Fair Attribute Completion on Graph with Missing Attributes

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Introduction

- Missing attributes in graph data
- Graph data might be biased [1]
- Fair Attribute Completion on Graph with Missing Attributes (FairAC) [2]

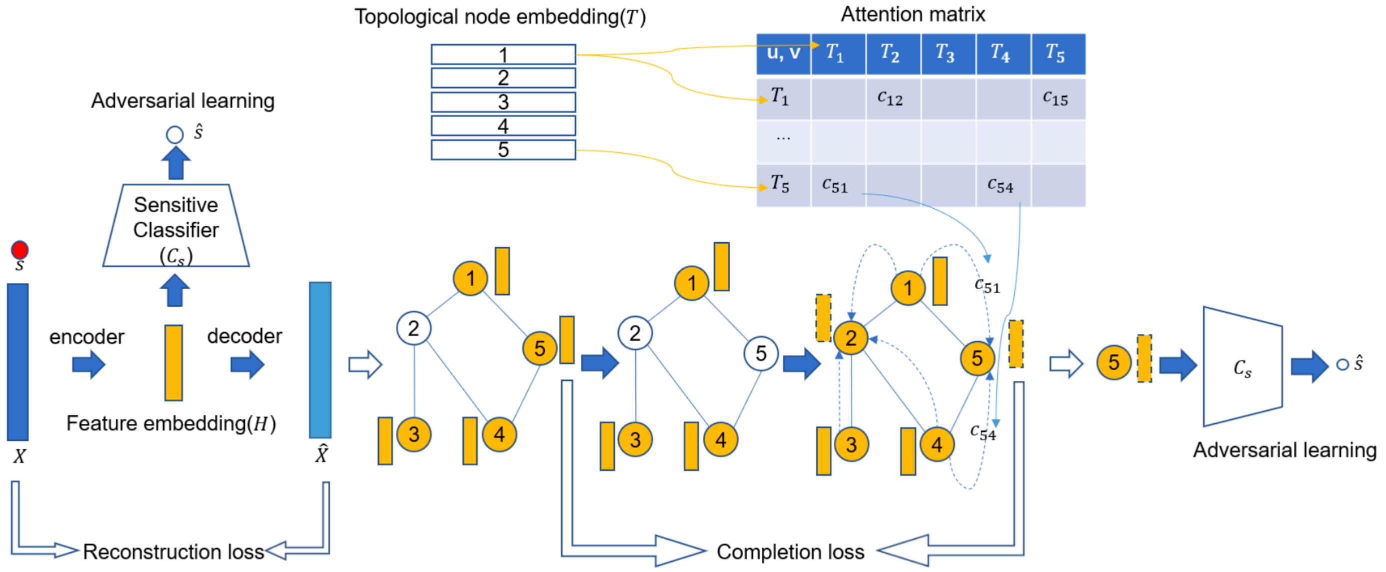

Figure 1: FairAC framework [2]

Metrics

Group fairness:

- Statistical Parity:
  - $\Delta\mathrm{SP} = P(\hat{y}|s=0) - P(\hat{y}|s=1)$ [3]
- Equal Opportunity:
  - $\Delta\mathrm{EO} = P(\hat{y}=1|s=0, y=1) - P(\hat{y}=1|s=1, y=1)$ [4]

Baselines

- GCN - Graph NN without fairness
- FairGNN - in-processing graph fairness method

Claims

1. FairAC can be used for graph attribute completion and addresses both **feature** and **topological** unfairness in the graph embeddings
2. FairAC is effective in eliminating unfairness while **maintaining an accuracy** comparable to other methods
3. **Adversarial learning** is necessary to obtain a better performance on group fairness
4. FairAC is effective even if a large amount of the **attributes** are **completely missing**
5. FairAC is **generic** and can be used in many graph-based **downstream** tasks

FairAC addresses both feature and topological unfairness in the graph embeddings

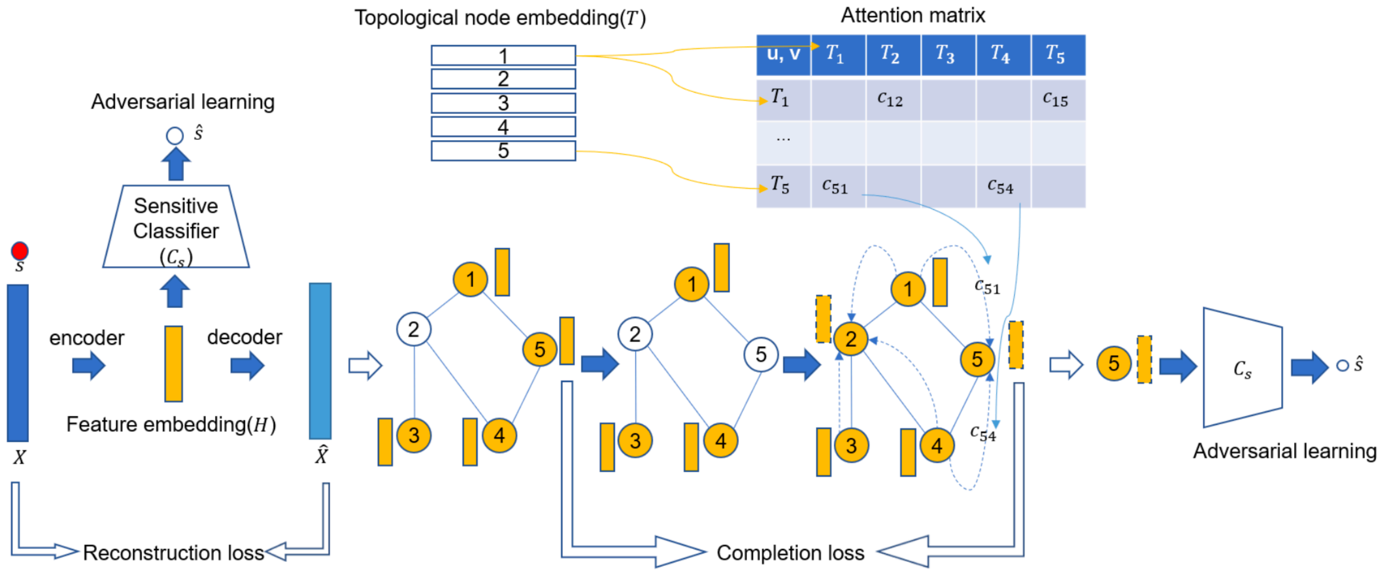

Figure 2: FairAC framework [2]

FairAC is effective in eliminating unfairness while maintaining an accuracy comparable to other methods

Model	Accuracy	AUC	ΔSP+ΔEO
GCN	65.10 ± 0.24	68.42 ± 0.12	3.08 ± 1.68
FairGNN	$\mathbf{68.16 \pm 0.59}$	$\mathbf{75.67 \pm 0.52}$	4.73 ± 1.47
FairAC	65.33 ± 0.30	71.20 ± 1.74	$\mathbf{0.68 \pm 0.09}$

Table 1: Results on Pokec-z dataset

Adversarial learning is necessary to obtain a better performance on group fairness

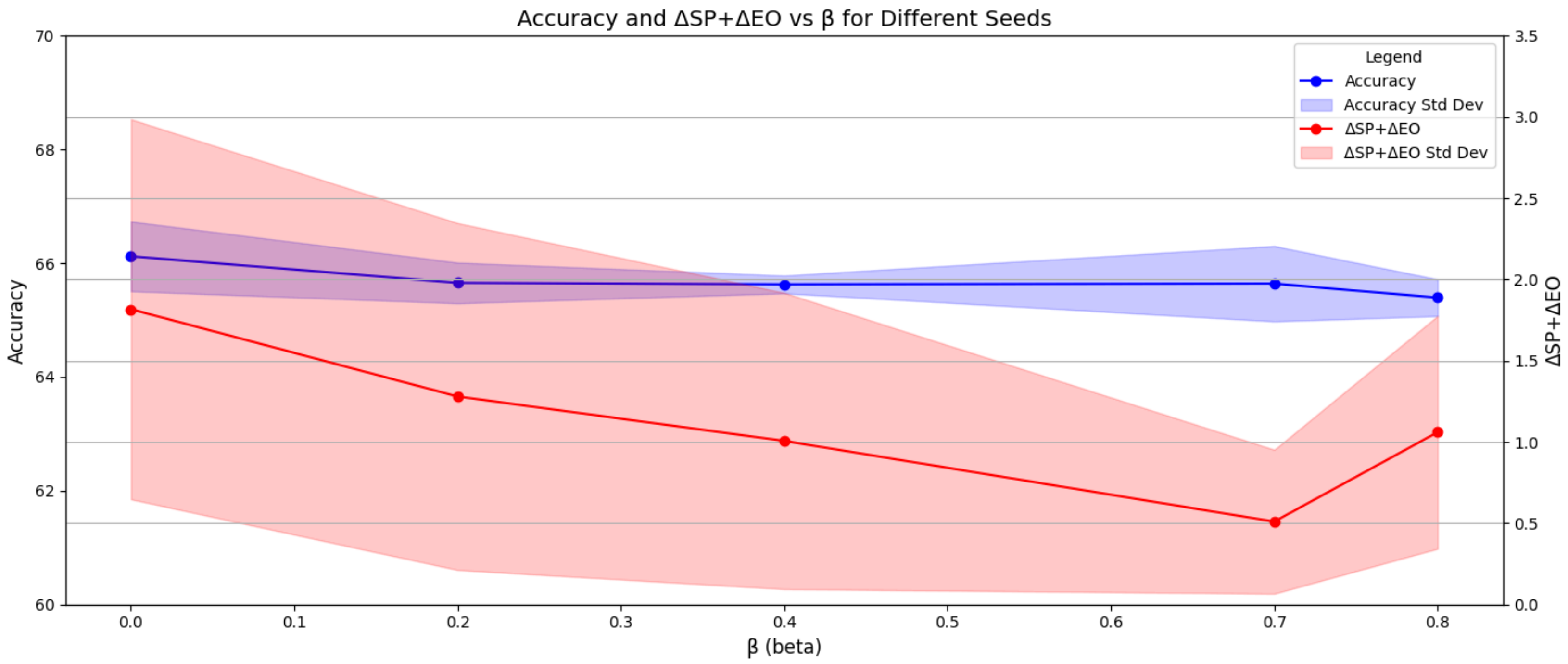

Figure 3: Adversarial learning experiment

FairAC is effective even if a large amount of the attributes are completely missing

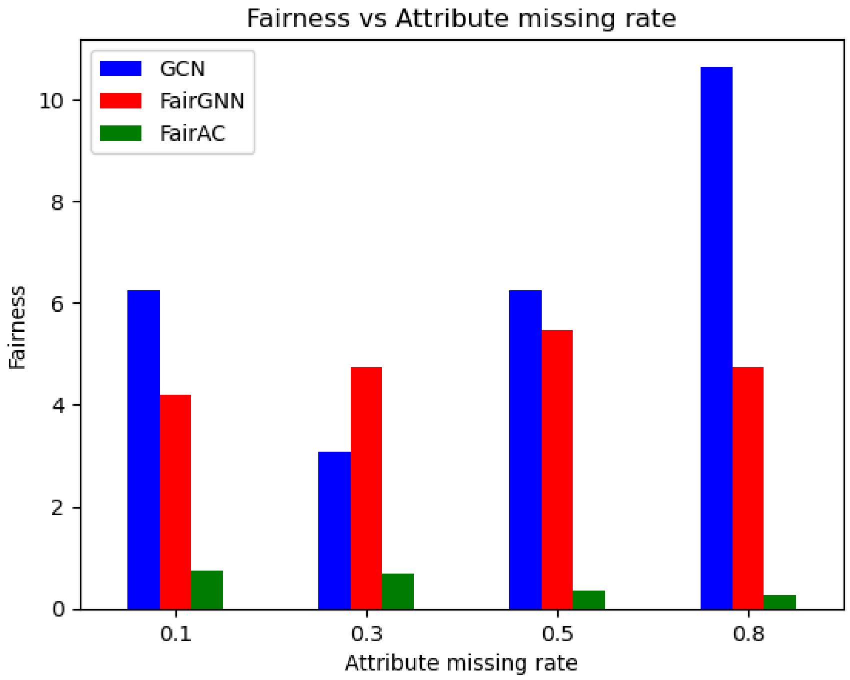

Figure 4: Attribute missing rate experiment

FairAC is generic and can be used in many graph-based downstream tasks

Dataset	Accuracy	AUC	ΔSP+ΔEO
NBA	66.51 ± 1.09	75.69 ± 1.31	0.19 ± 0.08
Pokec-n	67.00 ± 1.93	72.57 ± 1.68	0.58 ± 0.76
Pokec-z	65.33 ± 0.30	71.20 ± 1.74	0.68 ± 0.09

Table 2: Results of FairAC on various datasets

Additional work

Genericity of FairAC

- Other datasets
- Different sensitive attributes

Genericity: Datasets

- Original: Pokec and NBA
- New: Credit and Recidivism

Dataset	Accuracy ↑	AUC ↑	ΔSP+ΔEO ↓
Credit	69.78 ± 2.94	65.13 ± 0.07	1.18 ± 0.29
Recidivism	63.03 ± 1.17	70.32 ± 13.02	0.04 ± 0.08

Table 3: Results of FairAC on various datasets

Genericity: Sensitive attributes

- Feature that should not appear in node embeddings
- Gender and age in addition to region

Model	Accuracy ↑	AUC ↑	ΔSP+ΔEO ↓
GCN	63.40 ± 0.20	68.56 ± 0.40	6.24 ± 1.13
FairGNN	64.25 ± 0.41	72.25 ± 2.49	4.90 ± 0.77
FairAC	$\mathbf{66.44 \pm 0.47}$	$\mathbf{73.39 \pm 0.20}$	$\mathbf{0.96 \pm 0.52}$

Table 4: Results on Pokec-z dataset with gender as sensitive attribute

Genericity: Sensitive attributes

Model	Accuracy ↑	AUC ↑	ΔSP+ΔEO ↓
GCN	64.94 ± 1.11	71.33 ± 1.94	$\mathbf{45.26 \pm 6.96}$
FairGNN	65.79 ± 0.20	72.53 ± 1.42	77.07 ± 6.70
FairAC	$\mathbf{65.82 \pm 0.69}$	$\mathbf{74.26 \pm 0.42}$	47.36 ± 4.38

Table 5: Results on Pokec-z dataset with age as sensitive attribute

Claims

✓ FairAC can be used for graph attribute completion and addresses both **feature** and **topological** unfairness in the graph embeddings

✓ FairAC is effective in eliminating unfairness while **maintaining an accuracy** comparable to other methods

✓ **Adversarial learning** is necessary to obtain a better performance on group fairness

✓ FairAC is effective even if a large amount of the **attributes** are **completely missing**

∼ FairAC is **generic** and can be used in many graph-based **downstream** tasks

Additional work

Genericity of FairAC

- Other datasets
- Different sensitive attributes

Fairness trade-off

- Individual fairness

Individual fairness

- Trade-off between individual fairness and group fairness [5]
- Consistency [6]

Model	Accuracy ↑	AUC ↑	ΔSP+ΔEO ↓	Consistency ↑
GCN	65.10 ± 0.24	68.42 ± 0.12	3.08 ± 1.68	$\mathbf{41.35 \pm 0.01}$
FairGNN	$\mathbf{68.16 \pm 0.59}$	$\mathbf{75.67 \pm 0.52}$	4.73 ± 1.47	$\mathbf{41.35 \pm 0.01}$
FairAC	65.33 ± 0.30	71.20 ± 1.74	$\mathbf{0.68 \pm 0.09}$	41.33 ± 0.00

Table 6: Results on Pokec-z dataset

Conclusion

- FairAC is reproducible
- And generic **for the given task**
- Minimal group fairness-individual fairness trade-off

Bibliography

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[5] R. Binns, “On the apparent conflict between individual and group fairness,” in *Proceedings of the 2020 conference on fairness, accountability, and transparency*, 2020, pp. 514–524.

[6] P. Xu, Y. Zhou, B. An, W. Ai, and F. Huang, “GFairHint: Improving Individual Fairness for Graph Neural Networks via Fairness Hint.” 2023.