

Chasing Fairness in Graphs: A GNN Architecture Perspective

Zhimeng Jiang¹, Xiaotian Han¹, Chao Fan², Zirui Liu³, Na Zou⁴, Ali Mostafavi¹, Xia Hu³

¹Texas A&M University

²Clemson University

³Rice University

⁴University of Houston,

{zhimengj,han, amostafavi}@tamu.edu, cfan@g.clemson.edu, {zl105, xia.hu}@rice.edu, nzou2@central.uh.edu

Abstract

There has been significant progress in improving the performance of graph neural networks (GNNs) through enhancements in graph data, model architecture design, and training strategies. For fairness in graphs, recent studies achieve fair representations and predictions through either graph data pre-processing (e.g., node feature masking, and topology rewiring) or fair training strategies (e.g., regularization, adversarial debiasing, and fair contrastive learning). How to achieve fairness in graphs from the model architecture perspective is less explored. More importantly, GNNs exhibit worse fairness performance compared to multilayer perception since their model architecture (i.e., neighbor aggregation) amplifies biases. To this end, we aim to achieve fairness via a new GNN architecture. We propose Fair Message Passing (FMP) designed within a unified optimization framework for GNNs. Notably, FMP explicitly renders sensitive attribute usage in forward propagation for node classification task using cross-entropy loss without data pre-processing. In FMP, the aggregation is first adopted to utilize neighbors' information and then the bias mitigation step explicitly pushes demographic group node presentation centers together. In this way, FMP scheme can aggregate useful information from neighbors and mitigate bias to achieve better fairness and prediction tradeoff performance. Experiments on node classification tasks demonstrate that the proposed FMP outperforms several baselines in terms of fairness and accuracy on three real-world datasets. The code is available at <https://github.com/zhimengj0326/FMP>.

Introduction

Graph neural networks (GNNs) (Kipf and Welling 2017; Veličković et al. 2018; Wu et al. 2019; Ling et al. 2023a; Han et al. 2022a,b) are widely adopted in various domains, such as social media mining (Hamilton, Ying, and Leskovec 2017), knowledge graph (Hamaguchi et al. 2017) and recommender system (Ying et al. 2018), due to remarkable performance in learning representations. Graph learning, a topic with growing popularity, aims to learn node representation containing both topological and attribute information in a given graph. Despite the outstanding performance in various tasks, GNNs often inherit or even amplify societal bias from

input graph data (Dai and Wang 2021). The biased node representation largely limits the application of GNNs in many high-stake tasks, such as job hunting (Mehrabi et al. 2021) and crime ratio prediction (Suresh and Gutttag 2019). Hence, bias mitigation that facilitates the research on fair GNNs is in urgent need and we aim to achieve fair prediction for GNNs.

Data, model architecture, and training strategy are the most popular aspects to improve deep learning performance. For fairness in graphs, many existing works achieving fair prediction in graphs either rely on graph pre-processing (e.g., node feature masking (Köse and Shen 2021), and topology rewiring (Dong et al. 2022)) or fair training strategies (e.g., regularization (Jiang et al. 2022), adversarial debiasing (Dai and Wang 2021), or contrastive learning (Zhu et al. 2020, 2021b; Agarwal, Lakkaraju, and Zitnik 2021; Ling et al. 2023b)). The GNNs architecture perspective to improve fairness in graphs is less explored. More importantly, GNNs are notorious in terms of fairness since GNN aggregation amplifies bias compared to multilayer perception (MLP) (Dai and Wang 2021). From the GNNs architecture perspective, message passing is a critical component to improve fairness in graphs. Therefore, a natural question is raised:

Can we achieve fairness via fair message passing using vanilla training loss¹ without graph pre-processing?

In this work, we provide a positive answer by designing a fair message-passing scheme guided by a unified optimization framework² for GNNs. The key idea of achieving fair message passing is aggregation first and then conducting bias mitigation via explicitly chasing consistent demographic group representation centers. Specifically, we first formulate an optimization problem that integrates fairness and smoothness objectives for graph data. Then, we solve the formulated problem via Fenchel conjugate and gradient descent to generate fair and informative representations, where the property of softmax function is adopted to accelerate the gradient calculation over primal variables. We also interpret the optimization problem solver as two main steps

¹The sensitive attributes are not adopted in vanilla training loss. We only consider node classification tasks and vanilla loss is cross-entropy loss in this paper.

²Many aggregations in popular GNNs can be interpreted as gradient descent step for specific optimization problem with specific step size and initialization (Ma et al. 2021; Zhu et al. 2021b).

(e.g., aggregation first and then debiasing). Finally, we integrate FMP in graph neural networks to achieve fair and accurate prediction for node classification tasks. We demonstrate the superiority of FMP by examining its effectiveness and efficiency on various real-world datasets.

In short, the contributions can be summarized as follows:

- We demonstrate proof-of-concept that a meticulously crafted GNN architecture can improve fairness for graph data. Our work offers a fresh outlook in comparison to conventional approaches that focus on data pre-processing and fair training strategy design.
- We propose FMP to achieve fairness via explicitly incorporating sensitive attribute information in message passing, guided by a unified optimization framework. Additionally, we introduce an acceleration method based on softmax property to reduce gradient computational complexity.
- The effectiveness and efficiency of FMP are experimentally evaluated on three real-world datasets. The results show that compared to the state-of-the-art, our FMP exhibits a comparable or superior trade-off between prediction performance and fairness with negligibly computation overhead.

Preliminaries

Notations

We adopt bold upper-case letters to denote matrix such as \mathbf{X} , bold lower-case letters such as \mathbf{x} to denote vectors, and calligraphic font such as \mathcal{X} to denote sets. Given a matrix $\mathbf{X} \in \mathbb{R}^{n \times d}$, the i -th row and j -th column are denoted as \mathbf{X}_i and $\mathbf{X}_{\cdot,j}$, and the element in i -th row and j -th column is $\mathbf{X}_{i,j}$. We use the Frobenius norm, l_1 norm of matrix \mathbf{X} as $\|\mathbf{X}\|_F = \sqrt{\sum_{i,j} \mathbf{X}_{i,j}^2}$ and $\|\mathbf{X}\|_1 = \sum_{i,j} |\mathbf{X}_{i,j}|$, respectively. Given two matrices $\mathbf{X}, \mathbf{Y} \in \mathbb{R}^{n \times d}$, the inner product is defined as $\langle \mathbf{X}, \mathbf{Y} \rangle = \text{tr}(\mathbf{X}^\top \mathbf{Y})$, where $\text{tr}(\cdot)$ is the trace of a square matrix. $SF(\mathbf{X})$ represents softmax function with a default normalized column dimension. Let $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$ be a graph with the node set $\mathcal{V} = \{v_1, \dots, v_n\}$ and the undirected edge set $\mathcal{E} = \{e_1, \dots, e_m\}$, where n, m represent the number of node and edge, respectively. The graph structure \mathcal{G} can be represented as an adjacent matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$, where $\mathbf{A}_{ij} = 1$ if existing edge between node v_i and node v_j . $\mathcal{N}(i)$ denotes the neighbors of node v_i and $\tilde{\mathcal{N}}(i) = \mathcal{N}(i) \cup \{v_i\}$ denotes the self-inclusive neighbors. Suppose that each node is associated with a d -dimensional feature vector and a (binary) sensitive attribute, the feature for all nodes and sensitive attribute is denoted as $\mathbf{X}_{ori} = \mathbb{R}^{n \times d}$ and $\mathbf{s} \in \{-1, 1\}^n$ ³. Define the sensitive attribute incident vector as $\Delta_s = \frac{\mathbf{1}_{>0}(\mathbf{s})}{\|\mathbf{1}_{>0}(\mathbf{s})\|_1} - \frac{\mathbf{1}_{>0}(-\mathbf{s})}{\|\mathbf{1}_{>0}(-\mathbf{s})\|_1}$ to normalize each sensitive attribute group, where $\mathbf{1}_{>0}(\mathbf{s})$ is an element-wise indicator function.

³The sensitive attribute \mathbf{s} is not included in node features matrix \mathbf{X}_{ori} .

GNNs as Graph Signal Denoising

A GNN model is usually composed of several stacking GNN layers. Given a graph \mathcal{G} with N nodes, a GNN layer typically contains feature transformation $\mathbf{X}_{trans} = f_{trans}(\mathbf{X}_{ori})$ and aggregation $\mathbf{X}_{agg} = f_{agg}(\mathbf{X}_{trans})$, where $\mathbf{X}_{ori} \in \mathbb{R}^{n \times d_{in}}$, $\mathbf{X}_{trans}, \mathbf{X}_{agg} \in \mathbb{R}^{n \times d_{out}}$ represent the input and output features. The feature transformation operation transforms the node feature dimension, and *feature aggregation*, updates node features based on neighbors' features and graph topology. Recent works (Ma et al. 2021; Zhu et al. 2021a) have established the connections between many feature aggregation operations $AGG(\cdot)$ in representative GNNs and a graph signal denoising problem with Laplacian regularization, i.e., recovering a clean signal $\mathbf{F} \in \mathbb{R}^{n \times d_{out}}$ from \mathbf{X}_{trans} with the smooth assumption over graph \mathcal{G} . Here, we introduce several popular GNN architectures, including GCN/SGC, GAT, and PPNP/APPNP, as examples to show the connection from the perspective of graph signal denoising.

GCN/SGC. Feature aggregation in Graph Convolutional Network (GCN) or Simplifying Graph Convolutional Network (SGC) is given by $\mathbf{X}_{agg} = \tilde{\mathbf{A}}\mathbf{X}_{trans}$, where $\tilde{\mathbf{A}} = \tilde{\mathbf{D}}^{-\frac{1}{2}}\tilde{\mathbf{A}}\tilde{\mathbf{D}}^{-\frac{1}{2}}$ is a normalized self-loop adjacency matrix $\tilde{\mathbf{A}} = \mathbf{A} + \mathbf{I}$, and $\tilde{\mathbf{D}}$ is degree matrix of $\tilde{\mathbf{A}}$. Recent works (Ma et al. 2021; Zhu et al. 2021a) provably demonstrate that such feature aggregation can be interpreted as one-step gradient descent to minimize $\text{tr}(\mathbf{F}^\top (\mathbf{I} - \tilde{\mathbf{A}})\mathbf{F})$ with initialization $\mathbf{F} = \mathbf{X}_{trans}$.

GAT. Feature aggregation in GAT applies the normalized attention coefficient to compute a linear combination of neighbor's features as $\mathbf{X}_{agg,i} = \sum_{j \in \mathcal{N}(i)} \alpha_{ij} \mathbf{X}_{trans,j}$, where $\alpha_{ij} = \text{softmax}_j(e_{ij})$, $e_{ij} = \text{LeakyReLU}(\mathbf{X}_{trans,i}^\top \mathbf{w}_i + \mathbf{X}_{trans,j}^\top \mathbf{w}_j)$, and \mathbf{w}_i and \mathbf{w}_j are learnable column vectors. Prior study (Ma et al. 2021) demonstrates that one-step gradient descent with adaptive stepsize $\frac{1}{\sum_{j \in \tilde{\mathcal{N}}(i)} (c_i + c_j)}$ for the following objective problem:

$$\min_{\mathbf{F}} \sum_{i \in \mathcal{V}} \|\mathbf{F}_i - \mathbf{X}_{trans,i}\|_F^2 + \frac{1}{2} \sum_{i \in \mathcal{V}} c_i \sum_{j \in \tilde{\mathcal{N}}(i)} \|\mathbf{F}_i - \mathbf{F}_j\|_F^2.$$

is actually an attention-based feature aggregation, which is equivalent to GAT if $c_i + c_j$ is equivalent to e_{ij} , where c_i is a node-dependent coefficient that measures the local smoothness.

PPNP / APPNP. Feature aggregation in PPNP and APPNP adopt the aggregation rules as $\mathbf{X}_{agg} = \alpha (\mathbf{I} - (1 - \alpha)\tilde{\mathbf{A}})^{-1} \mathbf{X}_{trans}$ and $\mathbf{X}_{agg}^{k+1} = (1 - \alpha)\tilde{\mathbf{A}}\mathbf{X}_{agg}^k + \alpha\mathbf{X}_{trans}$. It is shown that they are equivalent to the exact solution and one gradient descent step with stepsize $\frac{\alpha}{2}$ to minimize the following objective problem:

$$\min_{\mathbf{F}} \|\mathbf{F} - \mathbf{X}_{trans}\|_F^2 + \left(\frac{1}{\alpha} - 1\right) \text{tr}(\mathbf{F}^\top (\mathbf{I} - \tilde{\mathbf{A}})\mathbf{F}).$$

Fair Message Passing

In this section, we propose a new fair message-passing scheme to aggregate useful information from neighbors while debiasing representation bias. In this way, fair prediction can be achieved from a model backbone perspective. Specifically, we formulate fair message passing as an optimization problem to pursue *smoothness* and *fair* node representation simultaneously⁴. Together with an effective and efficient optimization algorithm, we derive the closed-form fair message passing. Finally, the proposed FMP is shown to be integrated into fair GNNs at three stages, including transformation, aggregation, and debiasing step, as shown in Figure 1. These three stages adopted node feature, graph topology, and sensitive attributes respectively.

The Optimization Framework

Most of the existing works rely on hand-craft architecture (e.g., JKNet (Xu et al. 2018)) design for specific tasks, and thus lack of theoretical understanding how such architecture is designed. In our paper, starting from this unified optimization framework for GNNs, we design a new objective, including smoothness and fairness objective, and then derive the proposed FMP to explicitly chase the new objective via fair message passing.

In previous work (Ma et al. 2021), a general and universal framework is developed to understand aggregation operations in GNNs. Building on top of this framework, we formulate an optimization problem to achieve fair message passing operation (replace aggregation operations in GNNs). To achieve graph smoothness prior and fairness in the same process, a reasonable message passing should be a good solution for the following optimization problem:

$$\min_{\mathbf{F}} \underbrace{\frac{\lambda_s}{2} \text{tr}(\mathbf{F}^T \tilde{\mathbf{L}} \mathbf{F}) + \frac{1}{2} \|\mathbf{F} - \mathbf{X}_{trans}\|_{\mathbf{F}}^2}_{h_s(\mathbf{F})} + \underbrace{\lambda_f \|\Delta_s SF(\mathbf{F})\|_1}_{h_f(\Delta_s SF(\mathbf{F}))}. \quad (1)$$

where $\tilde{\mathbf{L}}$ represents normalized Laplacian matrix, $h_s(\cdot)$ and $h_f(\cdot)$ denotes the smoothness and fairness objectives⁵, respectively, and $\mathbf{X}_{trans} \in \mathbf{R}^{n \times d_{out}}$ is the transformed d_{out} -dimensional node features and $\mathbf{F} \in \mathbf{R}^{n \times d_{out}}$ is the aggregated node features of the same matrix size. The first two terms preserve the similarity of connected node representation and thus enforce graph smoothness. The last term enforces fair node representation so that the average predicted probability between groups of different sensitive attributes can remain constant. The regularization coefficients λ_s and λ_f adaptively control the trade-off between graph smoothness and fairness.

⁴Fair message passing is an alternative operation to replace GNNs aggregations.

⁵Such smoothness objective is the most common-used one in existing methods (Ma et al. 2021; Belkin and Niyogi 2001; Kalofolias 2016). The various other smoothness objectives could be considered to improve the performance of FMP and we leave it for future work.

Smoothness Objective $h_s(\cdot)$. The adjacent matrix in existing graph message passing schemes is normalized for improving numerical stability and achieving superior performance. Similarly, the graph smoothness term requires normalized Laplacian matrix, i.e., $\tilde{\mathbf{L}} = \mathbf{I} - \tilde{\mathbf{A}}$, $\tilde{\mathbf{A}} = \hat{\mathbf{D}}^{-\frac{1}{2}} \hat{\mathbf{A}} \hat{\mathbf{D}}^{-\frac{1}{2}}$, and $\hat{\mathbf{A}} = \mathbf{A} + \mathbf{I}$. From an edge-centric view, the smoothness objective enforces connected node representation to be similar since

$$\text{tr}(\mathbf{F}^T \tilde{\mathbf{L}} \mathbf{F}) = \sum_{(v_i, v_j) \in \mathcal{E}} \left\| \frac{\mathbf{F}_i}{\sqrt{d_i + 1}} - \frac{\mathbf{F}_j}{\sqrt{d_j + 1}} \right\|_{\mathbf{F}}^2, \quad (2)$$

where $d_i = \sum_k A_{ik}$ represents the degree of node v_i .

Fairness Objective $h_f(\cdot)$. The fairness objective measures the bias for node representation after aggregation. Recall sensitive attribute incident vector Δ_s indicates the sensitive attribute group and group size via the sign and absolute value summation. Recall that the sensitive attribute incident vector as

$$\Delta_s = \frac{\mathbf{1}_{>0}(\mathbf{s})}{\|\mathbf{1}_{>0}(\mathbf{s})\|_1} - \frac{\mathbf{1}_{>0}(-\mathbf{s})}{\|\mathbf{1}_{>0}(-\mathbf{s})\|_1}, \quad (3)$$

and $SF(\mathbf{F})$ represents the predicted probability for node classification task, where $SF(\mathbf{F})_{ij} = \hat{P}(y_i = j | \mathbf{X})$. Furthermore, we can show that our fairness objective is actually equivalent to demographic parity, i.e., $\left(\Delta_s SF(\mathbf{F}) \right)_j = \hat{P}(y_i = j | \mathbf{s}_i = 1, \mathbf{X}) - \hat{P}(y_i = j | \mathbf{s}_i = -1, \mathbf{X})$. Please see proof in Appendix . In other words, our fairness objective, l_1 norm of $\Delta_s SF(\mathbf{F})$ characterizes the predicted probability difference between two groups with different sensitive attributes. Therefore, our proposed optimization framework can pursue graph smoothness and fairness simultaneously.

Optimization Problem Solver

For smoothness objective, many existing popular message passing schemes can be derived based on gradient descent with appropriate step size choice (Ma et al. 2021; Zhu et al. 2021a). In this paper, we consider smoothness objective $h_s(\mathbf{F})$ and fairness objective $h_f(\Delta_s SF(\mathbf{F}))$ simultaneously for chasing fair and accurate prediction. However, directly solving the optimization problem (1) is much more challenging due to the nonsmoothness of the fairness objective, and the non-separability of smoothness objective $h_s(\mathbf{F})$ and fairness objective $h_f(\Delta_s SF(\mathbf{F}))$ due to incident vector Δ_s .

Bi-level Optimization Problem Formulation In the literature, many optimization algorithms are developed for optimization problems with l_1 norm, such as Alternating Direction Method of Multipliers (ADMM) and Newton type algorithms (Ghadimi et al. 2014; Varma et al. 2019). However, these algorithms require non-trivial sub-problem solving for each iteration. Therefore, computation complexity is high and is infeasible to integrate deep learning models. Fortunately, Fenchel conjugate (a.k.a. convex conjugate) (Rockafellar 2015) can transform the original problem as an equivalent saddle point problem using a primal-dual algorithm (Liu et al. 2021). In this way, the computa-

tion complexity can be reduced and compatible with back-propagation training. Similarly, to solve optimization problem 1 in a more effective and efficient manner, Fenchel conjugate (Rockafellar 2015) is introduced to transform the original problem into a bi-level optimization problem. For the general convex function $h(\cdot)$, its conjugate function is defined as $h^*(\mathbf{U}) \triangleq \sup_{\mathbf{X}} \langle \mathbf{U}, \mathbf{X} \rangle - h(\mathbf{X})$. Based on Fenchel conjugate, the fairness objective can be transformed as variational representation $h_f(\mathbf{p}) = \sup_{\mathbf{u}} \langle \mathbf{p}, \mathbf{u} \rangle - h_f^*(\mathbf{u})$, where $\mathbf{p} = \Delta_s SF(\mathbf{F}) \in \mathbb{R}^{1 \times d_{out}}$ is a predicted probability vector for classification. Furthermore, the original optimization problem is equivalent to

$$\min_{\mathbf{F}} \max_{\mathbf{u}} h_s(\mathbf{F}) + \langle \mathbf{p}, \mathbf{u} \rangle - h_f^*(\mathbf{u}) \quad (4)$$

where $\mathbf{u} \in \mathbb{R}^{1 \times d_{out}}$ and $h_f^*(\cdot)$ is the conjugate function of fairness objective $h_f(\cdot)$.

Problem Solution Motivated by Proximal Alternating Predictor-Corrector (PAPC) (Loris and Verhoeven 2011; Chen, Huang, and Zhang 2013), the min-max optimization problem (4) can be solved by the following fixed-point equations with per iteration low computation complexity and convergence guarantee

$$\begin{cases} \mathbf{F} = \mathbf{F} - \nabla h_s(\mathbf{F}) - \frac{\partial \langle \mathbf{p}, \mathbf{u} \rangle}{\partial \mathbf{F}}, \\ \mathbf{u} = \text{prox}_{h_f^*}(\mathbf{u} + \Delta_s SF(\mathbf{F})). \end{cases} \quad (5)$$

where $\text{prox}_{h_f^*}(\mathbf{u}) = \arg \min_{\mathbf{y}} \|\mathbf{y} - \mathbf{u}\|_{\mathbf{F}}^2 + h_f^*(\mathbf{y})$. Fortunately, the proximal operators can be obtained with a close form, which makes deep learning model integration feasible. Specifically we provide the close form of the proximal operators in the following proposition:

Proposition 0.1 (Proximal Operators). *The proximal operators $\text{prox}_{\beta h_f^*}(\mathbf{u})$ satisfies*

$$\text{prox}_{\beta h_f^*}(\mathbf{u})_j = \text{sign}(\mathbf{u})_j \min(|\mathbf{u}_j|, \lambda_f), \quad (6)$$

where $\text{sign}(\cdot)$ and λ_f are element-wise sign function and hyperparameter for fairness objective. In other words, such a proximal operator is an element-wise projection into l_∞ ball with radius λ_f .

Similar to ‘‘predictor-corrector’’ algorithm (Loris and Verhoeven 2011), we adopt an iterative algorithm to find the saddle point for the min-max optimization problem. Specifically, starting from $(\mathbf{F}^k, \mathbf{u}^k)$, we adopt a gradient descent step on the primal variable \mathbf{F} to arrive $(\bar{\mathbf{F}}^{k+1}, \mathbf{u}^k)$ and then followed by a proximal ascent step in the dual variable \mathbf{u} . Finally, a gradient descent step on a primal variable in point $(\bar{\mathbf{F}}^{k+1}, \mathbf{u}^k)$ to arrive at $(\mathbf{F}^{k+1}, \mathbf{u}^k)$. In short, the iteration can be summarized as

$$\begin{cases} \bar{\mathbf{F}}^{k+1} = \mathbf{F}^k - \gamma \nabla h_s(\mathbf{F}^k) - \gamma \frac{\partial \langle \mathbf{p}, \mathbf{u}^k \rangle}{\partial \mathbf{F}} \Big|_{\mathbf{F}^k}, \\ \mathbf{u}^{k+1} = \text{prox}_{\beta h_f^*}(\mathbf{u}^k + \beta \Delta_s SF(\bar{\mathbf{F}}^{k+1})), \\ \bar{\mathbf{F}}^{k+1} = \mathbf{F}^k - \gamma \nabla h_s(\mathbf{F}^k) - \gamma \frac{\partial \langle \mathbf{p}, \mathbf{u}^{k+1} \rangle}{\partial \mathbf{F}} \Big|_{\mathbf{F}^k}. \end{cases} \quad (7)$$

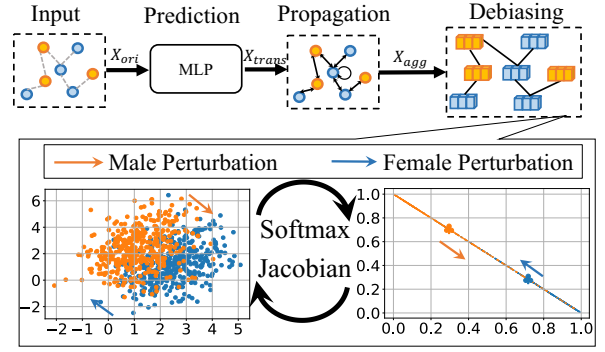


Figure 1: The model pipeline consists of three steps: MLP (feature transformation), propagation with skip connection, and debiasing in probability space.

where γ and β are the step size for primal and dual variables. Note that the close-form for $\frac{\partial \langle \mathbf{p}, \mathbf{u} \rangle}{\partial \mathbf{F}} \in \mathbb{R}^{n \times d_{out}}$ and $\text{prox}_{\beta h_f^*}(\cdot)$ are still not clear, we will provide the solution one by one.

FMP Scheme. Similar to works (Ma et al. 2021; Liu et al. 2021), choosing $\gamma = \frac{1}{1+\lambda_s}$ and $\beta = \frac{1}{2\gamma}$, we have

$$\begin{aligned} \mathbf{F}^k - \gamma \nabla h_s(\mathbf{F}^k) &= \left((1-\gamma)\mathbf{I} - \gamma \lambda_s \tilde{\mathbf{L}} \right) \mathbf{F}^k + \gamma \mathbf{X}_{trans} \\ &= \gamma \mathbf{X}_{trans} + (1-\gamma) \tilde{\mathbf{A}} \mathbf{F}^k, \end{aligned} \quad (8)$$

Therefore, we can summarize the proposed FMP as two phases, including propagation with skip connection (Step ①) and bias mitigation (Steps ②-⑤). For bias mitigation, Step ② updates the aggregated node features for fairness objective; Steps ③ and ④ aim to learn and ‘‘reshape’’ perturbation vector in probability space, respectively. Step ⑤ explicitly mitigates the bias of node features based on gradient descent on the primal variable. The mathematical formulation is given as follows:

$$\begin{cases} \mathbf{X}_{agg}^{k+1} = \gamma \mathbf{X}_{trans} + (1-\gamma) \tilde{\mathbf{A}} \mathbf{F}^k, & \text{Step ①} \\ \bar{\mathbf{F}}^{k+1} = \mathbf{X}_{agg}^{k+1} - \gamma \frac{\partial \langle \mathbf{p}, \mathbf{u}^k \rangle}{\partial \mathbf{F}} \Big|_{\mathbf{F}^k}, & \text{Step ②} \\ \bar{\mathbf{u}}^{k+1} = \mathbf{u}^k + \beta \Delta_s SF(\bar{\mathbf{F}}^{k+1}), & \text{Step ③} \\ \mathbf{u}^{k+1} = \min(|\bar{\mathbf{u}}^{k+1}|, \lambda_f) \cdot \text{sign}(\bar{\mathbf{u}}^{k+1}), & \text{Step ④} \\ \mathbf{F}^{k+1} = \mathbf{X}_{agg}^{k+1} - \gamma \frac{\partial \langle \mathbf{p}, \mathbf{u}^{k+1} \rangle}{\partial \mathbf{F}} \Big|_{\mathbf{F}^k}. & \text{Step ⑤} \end{cases}$$

where \mathbf{X}_{agg}^{k+1} represents the node features with normal aggregation and skip connection with the transformed input \mathbf{X}_{trans} .

Gradient Computation Acceleration The softmax property is also adopted to accelerate the gradient computation. Note that $\mathbf{p} = \Delta_s SF(\mathbf{F})$ and $SF(\cdot)$ represents softmax over column dimension, directly computing the gradient $\frac{\partial \langle \mathbf{p}, \mathbf{u} \rangle}{\partial \mathbf{F}}$ based on chain rule involves the three-dimensional tensor $\frac{\partial \mathbf{p}}{\partial \mathbf{F}}$ with gigantic computation complexity. Instead, we simplify the gradient computation based on the property of softmax function in the following theorem.

Theorem 0.2 (Gradient Computation). *The gradient over primal variable $\frac{\partial \langle \mathbf{p}, \mathbf{u} \rangle}{\partial \mathbf{F}}$ satisfies*

$$\frac{\partial \langle \mathbf{p}, \mathbf{u} \rangle}{\partial \mathbf{F}} = \mathbf{U}_s \odot SF(\mathbf{F}) - \text{Sum}_1(\mathbf{U}_s \odot SF(\mathbf{F}))SF(\mathbf{F}).$$

where $\mathbf{U}_s \triangleq \Delta_s^\top \mathbf{u}$, \odot represents the element-wise product and $\text{Sum}_1(\cdot)$ represents the summation over column dimension with preserved matrix shape.

Discussion on FMP

In this section, we provide the interpretation and analyze the *efficiency*, and *white-box usage for sensitive attribute* of the proposed FMP scheme. Furthermore, we also discuss how FMP identifies the influence of sensitive attributes from model forward propagation.

FMP Interpretation Note that the gradient of fairness objective over node features \mathbf{F} satisfies $\frac{\partial \langle \mathbf{p}, \mathbf{u} \rangle}{\partial \mathbf{F}} = \frac{\partial \langle \mathbf{p}, \mathbf{u} \rangle}{\partial SF(\mathbf{F})} \frac{\partial SF(\mathbf{F})}{\partial \mathbf{F}}$ and $\frac{\partial \langle \mathbf{p}, \mathbf{u} \rangle}{\partial SF(\mathbf{F})} = \Delta_s^\top \mathbf{u}$, such gradient calculation can be interpreted as three steps: Softmax transformation, perturbation in probability space, and debiasing in representation space. Specifically, we first map the node representation into probability space via softmax transformation. Subsequently, we calculate the gradient of fairness objective in probability space. It is seen that the perturbation $\Delta_s^\top \mathbf{u}$ actually poses *low-rank* debiasing in probability space, where the nodes with different sensitive attributes embrace opposite perturbations. In other words, *the dual variable \mathbf{u} represents the perturbation direction in probability space*. Finally, the perturbation in probability space will be transformed into representation space via Jacobian transformation $\frac{\partial SF(\mathbf{F})}{\partial \mathbf{F}}$.

Efficiency. FMP is an efficient message-passing scheme. The computation complexity for the aggregation (sparse matrix multiplications) is $O(md_{out})$, where m is the number of edges in graph. For FMP, the extra computation are the perturbation calculation, as shown in Theorem 0.2, with the computation complexity $O(nd_{out})$. The extra computation complexity is negligible in that the number of nodes n is far less than the number of edges m in the real-world graph. Additionally, if directly adopting backward propagation to calculate the gradient, we have to calculate the three-dimensional tensor $\frac{\partial \mathbf{p}}{\partial \mathbf{F}}$ with computation complexity $O(n^2 d_{out})$. In other words, thanks to the softmax property, we achieve an efficient fair message-passing scheme.

White-box Usage for Sensitive Attribute. The proposed FMP explicitly achieves graph smoothness and fairness objectives via alternative gradient descent. In other words, the usage of sensitive attributes in propagation to mitigate bias is in a white-box manner. Note that such white-box usage of sensitive attributes is a promising property to understand how sensitive attribute usage forces fairness, which is not achieved by previous fairness methods in GNNs. For example, fair training loss utilizes sensitive attributes to regularize the behavior of model prediction and obtain fairer model parameters via rectifying gradients w.r.t. model parameters. In other words, the sensitive attribute information is implicitly

encoded in the well-trained model parameters, which makes it hard to understand how sensitive attribute usage helps fair prediction. Pre-processing fairness methods adopt sensitive attributes to revise data (e.g., node masking and topology rewiring) either in a learnable way or via pre-defined several operations (e.g., node masking and edge deletions). Similarly, the sensitive attribute information is implicitly encoded in the processed data. The understanding of fairness prediction achievement is infeasible. Our FMP can provide a white-box usage for sensitive attributes since we can directly identify that the usage of sensitive attributes is to force the demographic group node representation centers together during forward propagation.

Experiments

In this section, we conduct experiments to validate the effectiveness and efficiency of the proposed FMP. We firstly validate that graph data with large sensitive homophily enhances bias in GNNs via synthetic experiments. Moreover, for experiments on real-world datasets, we introduce the experimental settings and then evaluate our proposed FMP compared with several baselines in terms of prediction performance and fairness metrics.

Experimental Settings

Datasets. We conduct experiments on real-world datasets Pokec-z, Pokec-n⁶, and NBA (Dai and Wang 2021). Pokec-z and Pokec-n are sampled, based on province information, from a larger Facebook-like social network Pokec (Takac and Zabovsky 2012) in Slovakia, where region information is treated as the sensitive attribute and the predicted label is the working field of the users. NBA dataset is extended from a Kaggle dataset⁷ consisting of around 400 NBA basketball players. The information of players includes age, nationality, and salary in the 2016-2017 season. The players' link relationships are from Twitter with the official crawling API. The binary nationality (U.S. and overseas player) is adopted as the sensitive attribute and the prediction label is whether the salary is higher than the median.

Evaluation Metrics. We adopt accuracy to evaluate the performance of node classification tasks. As for fairness metrics, we adopt two quantitative group fairness metrics to measure the prediction bias. According to works (Louizos et al. 2015; Beutel et al. 2017), we adopt *demographic parity* $\Delta_{DP} = |\mathbb{P}(\hat{y} = 1 | s = -1) - \mathbb{P}(\hat{y} = 1 | s = 1)|$ and *equal opportunity* $\Delta_{EO} = |\mathbb{P}(\hat{y} = 1 | s = -1, y = 1) - \mathbb{P}(\hat{y} = 1 | s = 1, y = 1)|$, where y and \hat{y} represent the ground-truth label and predicted label, respectively.

Baselines. We compare our proposed FMP with representative GNNs, such as GCN (Kipf and Welling 2017), GAT (Veličković et al. 2018), SGC (Wu et al. 2019), and APPNP (Klicpera, Bojchevski, and Günnemann 2019), JKNNet (Xu et al. 2018), and MLP. We also compared with method ‘‘ML1’’ directly using the gradient of Eq. (1) during model

⁶Pokec-z and Pokec-n datasets are available at <https://github.com/EnyanDai/FairGNN/tree/main>.

⁷<https://www.kaggle.com/noahgift/social-power-nba>

Models	Pokey-z			Pokey-n			NBA		
	Acc (%) \uparrow	Δ_{DP} (%) \downarrow	Δ_{EO} (%) \downarrow	Acc (%) \uparrow	Δ_{DP} (%) \downarrow	Δ_{EO} (%) \downarrow	Acc (%) \uparrow	Δ_{DP} (%) \downarrow	Δ_{EO} (%) \downarrow
MLP	70.48 \pm 0.77	1.61 \pm 1.29	2.22 \pm 1.01	72.48 \pm 0.26	1.53 \pm 0.89	3.39 \pm 2.37	65.56 \pm 1.62	22.37 \pm 1.87	18.00 \pm 3.52
GAT	69.76 \pm 1.30	2.39 \pm 0.62	2.91 \pm 0.97	71.00 \pm 0.48	3.71 \pm 2.15	7.50 \pm 2.88	57.78 \pm 10.65	20.12 \pm 16.18	13.00 \pm 13.37
GCN	71.78 \pm 0.37	3.25 \pm 2.35	2.36 \pm 2.09	73.09 \pm 0.28	3.48 \pm 0.47	5.16 \pm 1.38	61.90 \pm 1.00	23.70 \pm 2.74	17.50 \pm 2.63
SGC	71.24 \pm 0.46	4.81 \pm 0.30	4.79 \pm 2.27	71.46 \pm 0.41	2.22 \pm 0.29	3.85 \pm 1.63	63.17 \pm 0.63	22.56 \pm 3.94	14.33 \pm 2.16
APPNP	66.91 \pm 1.46	3.90 \pm 0.69	5.71 \pm 1.29	69.80 \pm 0.89	1.98 \pm 1.30	4.01 \pm 2.36	63.80 \pm 1.19	26.51 \pm 3.33	20.00 \pm 4.56
JKNet	66.89 \pm 3.79	1.28 \pm 0.96	1.79 \pm 0.82	63.59 \pm 6.36	1.91 \pm 2.14	0.70 \pm 0.92	67.94 \pm 2.73	27.80 \pm 8.41	20.33 \pm 7.52
ML1	70.42 \pm 0.40	2.35 \pm 0.83	2.00 \pm 0.50	72.36 \pm 0.26	1.47 \pm 1.12	3.03 \pm 1.77	72.70 \pm 1.19	26.46 \pm 4.93	25.50 \pm 8.38
FMP	70.50 \pm 0.50	0.81 \pm 0.40	1.73 \pm 1.03	72.16 \pm 0.33	0.66 \pm 0.40	1.47 \pm 0.87	73.33 \pm 1.85	18.92 \pm 2.28	13.33 \pm 5.89

Table 1: Comparative Results with Baselines on Node Classification.

forward propagation. For all models, we train 2 layers of neural networks with 64 hidden units for 300 epochs. Additionally, We also compare adversarial debiasing and adding demographic regularization methods to show the effectiveness of the proposed method⁸.

Implementation Details. We run the experiments 5 times and report the average performance for each method. We adopt Adam optimizer with 0.001 learning rate and 10^{-5} weight decay for all models. For adversarial debiasing, we adopt the train classifier and adversary with 70 and 30 epochs, respectively. The hyperparameter for adversary loss is tuned in $\{0.0, 1.0, 2.0, 5.0, 8.0, 10.0, 20.0, 30.0\}$. For adding regularization, we adopt the hyperparameter set $\{0.0, 1.0, 2.0, 5.0, 8.0, 10.0, 20.0, 50.0, 80.0, 100.0\}$.

Experimental Results

Comparison with Existing GNNs. The accuracy, demographic parity, and equal opportunity metrics of proposed FMP for Pokey-z, Pokey-n, NBA datasets are shown in Table 1 compared with MLP, GAT, GCN, SGC, and APPNP. The detailed statistical information for these three datasets is shown in Table 3. From these results, we can obtain the following observations:

- Many existing GNNs underperform MLP model on all three datasets in terms of fairness metric. For instance, the demographic parity of MLP is lower than GAT, GCN, SGC and APPNP by 32.64%, 50.46%, 66.53% and 58.72% on Pokey-z dataset. The higher prediction bias comes from the aggregation within the same sensitive attribute nodes and topology bias in graph data.
- Our proposed FMP consistently achieves the lowest prediction bias in terms of demographic parity and equal opportunity on all datasets. Specifically, FMP reduces demographic parity by 49.69%, 56.86%, and 5.97% compared with the lowest bias among all baselines in Pokey-z, Pokey-n, and NBA datasets. Meanwhile, our proposed FMP achieves the best accuracy in NBA dataset, and com-

parable accuracy in Pokey-z and Pokey-n datasets. In a nutshell, the proposed FMP can effectively mitigate prediction bias while preserving the prediction performance.

Comparison with Adversarial Debiasing and Regularization. To validate the effectiveness of the proposed FMP, we also show the prediction performance and fairness metric trade-off compared with fairness-boosting methods, including adversarial debiasing (Fisher et al. 2020) and adding regularization (Chuang and Mroueh 2020). Similar to (Louppe, Kagan, and Cranmer 2017), the output of GNNs is the input of the adversary and the goal of the adversary is to predict the node sensitive attribute. We also adopt several backbones for these two methods, including MLP, GCN, GAT, and SGC. We randomly split 50%/25%/25% for training, validation, and test dataset. Figure 2 shows the Pareto optimality curve for all methods, where the right-bottom corner point represents the ideal performance (highest accuracy and lowest prediction bias). From the results, we list the following observations as follows:

- Our proposed FMP can achieve better DP-Acc trade-off compared with adversarial debiasing and adding regularization for many GNNs and MLP. Such observation validates the effectiveness of the key idea in FMP: aggregation first and then debiasing. Additionally, FMP can reduce demographic parity with negligible performance cost due to transparent and efficient debiasing.
- Message passing in GNNs does matter. For adding regularization or adversarial debiasing, different GNNs embrace huge distinctions, which implies that an appropriate message passing manner potentially leads to better trade-off performance. Additionally, many GNNs underperforms MLP in low-label homophily coefficient dataset, such as NBA. The rationale is that aggregation may not always bring benefit in terms of accuracy when the neighbors have low probability with the same label.

Related Works

Graph Neural Networks. GNNs generalizing neural networks for graph data show great success in various real-world applications. There are two streams in GNNs model

⁸Please see the comparison with Fair Mixup (Chuang and Mroueh 2021) in Appendix

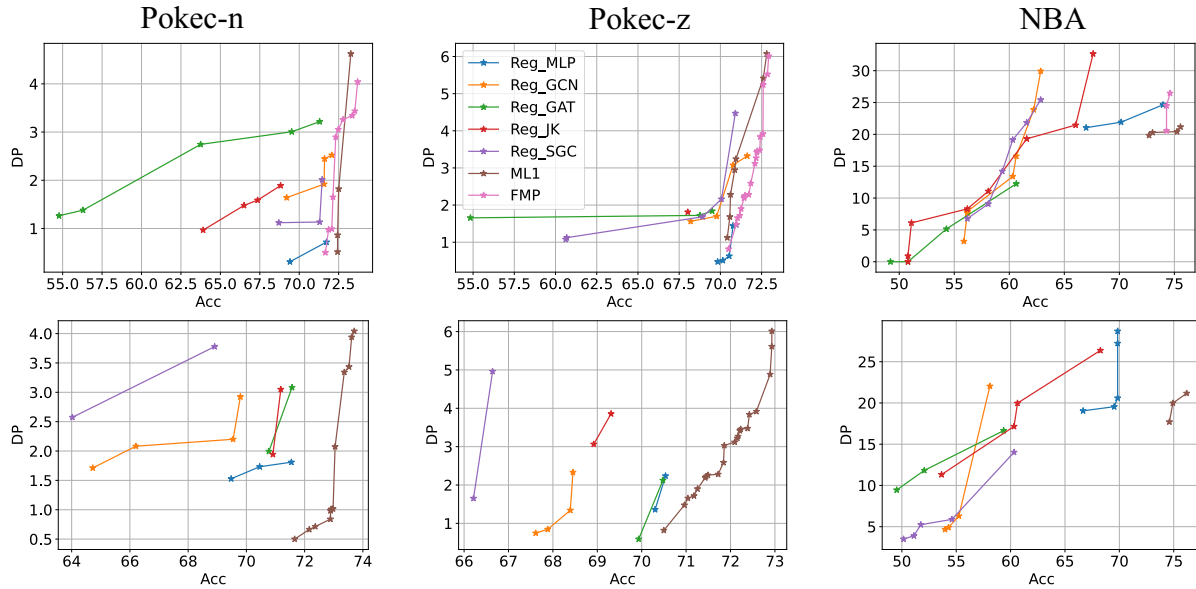


Figure 2: DP and Acc trade-off performance on three real-world datasets compared with adding regularization (Top) and adversarial debiasing (Bottom). The trade-off curve close to the right bottom corner means better trade-off performance. The units for x- and y-axis are percentages (%).

design, i.e., spectral-based and spatial-based. Spectral-based GNNs provide graph convolution definition based on graph theory, which is utilized in GNN layers together with feature transformation (Bruna et al. 2013; Defferrard, Bresson, and Vandergheynst 2016; Henaff, Bruna, and LeCun 2015). Graph convolutional networks (GCN) (Kipf and Welling 2017) simplify spectral-based GNN model into spatial aggregation scheme. Since then, many spatial-based GNNs variant is developed to update node representation via aggregating its neighbors’ information, including graph attention network (GAT) (Veličković et al. 2018), GraphSAGE (Hamilton, Ying, and Leskovec 2017), SGC (Wu et al. 2019), APPNP (Klicpera, Bojchevski, and Günnemann 2019), et al (Gao, Wang, and Ji 2018; Monti et al. 2017). Graph signal denoising is another perspective to understand GNNs. Recently, there are several works show that GCN is equivalent to the first-order approximation for graph denoising with Laplacian regularization (Henaff, Bruna, and LeCun 2015; Zhao and Akoglu 2019). The unified optimization framework is provided to unify many existing message passing schemes (Ma et al. 2021; Zhu et al. 2021a).

Fairness-aware Learning on Graphs. Many works have been developed to achieve fairness in machine learning community (Jiang et al. 2022; Han et al. 2023; Jiang et al. 2023; Chuang and Mroueh 2020; Zhang, Lemoine, and Mitchell 2018; Du et al. 2021; Yurochkin and Sun 2020; Creager et al. 2019; Feldman et al. 2015). A pilot study on fair node representation learning is developed based on random walk (Rahman et al. 2019). Additionally, adversarial debiasing is adopted to learn fair prediction or node representation so that the well-trained adversary can not predict the sensitive attribute based on node representation or prediction (Dai and

Wang 2021; Bose and Hamilton 2019; Fisher et al. 2020). A Bayesian approach is developed to learn fair node representation via encoding sensitive information in the prior distribution in (Buyl and De Bie 2020). Work (Ma, Deng, and Mei 2021) develops a PAC-Bayesian analysis to connect subgroup generalization with accuracy parity. (Laclau et al. 2021; Li et al. 2021) aims to mitigate prediction bias for link prediction. Fairness-aware graph contrastive learning is proposed in (Agarwal, Lakkaraju, and Zitnik 2021; Köse and Shen 2021; Ling et al. 2023b). Graph data preprocessing, such as node feature masking and graph topology rewire, are also developed in (Laclau et al. 2021; Li et al. 2021; Dong et al. 2021; Wang et al. 2022; Zha et al. 2023) for node classification and link prediction tasks. However, the aforementioned works ignore the requirement of transparency in fairness. In this work, we develop an efficient and transparent fair message passing scheme explicitly rendering sensitive attribute usage.

Conclusion

In this work, we improve fairness in graphs from the model architecture perspective. We design a fair message-passing scheme to achieve fair prediction for node classification using vanilla training loss without data pre-processing. Specifically, motivated by the unified optimization framework for GNNs, FMP is designed as aggregation first and then bias mitigation to chase smoothness and fairness objectives. We provide a comprehensive discussion of FMP from model architecture interpretation, efficiency, and the white-box usage of sensitive attributes aspects. Experimental results on real-world datasets demonstrate the effectiveness of FMP compared with several baselines in node classification tasks.

Acknowledgements

We would like to sincerely thank everyone who has provided their generous feedback for this work. Thank the anonymous reviewers for their thorough comments and suggestions. The work is in part supported by NSF grants IIS-1900990, IIS-1939716, and IIS-2239257. The views and conclusions contained in this paper are those of the authors and should not be interpreted as representing any funding agencies.

References

- Agarwal, C.; Lakkaraju, H.; and Zitnik, M. 2021. Towards a Unified Framework for Fair and Stable Graph Representation Learning. *arXiv preprint arXiv:2102.13186*.
- Belkin, M.; and Niyogi, P. 2001. Laplacian eigenmaps and spectral techniques for embedding and clustering. *Advances in neural information processing systems*, 14.
- Beutel, A.; Chen, J.; Zhao, Z.; and Chi, E. H. 2017. Data decisions and theoretical implications when adversarially learning fair representations. *arXiv preprint arXiv:1707.00075*.
- Bose, A.; and Hamilton, W. 2019. Compositional fairness constraints for graph embeddings. In *International Conference on Machine Learning*, 715–724. PMLR.
- Bruna, J.; Zaremba, W.; Szlam, A.; and LeCun, Y. 2013. Spectral networks and locally connected networks on graphs. *arXiv preprint arXiv:1312.6203*.
- Buyl, M.; and De Bie, T. 2020. Debayes: a bayesian method for debiasing network embeddings. In *International Conference on Machine Learning*, 1220–1229. PMLR.
- Chen, P.; Huang, J.; and Zhang, X. 2013. A primal–dual fixed point algorithm for convex separable minimization with applications to image restoration. *Inverse Problems*, 29(2): 025011.
- Chuang, C.-Y.; and Mroueh, Y. 2020. Fair Mixup: Fairness via Interpolation. In *International Conference on Learning Representations*.
- Chuang, C.-Y.; and Mroueh, Y. 2021. Fair Mixup: Fairness via Interpolation. In *International Conference on Learning Representations*.
- Creager, E.; Madras, D.; Jacobsen, J.-H.; Weis, M.; Swersky, K.; Pitassi, T.; and Zemel, R. 2019. Flexibly fair representation learning by disentanglement. In *International conference on machine learning*, 1436–1445. PMLR.
- Dai, E.; and Wang, S. 2021. Say no to the discrimination: Learning fair graph neural networks with limited sensitive attribute information. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*, 680–688.
- Defferrard, M.; Bresson, X.; and Vandergheynst, P. 2016. Convolutional neural networks on graphs with fast localized spectral filtering. *Advances in neural information processing systems*, 29: 3844–3852.
- Dong, Y.; Kang, J.; Tong, H.; and Li, J. 2021. Individual fairness for graph neural networks: A ranking based approach. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, 300–310.
- Dong, Y.; Liu, N.; Jalaian, B.; and Li, J. 2022. Edits: Modeling and mitigating data bias for graph neural networks. In *Proceedings of the ACM Web Conference 2022*, 1259–1269.
- Du, M.; Mukherjee, S.; Wang, G.; Tang, R.; Awadallah, A. H.; and Hu, X. 2021. Fairness via Representation Neutralization. *arXiv preprint arXiv:2106.12674*.
- Feldman, M.; Friedler, S. A.; Moeller, J.; Scheidegger, C.; and Venkatasubramanian, S. 2015. Certifying and removing disparate impact. In *proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining*, 259–268.
- Fisher, J.; Mittal, A.; Palfrey, D.; and Christodoulopoulos, C. 2020. Debiasing knowledge graph embeddings. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 7332–7345.
- Gao, H.; Wang, Z.; and Ji, S. 2018. Large-scale learnable graph convolutional networks. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 1416–1424.
- Ghadimi, E.; Teixeira, A.; Shames, I.; and Johansson, M. 2014. Optimal parameter selection for the alternating direction method of multipliers (ADMM): quadratic problems. *IEEE Transactions on Automatic Control*, 60(3): 644–658.
- Hamaguchi, T.; Oiwa, H.; Shimbo, M.; and Matsumoto, Y. 2017. Knowledge transfer for out-of-knowledge-base entities: A graph neural network approach. *arXiv preprint arXiv:1706.05674*.
- Hamilton, W. L.; Ying, R.; and Leskovec, J. 2017. Inductive representation learning on large graphs. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, 1025–1035.
- Han, X.; Jiang, Z.; Jin, H.; Liu, Z.; Zou, N.; Wang, Q.; and Hu, X. 2023. Retiring DP: New Distribution-Level Metrics for Demographic Parity. *Transactions on Machine Learning Research*.
- Han, X.; Jiang, Z.; Liu, N.; and Hu, X. 2022a. G-Mixup: Graph Data Augmentation for Graph Classification. In *International Conference on Machine Learning*, 1–9. PMLR.
- Han, X.; Jiang, Z.; Liu, N.; Song, Q.; Li, J.; and Hu, X. 2022b. Geometric Graph Representation Learning via Maximizing Rate Reduction. In *Proceedings of the ACM Web Conference 2022*, 1226–1237.
- Henaff, M.; Bruna, J.; and LeCun, Y. 2015. Deep convolutional networks on graph-structured data. *arXiv preprint arXiv:1506.05163*.
- Jiang, Z.; Han, X.; Fan, C.; Yang, F.; Mostafavi, A.; and Hu, X. 2022. Generalized demographic parity for group fairness. In *International Conference on Learning Representations*.
- Jiang, Z.; Han, X.; Jin, H.; Wang, G.; Zou, N.; and Hu, X. 2023. Weight Perturbation Can Help Fairness under Distribution Shift. *arXiv preprint arXiv:2303.03300*.
- Kalofolias, V. 2016. How to learn a graph from smooth signals. In *Artificial Intelligence and Statistics*, 920–929. PMLR.

- Kipf, T. N.; and Welling, M. 2017. Semi-Supervised Classification with Graph Convolutional Networks. In *International Conference on Learning Representations (ICLR)*.
- Klicpera, J.; Bojchevski, A.; and Günnemann, S. 2019. Predict then Propagate: Graph Neural Networks meet Personalized PageRank. In *International Conference on Learning Representations*.
- Köse, Ö. D.; and Shen, Y. 2021. Fairness-Aware Node Representation Learning. *arXiv preprint arXiv:2106.05391*.
- Laclau, C.; Redko, I.; Choudhary, M.; and Langeron, C. 2021. All of the Fairness for Edge Prediction with Optimal Transport. In *International Conference on Artificial Intelligence and Statistics*, 1774–1782. PMLR.
- Li, P.; Wang, Y.; Zhao, H.; Hong, P.; and Liu, H. 2021. On dyadic fairness: Exploring and mitigating bias in graph connections. In *International Conference on Learning Representations*.
- Ling, H.; Jiang, Z.; Liu, M.; Ji, S.; and Zou, N. 2023a. Graph Mixup with Soft Alignments. In *International Conference on Machine Learning*. PMLR.
- Ling, H.; Jiang, Z.; Luo, Y.; Ji, S.; and Zou, N. 2023b. Learning fair graph representations via automated data augmentations. In *The Eleventh International Conference on Learning Representations*.
- Liu, X.; Jin, W.; Ma, Y.; Li, Y.; Liu, H.; Wang, Y.; Yan, M.; and Tang, J. 2021. Elastic graph neural networks. In *International Conference on Machine Learning*, 6837–6849. PMLR.
- Loris, I.; and Verhoeven, C. 2011. On a generalization of the iterative soft-thresholding algorithm for the case of non-separable penalty. *Inverse Problems*, 27(12): 125007.
- Louizos, C.; Swersky, K.; Li, Y.; Welling, M.; and Zemel, R. 2015. The variational fair autoencoder. *arXiv preprint arXiv:1511.00830*.
- Louppe, G.; Kagan, M.; and Cranmer, K. 2017. Learning to pivot with adversarial networks. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, 982–991.
- Ma, J.; Deng, J.; and Mei, Q. 2021. Subgroup generalization and fairness of graph neural networks. *Advances in Neural Information Processing Systems*, 34.
- Ma, Y.; Liu, X.; Zhao, T.; Liu, Y.; Tang, J.; and Shah, N. 2021. A unified view on graph neural networks as graph signal denoising. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, 1202–1211.
- Mehrabani, N.; Morstatter, F.; Saxena, N.; Lerman, K.; and Galstyan, A. 2021. A survey on bias and fairness in machine learning. *ACM Computing Surveys (CSUR)*, 54(6): 1–35.
- Monti, F.; Boscaini, D.; Masci, J.; Rodola, E.; Svoboda, J.; and Bronstein, M. M. 2017. Geometric deep learning on graphs and manifolds using mixture model cnns. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 5115–5124.
- Rahman, T.; Surma, B.; Backes, M.; and Zhang, Y. 2019. Fairwalk: Towards fair graph embedding. In *Proceedings of the Twenty-Ninth International Conference on International Joint Conferences on Artificial Intelligence*.
- Rockafellar, R. T. 2015. *Convex analysis*. Princeton university press.
- Suresh, H.; and Guttag, J. V. 2019. A framework for understanding unintended consequences of machine learning. *arXiv preprint arXiv:1901.10002*, 2.
- Takac, L.; and Zabovsky, M. 2012. Data analysis in public social networks. In *International scientific conference and international workshop present day trends of innovations*.
- Varma, R.; Lee, H.; Kovačević, J.; and Chi, Y. 2019. Vector-valued graph trend filtering with non-convex penalties. *IEEE transactions on signal and information processing over networks*, 6: 48–62.
- Veličković, P.; Cucurull, G.; Casanova, A.; Romero, A.; Liò, P.; and Bengio, Y. 2018. Graph Attention Networks. In *International Conference on Learning Representations*.
- Wang, Y.; Zhao, Y.; Dong, Y.; Chen, H.; Li, J.; and Derr, T. 2022. Improving fairness in graph neural networks via mitigating sensitive attribute leakage. In *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, 1938–1948.
- Wu, F.; Souza, A.; Zhang, T.; Fifty, C.; Yu, T.; and Weinberger, K. 2019. Simplifying graph convolutional networks. In *International conference on machine learning*, 6861–6871. PMLR.
- Xu, K.; Li, C.; Tian, Y.; Sonobe, T.; Kawarabayashi, K.-i.; and Jegelka, S. 2018. Representation learning on graphs with jumping knowledge networks. In *International conference on machine learning*, 5453–5462. PMLR.
- Ying, R.; He, R.; Chen, K.; Eksombatchai, P.; Hamilton, W. L.; and Leskovec, J. 2018. Graph convolutional neural networks for web-scale recommender systems. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 974–983.
- Yurochkin, M.; and Sun, Y. 2020. SenSel: Sensitive Set Invariance for Enforcing Individual Fairness. In *International Conference on Learning Representations*.
- Zha, D.; Bhat, Z. P.; Lai, K.-H.; Yang, F.; Jiang, Z.; Zhong, S.; and Hu, X. 2023. Data-centric artificial intelligence: A survey. *arXiv preprint arXiv:2303.10158*.
- Zhang, B. H.; Lemoine, B.; and Mitchell, M. 2018. Mitigating unwanted biases with adversarial learning. In *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*, 335–340.
- Zhao, L.; and Akoglu, L. 2019. Pairnorm: Tackling over-smoothing in gnns. *arXiv preprint arXiv:1909.12223*.
- Zhu, M.; Wang, X.; Shi, C.; Ji, H.; and Cui, P. 2021a. Interpreting and unifying graph neural networks with an optimization framework. In *Proceedings of the Web Conference 2021*, 1215–1226.
- Zhu, Y.; Xu, Y.; Yu, F.; Liu, Q.; Wu, S.; and Wang, L. 2020. Deep Graph Contrastive Representation Learning. In *ICML Workshop on Graph Representation Learning and Beyond*.
- Zhu, Y.; Xu, Y.; Yu, F.; Liu, Q.; Wu, S.; and Wang, L. 2021b. Graph contrastive learning with adaptive augmentation. In *Proceedings of the Web Conference 2021*, 2069–2080.