On Generalized Degree Fairness in Graph Neural Networks

Zemin Liu, 1* Trung-Kien Nguyen, 2 Yuan Fang 2
National University of Singapore, Singapore
Singapore Management University, Singapore
zeminliu@nus.edu.sg, {tknguyen, yfang}@smu.edu.sg

Code： https://github.com/ntkien1904/DegFairGNN

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Reported by Renhui Luo

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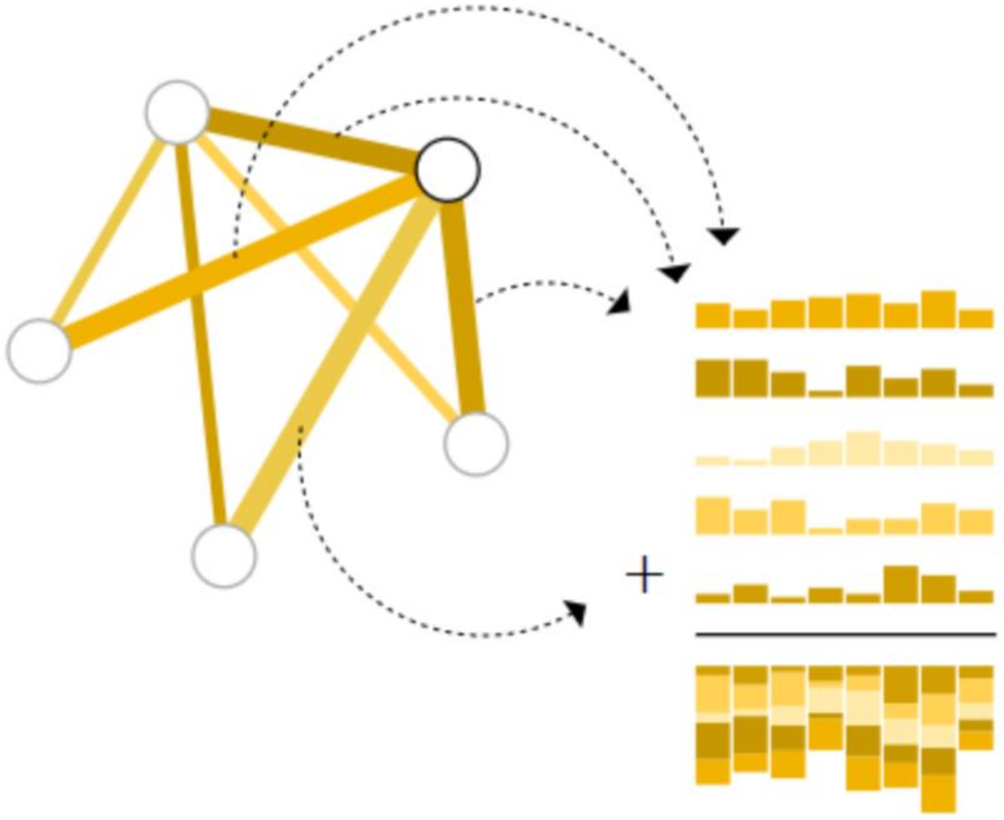
Leibniz-Institut für Sozialwissenschaften

Introduction



Conventional graph neural networks (GNNs) confronted with fairness issues that may stem from their input,including node attributes and neighbors surrounding a node.

Existing studies have shown that the structure of graph neural networks can further strengthen the biases hidden in data, thus leading to discriminatory decisions regarding age, gender, race, etc

GNN , aggregate information from adjacent nodes

Introduction

QUESTION:

1. drastic differences in node degrees could lead to differential node behaviors and biased outcomes.

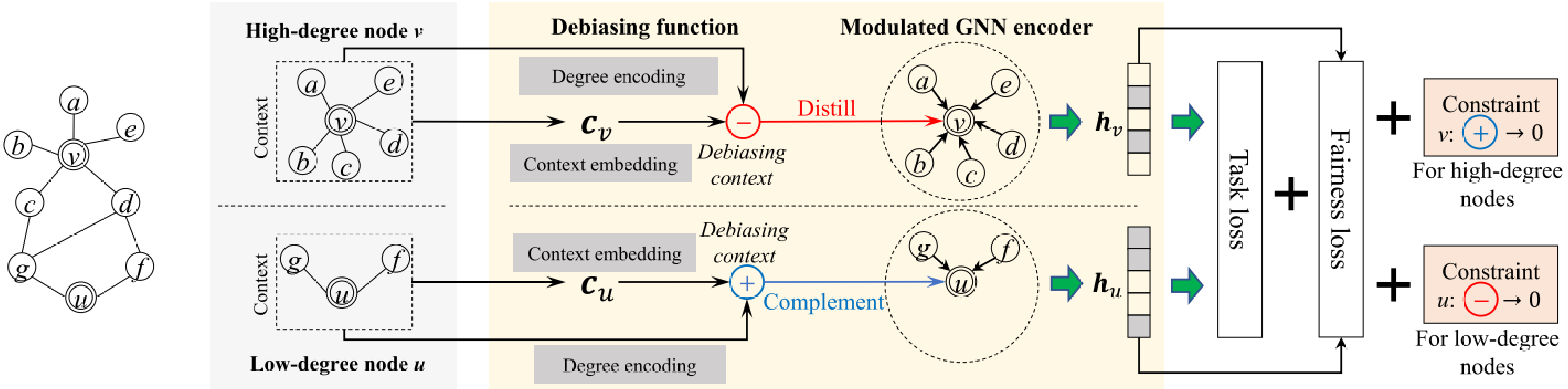
2. a node of larger degree is more likely to possess crucial advantages and thus receives more favorable outcomes than warranted.

WORK:

1. Defining and addressing generalized degree fairness in GNNs.

2. DegFairGNN that can flexibly work with neighborhood aggregation-based GNNs, to eliminate the generalized degree bias rooted in the layer-wise neighborhood aggregation.

Overview



(a) Toy graph (b) Structural contrast (c) Debiasing neighborhood aggregation (d) Overall objective

Method

Generalized degree

$$\deg_r(v) = [\mathbf{A}^r \mathbf{1}]_v, \quad (1)$$

Generalized degree fairness

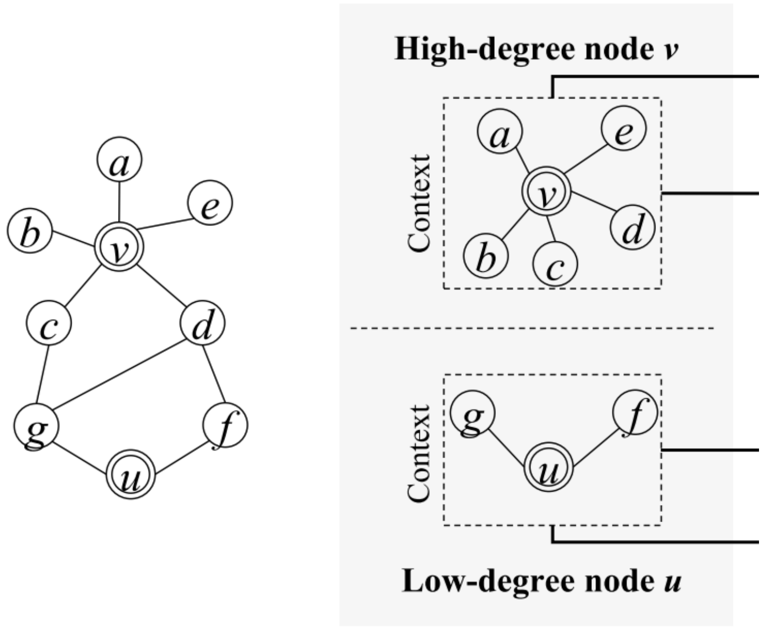
$$\mathcal{G}_i = \{v \in \mathcal{V} \mid d_i \leq \deg_r(v) < d_{i+1}\}, \quad (2)$$

Degree Statistical Parity (DSP)

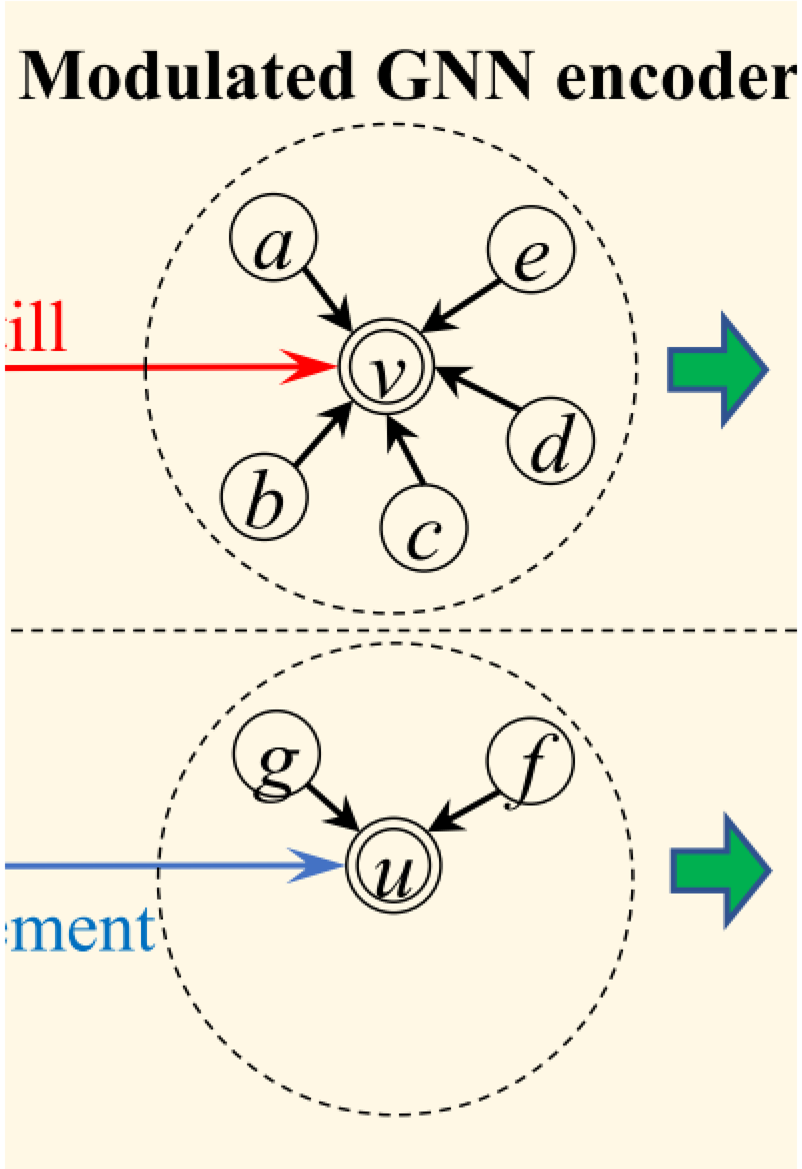
$$P(\hat{y}_v = y | v \in \mathcal{G}_i) = P(\hat{y}_v = y | v \in \mathcal{G}_j), \quad (3)$$

Degree Equal Opportunity (DEO)

$$P(\hat{y}_v = y | y_v = y, v \in \mathcal{G}_i) = P(\hat{y}_v = y | y_v = y, v \in \mathcal{G}_j).$$



(a) Toy graph (b) Structural contrast

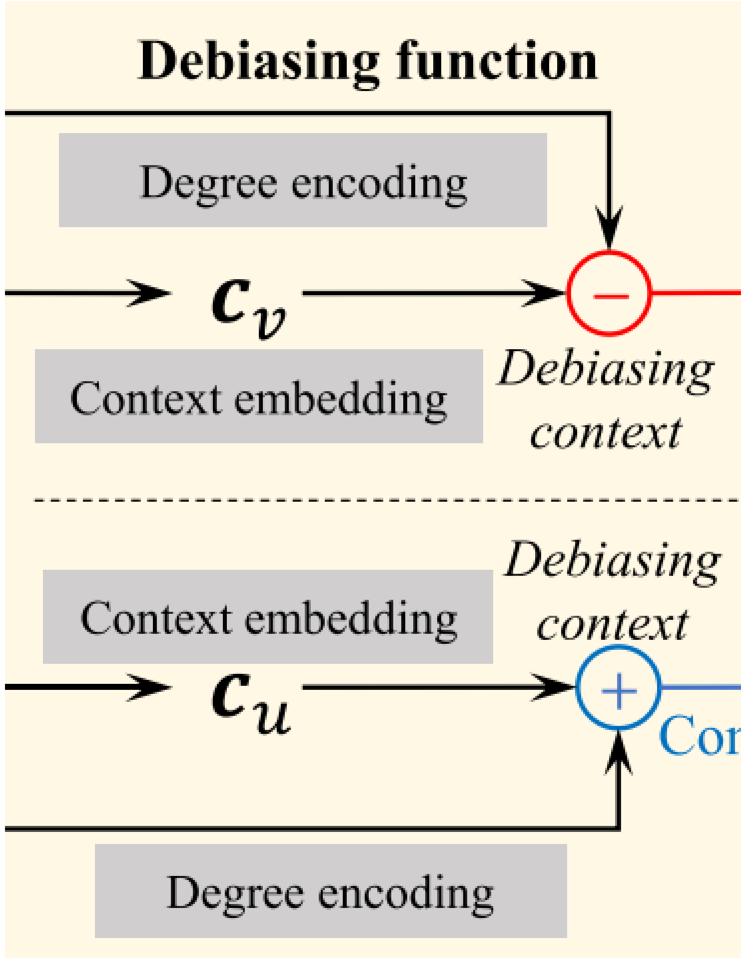


Method

$$\mathbf{h}_v^l = \sigma\left(\mathrm{AGGR}\left(\{\mathbf{h}_u^{l-1} \mid u \in \mathcal{N}_v\}; \omega^l\right)\right), \quad (4)$$

$$\mathbf{h}_v^l = \sigma\Big(\mathrm{AGGR}(\{\mathbf{h}_u^{l-1} \mid u \in \mathcal{N}_v\}; \omega^l) + \epsilon \cdot \big(\underbrace{I(v \in \mathcal{S}_0)\mathcal{D}(v; \theta_0^l)}_{\text{complement low-deg. group}} + \underbrace{I(v \in \mathcal{S}_1)\mathcal{D}(v; \theta_1^l)}_{\text{distill high-deg. group}}\big)\Big), \quad (9)$$

Method



Comprehensiveness

$$\mathbf{c}_v^l = \textsc{Pool}(\{\mathbf{h}_u^{l-1} \mid u \in \mathcal{C}_r(v)\}), \tag{5}$$

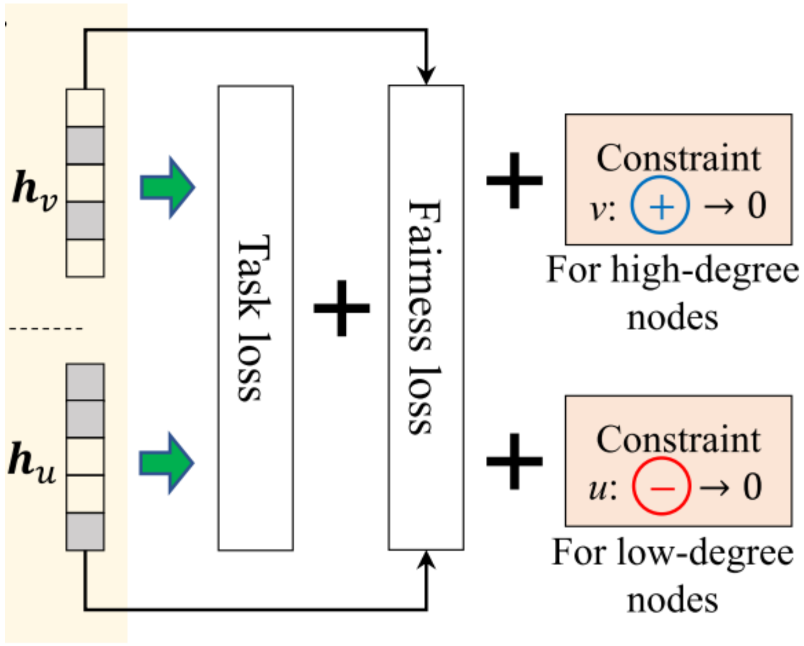
$$\mathcal{D}(v;\theta_*^l) = f(\mathbf{c}_v^l;\theta_{c,*}^l), \tag{6}$$

Adaptiveness

$$\mathcal{D}(v;\theta_*^l) = (\gamma_v^l + \mathbf{1}) \odot f(\mathbf{c}_v^l;\theta_{c,*}^l) + \beta_v^l, \tag{7}$$

$$\gamma_v^l = \phi_\gamma(\delta^l(v);\theta_\gamma^l), \quad \beta_v^l = \phi_\beta(\delta^l(v);\theta_\beta^l), \tag{8}$$

Method



(d) Overall objective

Fairness loss

$$\mathcal{L}_2 = \left\| \frac{1}{|\mathcal{S}_0^{\text{tr}}|} \sum_{v\in\mathcal{S}_0^{\text{tr}}} \mathbf{h}_v^\ell - \frac{1}{|\mathcal{S}_1^{\text{tr}}|} \sum_{v\in\mathcal{S}_1^{\text{tr}}} \mathbf{h}_v^\ell \right\|_2^2, \quad (11)$$

Constraints on debiasing contexts

$$\mathcal{L}_3 = \sum_{l=1}^{\ell} \left(\sum_{v\in\mathcal{S}_0^{\text{tr}}} \|\mathcal{D}(v;\theta_1^l)\|_2^2 + \sum_{v\in\mathcal{S}_1^{\text{tr}}} \|\mathcal{D}(v;\theta_0^l)\|_2^2 \right). \quad (12)$$

Constraints on scaling and shifting

$$\mathcal{L}_4 = \sum_{l=1}^{\ell} \sum_{v\in\mathcal{V}^{\text{tr}}} (\|\gamma_v^l\|_2^2 + \|\beta_v^l\|_2^2). \quad (13)$$

Classification loss

$$\mathcal{L}_1 = -\sum_{v\in\mathcal{V}^{\text{tr}}} \sum_{y=1}^{|\mathcal{Y}|} [\mathbf{y}_v]_y \ln[\mathbf{h}_v^\ell]_y, \quad (10)$$

Overall loss

$$\mathcal{L} = \mathcal{L}_1 + \mu\mathcal{L}_2 + \lambda(\mathcal{L}_3 + \mathcal{L}_4), \quad (14)$$

Experiments

Table 2: Comparison with baselines ($r = 1$, 20% Top/Bottom).

Henceforth, tabular results are in percent with standard deviation over 5 runs; the best fairness result is **bolded** and the runner-up is underlined.

		GCN	DSGCN	Residual2Vec	Tail-GNN	FairWalk	CFC	FairGNN	FairAdj	FairVGNN	DegFairGCN
Chamel.	Acc. ↑	62.45 ± 0.21	63.90 ± 1.28	49.04 ± 0.01	66.08 ± 0.19	56.36 ± 0.75	63.02 ± 0.84	70.70 ± 0.52	51.71 ± 1.13	72.32 ± 0.50	69.91 ± 0.19
	Δ_{DSP} ↓	9.68 ± 1.37	8.81 ± 1.15	14.52 ± 0.69	8.51 ± 1.72	8.18 ± 0.93	10.12 ± 1.28	7.33 ± 1.09	9.79 ± 1.91	8.86 ± 1.11	**5.85** ± 0.32
	Δ_{DEO} ↓	36.08 ± 2.65	25.14 ± 2.67	37.31 ± 1.99	26.09 ± 3.25	22.89 ± 2.75	29.54 ± 1.95	26.83 ± 1.95	27.48 ± 2.06	26.02 ± 2.39	**21.60** ± 0.71
Squirrel	Acc. ↑	47.85 ± 1.33	40.71 ± 2.17	28.47 ± 0.01	42.62 ± 0.06	37.68 ± 0.65	45.64 ± 2.19	57.29 ± 0.77	35.18 ± 1.22	46.97 ± 0.48	59.21 ± 0.97
	Δ_{DSP} ↓	13.37 ± 2.83	16.08 ± 0.86	25.11 ± 0.48	18.91 ± 0.26	**7.94** ± 0.36	12.40 ± 0.48	12.96 ± 1.03	16.63 ± 1.56	26.67 ± 0.52	9.54 ± 1.02
	Δ_{DEO} ↓	27.00 ± 3.79	32.61 ± 3.74	34.49 ± 0.72	33.60 ± 0.72	17.12 ± 1.50	21.60 ± 2.69	17.62 ± 2.40	27.54 ± 1.73	35.80 ± 1.76	**16.42** ± 1.38
EMNLP	Acc. ↑	78.92 ± 0.43	82.19 ± 0.77	80.69 ± 0.01	83.72 ± 0.28	82.23 ± 0.18	80.15 ± 1.13	86.81 ± 0.22	76.50 ± 1.55	84.03 ± 0.34	79.92 ± 0.77
	Δ_{DSP} ↓	44.55 ± 1.90	50.00 ± 2.98	12.90 ± 0.15	41.18 ± 1.58	33.52 ± 1.46	56.60 ± 1.95	58.23 ± 1.44	40.38 ± 4.64	43.92 ± 1.43	**12.38** ± 3.72
	Δ_{DEO} ↓	34.05 ± 3.56	46.92 ± 2.91	11.26 ± 0.67	36.76 ± 1.48	30.67 ± 1.42	45.21 ± 2.27	51.56 ± 1.38	41.89 ± 4.78	40.95 ± 1.71	**8.52** ± 2.26

Experiments

Table 3: Comparison to baselines ($r = 2$, 20% Top/Bottom).

		GCN	FairWalk	FairGNN	DegFairGCN
Chamel.	Acc. ↑	62.45 ± 0.21	56.36 ± 0.75	70.70 ± 0.52	69.91 ± 0.19
	Δ_{DSP} ↓	5.96 ± 0.89	10.38 ± 0.85	6.70 ± 0.32	**5.25** ± 0.39
	Δ_{DEO} ↓	26.92 ± 2.09	25.46 ± 1.66	23.66 ± 0.93	**19.05** ± 0.74
Squirrel	Acc. ↑	47.85 ± 1.33	37.68 ± 0.65	57.29 ± 0.77	59.21 ± 0.97
	Δ_{DSP} ↓	14.61 ± 2.63	9.64 ± 0.50	11.11 ± 0.93	**8.26** ± 0.57
	Δ_{DEO} ↓	28.62 ± 3.89	17.37 ± 1.10	16.29 ± 2.07	**14.95** ± 1.22
EMNLP	Acc. ↑	78.92 ± 0.43	82.23 ± 0.18	86.81 ± 0.22	79.92 ± 0.77
	Δ_{DSP} ↓	45.03 ± 1.77	34.80 ± 1.26	52.88 ± 1.39	**10.87** ± 4.00
	Δ_{DEO} ↓	34.71 ± 3.31	31.11 ± 1.34	45.78 ± 1.36	**8.72** ± 2.17

Table 4: Comparison to baselines ($r = 1$, 30% Top/Bottom).

		GCN	FairWalk	FairGNN	DegFairGCN
Chamel.	Acc. ↑	62.45 ± 0.21	56.36 ± 0.75	70.70 ± 0.52	69.91 ± 0.19
	Δ_{DSP} ↓	5.95 ± 1.02	8.16 ± 0.38	6.92 ± 0.29	**4.15** ± 0.02
	Δ_{DEO} ↓	18.00 ± 1.76	16.65 ± 1.32	14.52 ± 1.09	**8.39** ± 0.37
Squirrel	Acc. ↑	47.85 ± 1.33	37.68 ± 0.65	57.29 ± 0.77	59.21 ± 0.97
	Δ_{DSP} ↓	10.34 ± 2.15	**6.17** ± 0.36	9.27 ± 0.68	7.39 ± 0.63
	Δ_{DEO} ↓	22.62 ± 3.10	**14.97** ± 1.12	17.42 ± 1.11	17.71 ± 1.05
EMNLP	Acc. ↑	78.92 ± 0.43	82.23 ± 0.18	86.81 ± 0.22	79.92 ± 0.77
	Δ_{DSP} ↓	42.87 ± 1.40	34.19 ± 0.91	48.25 ± 1.97	**14.46** ± 3.35
	Δ_{DEO} ↓	37.89 ± 3.27	34.49 ± 0.91	48.83 ± 1.97	**10.92** ± 2.87

Experiments

Table 5: With other base GNNs ($r = 1$, 20% Top/Bottom).

		GAT	DegFairGAT	GraphSAGE	DegFairSAGE
Chamel.	Acc. ↑	63.15 ± 0.40	69.64 ± 0.44	53.15 ± 0.56	60.95 ± 0.84
	Δ_{DSP} ↓	9.35 ± 1.61	**7.88** ± 1.30	10.86 ± 0.74	**8.22** ± 1.22
	Δ_{DEO} ↓	29.59 ± 1.43	**26.12** ± 2.06	29.42 ± 1.57	**26.40** ± 2.32
Squirrel	Acc. ↑	41.44 ± 0.21	45.55 ± 1.44	34.39 ± 0.62	34.63 ± 1.31
	Δ_{DSP} ↓	12.60 ± 0.77	**12.03** ± 0.63	5.39 ± 0.66	**3.76** ± 0.23
	Δ_{DEO} ↓	24.89 ± 0.69	**20.64** ± 3.06	17.13 ± 2.86	**14.91** ± 1.35
EMNLP	Acc. ↑	70.42 ± 0.77	81.57 ± 1.14	83.96 ± 0.31	83.57 ± 0.44
	Δ_{DSP} ↓	24.40 ± 3.06	**14.11** ± 6.28	56.33 ± 1.12	**28.43** ± 3.79
	Δ_{DEO} ↓	**8.36** ± 1.29	12.28 ± 6.19	51.71 ± 0.88	**24.65** ± 3.35

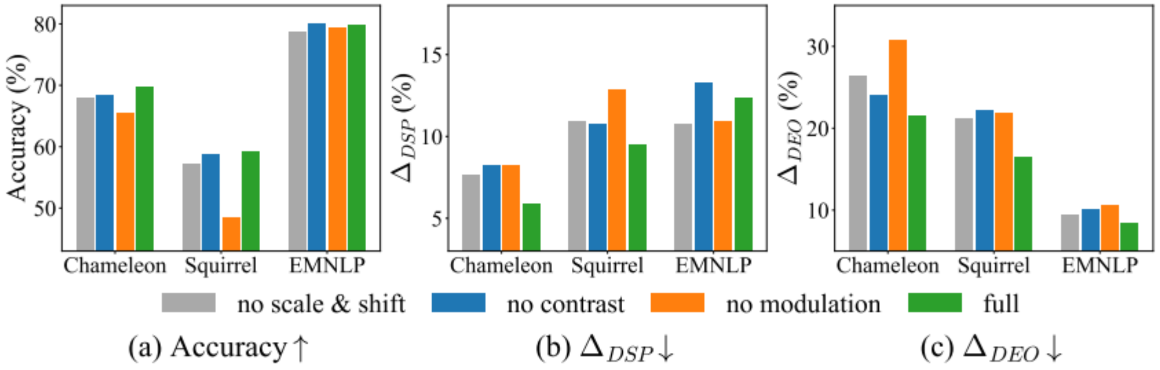


Figure 2: Ablation study on the effect of each module.

THANKS