilization of nodal features provides better utility with less queried labels
- Direct concatenation not an optimal fusion strategy
- Typically increased bias together with nodal features
- **Fairness Enhancement**

	Pokec-z				Pokec-n			
	ER (%)	Δ_{SP} (%)	Δ_{EO} (%)	Q_{num}	ER (%)	Δ_{SP} (%)	Δ_{EO} (%)	Q_{num}
Fair-OLLGC	42.60	7.26	1.58	-	43.30	5.33	5.37	-
Fair-SSLGC	40.93	7.64	0.58	2636	42.11	9.46	4.12	2437
Fair-AGS	39.48	10.04	3.65	3827	40.25	5.91	3.74	3222
Fair-OLLGC, Kernel Fusion	40.23	2.42	4.12	-	40.94	1.95	2.97	-
Fair-SSLGC, Kernel Fusion	37.64	1.84	5.40	2064	39.47	1.19	2.42	2631
Fair-AGS, Kernel Fusion	36.34	5.48	2.14	3500	37.67	7.77	6.52	3009

- Fairness improvement in terms of statistical parity and equal opportunity
- Increased effectiveness together with nodal features

Conclusions

- An improvement over existing selective sampling algorithms by enabling the use of nodal features
- Amplified bias together with the employment of nodal features
- A fairness enhancement method through fairness-aware dimensionality reduction
- Demonstration of the efficacy of the proposed bias-reduction method on real social networks
- Future work: Proposed bias reduction method in a more general setting

[1] Gu, Quanquan, et al. "Selective sampling on graphs for classification." Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining. 2013.

[2] P. Yang, P. Zhao, V. W. Zheng, and X.-L. Li, "An aggressive graph-based selective sampling algorithm for classification," in IEEE Int. Conf. on Data Mining, Nov. 2015, pp. 509–518.