Paper Title

Presenters

Task Description / Notations

- Describe task (in words & mathematical Eqn.)
- Define all variables with notations

Previous / Related Works

- Describe previous works with proper citations
- Ex) Spectral-based GNN [1] : it ~~~

Limitations of previous works

- Specific bottlenecks / limitations of previous works

Novelty

- Novelty of paper to overcome above bottleneck / limitation

Method / algorithm / architecture

- Describe method / algorithm / architecture of the paper

Experiment

- Describe benchmark dataset
- Describe performance measure with meaning and eqn.
- Describe performance of proposed algorithm

Experiment (contd.)

- Compare with other methods / algorithms / architectures
  - Example for Cora, Citeseer, and Pubmed datasets [1]

Method	Cora [1]	Citeseer [1]	Pubmed [1]
GCN [2]	81.5	70.3	79.0
DGCN [3]	83.5	72.6	80.0
GAT [4]	83.0	72.5	79.0
MoNet [5]	81.7	-	78.8
DGI [6]	82.3	71.8	76.8
How about your paper?			

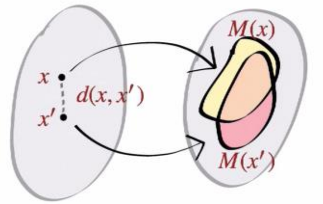
Table 1. Reported experimental results for on three frequently used citation network datasets evaluated by classification accuracy (%).

Summary of Fairness Metrics

Fairness Metrics	Key Features	Pros	Cons
Demographic Parity [14]	C is independent of A: P_0 [C = c] = P_1 [C = c] ∀ c ∈ {0,1}	Legal Support ("Four-fifth Rule")	Ignorance of any possible correlation between Label and Protective Attribute
Equalized Odds [15]	P_0 [C = r | Y = y] = P_1 [C = r | Y = y] ∀ r, y	Reducing error uniformly in all groups	May not helping the gap between two groups
Predictive Rate Parity [16]	P_0 [Y = y| C= c] = P_1 [Y = y| C= c] ∀ y, c ∈ {0,1}	Optimality compatibility; It is possible to match between prediction and grou nd truth.	May not helping the gap between two groups
Individual Fairness [17]	D(M(X),M(X'))≤ d(X,X') (*)	The metric focusing on the individuals. It restricts the treatment for each pair of individuals	Hard to determine the appropriate me tric function to measure the similarity of two inputs.
Counterfactual Fairness [18]	P[C_{A← 0}=c|X, A=a]=P[C_{A← 1}=c|X, A=a]	Revealing the relationships among the various factors and finding the cause of the unfairness phenomenon	Needs of the causal graph which is us ually hard to find
How about your paper?	* You may add another column of your own	* You may add another column of your own	* You may add another column of your own

Notations:
- X ∈ R^d : Input features
- A ∈ {0, 1} : Sensitive Attribute
- C :=c(X,A) ∈ {0,1} : Binary Predictor
- Y ∈ {0, 1} : Target Variable (label)
- P_0 [c] := P [c | s = 0].

(*) Individual Fairness
- X, X' ∈ R^d
- D and d are two metric functions on the input space and the output spac e respectively



Summary of GNNs

Method	Category	Time Complexity	Key Features
Spectral CNN [7]	Spectral-based ConvGNN	$O(n^3)$	Parametrize a filter as a learnable diagonal matrix
ChebNet [8]	Spectral-based ConvGNN	$O(m)$	Eliminate the need for eigendecomposition by approximating the filter by Chebyshev polynomials
GCN [2]	Spectral-based ConvGNN	$O(m)$	Introduce first-order approximation of ChebNet [2]
AGCN [9]	Spectral-based ConvGNN	$O(n^2)$	Construct a residual graph adjacency matrix through a learnable distance function
DGCN [10]	Spectral-based ConvGNN	$O(m)$	Capture both local- and global- consistency knowledge by ensembling outputs from dual graph convolutional layers
NN4G [11]	Spatial-based ConvGNN	$O(m)$	Sum up node's neighborhood information with residual connections and skip connections
DCNN [12]	Spatial-based ConvGNN	$O(n^2)$	Transfer node information with a certain transition probability like a diffusion process
MPNN [13]	Spatial-based ConvGNN	$O(m)$	Define a general framework of spatial-based ConvGNNs by introducing the concepts of a message/update/readout function
GAT [4]	Spatial-based ConvGNN	$O(m)$	Adopt attention mechanisms to learn relative weights between two connected nodes
How about your paper?	* You may add another column of your own		

Conclusion

References

- [1] authors / title of the paper / Conference name / Year

Example

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[14] Zafar, Muhammad Bilal, et al / "Fairness constraints: Mechanisms for fair classification." / *AISTATS / 2017.*

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