EqGNN: Equalized Node Opportunity in Graphs

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ABSTRACT

Graph neural networks (GNNs), has been widely used for supervised learning tasks in graphs reaching state-of-the-art results. However, little work was dedicated to creating unbiased GNNs, i.e., where the classification is uncorrelated with sensitive attributes, such as race or gender. Some ignore the sensitive attributes or optimize for the criteria of statistical parity for fairness. However, it has been shown that neither approaches ensure fairness, but rather cripple the utility of the prediction task. In this work, we present a GNN framework that allows optimizing representations for the notion of Equalized Odds fairness criteria. The architecture is composed of three components: (1) a GNN classifier predicting the utility class, (2) a sampler learning the distribution of the sensitive attributes of the nodes given their labels. It generates samples fed into a (3) discriminator that discriminates between true and sampled sensitive attributes using a novel "permutation loss" function. Using these components, we train a model to neglect information regarding the sensitive attribute only with respect to its label. To the best of our knowledge, we are the first to optimize GNNs for the equalized odds criteria. We evaluate our classifier over several graph datasets and sensitive attributes and show our algorithm reaches state-of-the-art results.1

CCS CONCEPTS
• Computing methodologies → Artificial intelligence; Machine learning.

KEYWORDS
Neural-Networks, Graphs, Graph-Neural-Networks, Fairness

1 INTRODUCTION

Supervised learning was shown to exhibit bias depending on the data it was trained on [21]. This problem is further amplified in graphs, where the graph topology was shown to exhibit different biases [14, 27]. Many popular supervised-learning graph algorithms, such as graph neural networks (GNNs), employ message-passing with features aggregated from neighbors; which might further intensify this bias. For example, in social networks, communities are usually more connected between themselves. As GNNs aggregate information from neighbors, it makes it even harder for a classifier to realize the potential of an individual from a discriminated community.

Despite their success [32], little work has been dedicated to creating unbiased GNNs, where the classification is uncorrelated with sensitive attributes, such as race or gender. The little existing work, focused on ignoring the sensitive attributes [19]. However, “fairness through unawareness” has already been shown to predict sensitive attributes from other features [1]. Others [4, 5, 7, 23] focused on the criteria of Statistical Parity (SP) for fairness when training node embeddings, which is defined as follows:

Definition 1.1 (Statistical parity). A predictor \( \hat{Y} \) satisfies statistical parity with respect to a sensitive attribute \( A \), if \( \hat{Y} \) and \( A \) are independent:

\[
\hat{Y} \perp A
\]

Recently, [8] showed that SP does not ensure fairness and might actually cripple the utility of the prediction task. Consider the target of college acceptance and the sensitive attribute of demographics. If the target variable correlates with the sensitive attribute, statistical parity would not allow an ideal predictor. Additionally, the criterion allows accepting qualified applicants in one demographic, but unqualified in another, as long as the percentages of acceptance match.

In recent years, the notion of Equalized Odds (EO) was presented as an alternative fairness criteria [12]. Unlike SP, EO allows dependence on the sensitive attribute \( A \) but only through the target variable \( Y \):

Definition 1.2 (Equalized odds). A predictor \( \hat{Y} \) satisfies equalized odds with respect to a sensitive attribute \( A \), if \( \hat{Y} \) and \( A \) are independent conditional on the true label \( Y \):

\[
\hat{Y} \perp A \mid Y
\]

The definition encourages the use of features that allow to directly predict \( Y \), while not allowing to leverage \( A \) as a proxy for \( Y \). Consider our college acceptance example. For the outcome of \( Y=Accept \), we require \( \hat{Y} \) to have similar true and false positive rates across all demographics. Notice that, \( \hat{Y} = Y \) aligns with the equalized odds constraint, but we enforce that the accuracy is equally high in all demographics, and penalize models that have good performance on only the majority of demographics.

In this work, we present an architecture that optimizes graph classification for the EO criteria. Given a GNN classifier predicting...
a target class, our architecture expands it with a sampler and a discriminator. The goal of the sampler component is to learn the distribution of the sensitive attributes of the nodes given their labels. The sampler generates examples that are then fed into a discriminator. The goal of the latter is to discriminate between true and sampled sensitive attributes. We present a novel loss function the discriminator minimizes – the permutation loss. Unlike cross-entropy loss, which compares two independent or unrelated groups, the permutation loss compares items under two separate scenarios – with sensitive attribute or with a generated balanced sensitive attribute.

We start by pretraining the sampler, and then train the discriminator along with the GNN classifier using adversarial training. This joint training allows the model to neglect information regarding the sensitive attribute only with respect to its label, as requested by the equalized odds fairness criteria. To the best of our knowledge, our work is the first to optimize GNNs for the equalized odds criteria.

The contributions of this work are fourfold:

- We propose EqGNN, an algorithm with equalized odds regulation for graph classification tasks.
- We propose a novel permutation loss which allows us to compare pairs. We use this loss in the special case of nodes in two different scenarios – one under the bias sensitive distribution, and the other under the generated unbiased distribution.
- We empirically evaluate EqGNN on several real-world datasets and show superior performance to several baselines both in utility and in bias reduction.
- We empirically evaluate the permutation loss over both synthetic and real-world datasets and show the importance of leveraging the pair information.

## 2 RELATED WORK

Supervised learning in graphs has been applied in many applications, such as protein-protein interaction prediction [10, 26], human movement prediction [33], traffic forecasting [6, 35] and other urban dynamics [31]. Many supervised learning algorithms have been suggested for those tasks on graphs, including matrix factorization approaches [2, 25, 29, 34], random walks approaches [10, 22] and graph neural network, which recently showed state-of-the-art results on many tasks [32]. The latter is an adaptation of neural networks to the graph domain. GNNs create different differential layers that can be added to many different architectures and tasks. GNNs utilize the graph structure by propagating information through the edges and nodes. For instance, GCN [17] and graphSAGE [11] update the nodes representation by averaging over the representations of all neighbors, while [30] proposed an attention mechanism to learn the importance of each specific neighbor.

Fairness in graphs was mostly studied in the context of group fairness, by optimizing the SP fairness criteria. [23] creates fair random walks by first sampling a sensitive attribute and only then sampling a neighbor from those who hold that specific sensitive attribute. For instance, if most nodes represent men while the minority represent women, the fair random walk promises that the presence of men and women in the random walks will be equal. [5] proposed a Bayesian method for learning embeddings by using a biased prior. Others, focus on unbiased the graph prediction task itself rather than the node embeddings. For example, [4] uses a set of adversarial filters to remove information about predefined sensitive attributes. It is learned in a self-supervised way by using a graph-auto-encoder to reconstruct the graph edges. [7] offers a discriminator that discriminates between the nodes sensitive attributes. In their setup, not all nodes sensitive attributes are known, and therefore, they add an additional component that predicts the missing attributes. [15] tackles the challenge of individual fairness in graphs. In this work, we propose a GNN framework optimizing the EO fairness criteria. To the best of our knowledge, our work is the first to study fairness in graphs in the context of EO fairness.

## 3 EQUALIZED-ODDS FAIR GRAPH NEURAL NETWORK

Let \( G = (V, E) \) be a graph, where \( E \) is the list of edges, \( V \) the list of nodes, \( Y \) the labels, and \( A \) the sensitive attributes. Each node is represented via \( n \) features. We denote \( X^{V \times n} \) as the feature matrix for the nodes in \( V \). Our goal is to learn a function \( F(\cdot) \) with parameters \( \theta \), that given a graph \( G \), maps a node \( v \in V \) represented by a feature vector, to its label.

In this work, we present an architecture that can leverage any graph neural network classifier. For simplicity, we consider a simple GNN architecture for \( F(\cdot) \) as suggested by [17]; we define \( F(\cdot) \) to be two GCN [17] layers, outputting a hidden representation \( h \) for each node. This representation then enters a fully connected layer that outputs \( \hat{Y} \). The GNN optimization goal is to minimize the distance between \( \hat{Y} \) and \( Y \) using a loss function \( \ell \). \( \ell \) can be categorical cross-entropy (CCE) for multi-class classification, binary cross-entropy (BCE) for binary classification, or mean square error (L2) for regression problems. In this work, we extend the optimization to minimize \( \min_{\theta} \ell_{task} + \ell(Y, \hat{Y}) \) while satisfying Eq. 2 for fair prediction.

We propose a method, EqGNN, that trains a GNN model to neglect information regarding the sensitive attribute only with respect to its label. The full architecture of EqGNN is depicted in Figure 1. Our method pretrains a sampler (Section 3.1), to learn the distribution \( P_{A|X} \), of the sensitive attributes of the nodes given their labels (marked in blue in Figure 1). We train a GNN classifier (marked in green in Figure 1), while regularizing it with a discriminator (marked in red in Figure 1) that discriminates between true and sampled sensitive attributes. Section 3.2 presents the EO regulation. The regularization is done using a novel loss function – the “permutation loss”, which is capable of comparing paired samples (formally presented in Section 3.3, and implementation details are discussed in Section 3.4). For the unique setup of adversarial learning over graphs, we show that incorporating the permutation loss in a discriminator, brings performance gains both in utility and in EO. Section 3.5 presents the full EqGNN model optimization procedure.

### 3.1 Sampler

To comply with the SP criteria (Eq. 1), given a sample \( i \), we wish the prediction of the classifier, \( \hat{Y}_i \), to be independent of the sample’s sensitive attribute \( A_i \). In order to check if this criteria is kept, we can sample a fake attribute out of \( \mathbb{Z}_A \) (e.g., in case of equal sized groups, a random attribute), and check if \( \hat{Y}_i \) can predict the true or fake attribute. If it is not able to predict, this means that \( \hat{Y}_i \) is
3.1.1 Sensitive Attribute Distribution Learning. Here, our goal is to learn the distribution \( P_{A \mid Y}(A \mid Y) \). For a specific sensitive attribute \( a \) and label \( y \), the probability can be expressed using Bayes’ rule as:

\[
P_{A \mid Y}(A = a \mid Y = y) = \frac{P(Y = y \mid A = a)P(A = a)}{\sum_{a' \in A} P(Y = y \mid A = a')P(A = a')} \quad (3)
\]

The term \( P(Y = y \mid A = a) \) can be derived from the data by counting the number of samples that are both with label \( y \) and sensitive attribute \( a \), divided by the number of samples with sensitive attribute \( a \). Similarly, \( P(A = a) \) is calculated as the number of samples with sensitive attribute \( a \), divided by the total number of samples. In a regression setup, these can be approximated using a linear kernel density estimation.

3.1.2 Fair Dummy Attributes. During training of the end-to-end model (Section 3.5), the sampler receives a training example \((X_i, Y_i, A_i)\) and generates a dummy attribute by sampling \( \tilde{A}_i \sim P_{A \mid Y}(A_i \mid Y_i) \). Notice that \( A_i \) and \( \tilde{A}_i \) are equally distributed given \( Y_i \). This ensures that if the classifier holds the EO criteria, then \((X_i, Y_i, A_i)\) and \((X_i, Y_i, \tilde{A}_i)\) will receive an identical classification, whereas otherwise it will result in different classifications. In Section 3.2 we further explain the optimization process that utilizes the dummy attributes for regularizing the classifier for EO.

3.2 Discriminator

A GNN classifier without regulation might learn to predict biased node labels based on their sensitive attributes. To satisfy EO, the classifier should be unable to distinguish between real examples and generated examples with dummy attributes. Therefore, we utilize an adversarial learning process and add a discriminator that learns to distinguish between real and fake examples with dummy attributes. Intuitively, this regularizes the classifier to comply with the EO criterion.
Intuitively, one might consider \( h_i \) the last hidden layer of the classifier \( F(\cdot) \), as the unbiased representation of node \( i \). The discriminator receives two types of examples: (1) real examples \((Y_i, A_i, Y', h_i)\) and (2) negative examples \((Y_i, A_i, Y', h_i)\), where \( A_i \sim P_{AY}(A_i | Y) \) is generated by the pretrained sampler. The discriminator learns a function \( D(\cdot) \) with parameters \( \theta_D \), that given a sample, classifies it to be true or fake. The classifier in its turn tries to "fool" it. This ensures the classifier doesn’t hold bias towards specific labels and sensitive attributes and keeps the EO criterion. The formal adversarial loss is defined as:

\[
\min_{\theta_F} \max_{\theta_D} L_{adv} = \mathbb{E} \left[ \log(D(Y || A || F(X, G) || h)) \right] + \mathbb{E}_{\tilde{A} \sim P_{AY}(A|Y)} \left[ \log(1 - D(Y || \tilde{A} || F(X, G) || h)) \right]
\]

where \( \mathbb{E} \) is the expected value, and \( || \) represents the concatenation operator. The discriminator tries to maximize \( L_{adv} \) to distinguish between true and fake samples, while the classifier tries to minimize it, in order to "fool" him. In our implementation, \( D(\cdot) \) is a GNN with two GCN layers outputting the probability of being a true sample.

we observe that fake and attributes are paired (the same node, with a real sensitive attribute or a dummy attribute). A binary loss as defined in Eq. 4 holds for unpaired examples, and does not take advantage of knowing the fake and true attributes are paired. Therefore, we upgrade the loss to handle paired nodes by utilizing the permutation loss. We first formally define and explain the permutation loss in Section 3.3, and then continue discussing its implementation details in our architecture in Section 3.4.

### 3.3 Permutation Loss

In this section, we formally define the new permutation loss test presented in this work. Let us assume \( X_1 \) and \( X_2 \) are two groups of subjects. Many applications are interested of learning and understanding the difference between the two. For example, in the case where \( X_1 \) represents test results of students in one class, while \( X_2 \) represents test results of a different class, it will be interesting to check if the two classes are equally distributed (i.e., \( P(X_1) = P(X_2) \)).

**Definition 3.1 (T-test).** Given two groups \( X_1, X_2 \subset \mathbb{R} \), the statistical difference can be measured by the t-statistic:

\[
t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}
\]

Where \( \bar{X}_i \), \( s_i \), and \( n_i \) are the means, variances, and group sizes respectively.

While this test assumes \( X_1, X_2 \) are scalars that are normally distributed, [18] proposed a method called C2ST that handles cases where \( X_1, X_2 \subset \mathbb{R}^d \) for \( d \geq 1 \). They proposed a classifier that is trained to predict the correct group of a given sample, which belongs to either \( X_1 \) or \( X_2 \). By doing so, given a test-set, they are able to calculate the t-statistic by simply checking the number of correct predictions:

**Definition 3.2 (C2ST).** Given two groups \( X_1, X_2 \subset \mathbb{R}^d \) (labeled 0 and 1 respectively), the statistical difference can be measured by the t-statistic:

\[
t = \frac{\bar{X}_D}{\sqrt{\frac{s_D^2}{n_D}}}
\]

where \( \bar{X}_D, s_D \) are the mean and standard deviation of \( X_D \), and \( n = |X_D| \) is the number of pairs.
At each step we randomly permute the sensitive attribute and its attributes are paired (the same node, with a real sensitive attribute or a dummy attribute). We create paired samples: \((Y_i, A_i, \tilde{A}_i, \tilde{Y}_i, h_i)\). At each step we randomly permute the sensitive attribute and its dummy attribute, creating a sample labeled as permuted or not. Now our samples are \((Y_i, A_i, \tilde{A}_i, \tilde{Y}_i, h_i)\) with label 0 indicating no permutation was applied, while \((Y_i, A_i, A_i, \tilde{Y}_i, h_i)\) with label 1 indicating a permutation was applied. The discriminator therefore receives the samples and predicts the probability of whether a permutation was applied. We therefore adapt the adversarial loss of Eq. 4 to:

\[
\min_{\theta_F} \max_{\theta_D} L_{adv} = \mathbb{E}_{\tilde{A}} \mathbb{E}_{A|Y}(A, Y) \left[ \log(D(Y \parallel \tilde{A} \parallel A \parallel F(X, G) \parallel h)) + \mathbb{E}_{\tilde{A}} \mathbb{E}_{A|Y}(A, Y) \left[ \log(1 - D(Y \parallel A \parallel \tilde{A} \parallel F(X, G) \parallel h)) \right] \right]
\]

The loss used in the permutation test is a binary cross-entropy and therefore convex.

As an additional final regulation and to improve stability of the classifier, similarly to [24], we propose to minimize the absolute difference between the covariance of \(\tilde{Y}\) and \(A\) from the covariance of \(Y\) and \(A\):

\[
\min_{\theta_F} L_{cov} = \|\text{cov}(\tilde{Y}, A) - \text{cov}(Y, A)\|^2
\]

### 3.5 EqGNN

The sampler is pretrained using Eq. 3. We then jointly train the classifier and the discriminator optimizing the objective function:

\[
\min_{\theta_F} \max_{\theta_D} \left( \min_{\theta_F} \max_{\theta_D} L_{task} + \lambda (L_{adv} + \gamma L_{cov}) \right)
\]

where \(\theta_F\) are the parameters of the classifier and \(\theta_D\) are the parameters of the discriminator. \(\lambda\) and \(\gamma\) are hyper-parameters that are used to tune the different regulations. This objective is then optimized for \(\theta_F\) and \(\theta_D\) one step at a time using the Adam optimizer [16], with learning rate \(10^{-3}\) and weight-decay \(10^{-5}\). The training is further detailed in Algorithm 2.
Table 1: Datasets’ characteristics.

| Dataset          | Pokec-region | Pokec-gender | NBA   |
|------------------|--------------|--------------|-------|
| # of nodes       | 67,796       | 67,796       | 355   |
| # of attributes  | 276          | 276          | 95    |
| # of edges       | 617,958      | 617,958      | 9,477 |
| sensitive groups | 1.84         | 1.02         | 3.08  |
| ratio            |              |              |       |
| # of inter-group | 30,519       | 339,461      | 2,472 |
| edges            | 587,439      | 278,497      | 7,005 |

4 EXPERIMENTAL SETUP

In this section, we describe our datasets, baselines, and metrics. Our baselines include fair baselines designed specifically for graphs, and general fair baselines that we adapted to the graph domain.

4.1 Datasets

Table 1 summarizes the datasets’ characteristics used for our experiments. Intra-group edges are the edges between similar sensitive attributes, while inter-group edges are edges between different sensitive attributes.

Pokec [28]. Pokec is a popular social network in Slovakia. An anonymized snapshot of the network was taken in 2012. User profiles include gender, age, hobbies, interest, education, etc. The original Pokec dataset contains millions of users. We sampled a subnetwork of the “Zilinsky” province. We create two datasets, where the sensitive attribute in one is the gender, and region in the other. The label used for classification is the job of the user. The job field was grouped in the following way: (1)“education” and “student”, (2)“services & trade” and “construction”, and (3) “unemployed”.

NBA [7] This dataset was presented in the FairGNN baseline paper. The NBA Kaggle dataset contains around 400 basketball players with features including performance statistics, nationality, age, etc. This dataset was extended in [7] to include the relationships of the NBA basketball players on Twitter. The binary sensitive attribute is whether a player is a U.S. player or an overseas player, while the task is to predict whether a salary of the player is over the median.

4.2 Baselines

In our evaluation, we compare to the following baselines:

GCN [17]: GCN is a classic GNN layer that updates a node representation by averaging the representations of its neighbors. For fair comparison, we implemented GCN as the classifier of the EqGNN architecture (i.e., an unregulated baseline, with the only difference of $\lambda = 0$).

Debias [36]: Debias optimizes EO by using a discriminator that given $Y$ and $\hat{Y}$ predicts the sensitive attribute. While Debias is a non-graph architecture, for fair comparison, we implemented Debias with the exact architecture as EqGNN. Unlike EqGNN, Debias’s discriminator receives as input only $Y$ and $\hat{Y}$ (without the sensitive attribute or dummy attribute) and predicts the sensitive attribute. As the discriminator receives $Y$, it neglects the sensitive information with respect to $Y$ and, therefore optimizes for EO.

FairGNN [7]: FairGNN uses a discriminator that, given $h$, predicts the sensitive attribute. By doing so, they neglect the sensitive information from $h$. As this is without respect to $Y$, they optimize SP (further explained in Section 3.1). FairGNN offers an additional predictor for nodes with unknown sensitive attributes. As our setup includes all nodes’ sensitive attributes, this predictor is irrelevant. We opted to use FairGNN for fair comparison. In addition, we generalized their architecture to support multi-class classification.

For all baselines, 50% of nodes are used for training, 25% for validation and 25% for testing. The validation set is used for choosing the best model for each baseline throughout the training. As the classifier is the only part of the architecture used for testing, an early stopping was implemented after its validation loss (Eq. 7) hasn’t improved for 50 epochs. The epoch with the best validation loss was then used for testing. All results are averaged over 20 different train/validation/test splits for Pokec datasets and 40 for the NBA dataset. For fair comparison, we implemented grid-search for all baselines over $\lambda \in \{0.01, 0.1, 1, 10\}$ for baselines with a discriminator, and $\gamma \in \{0, 50\}$ for baselines with a covariance expression. For both Pokec datasets and for all baselines $\lambda = 1$ and $\gamma = 50$, while for NBA we end up using $\lambda = 0.1$ and $\gamma = 50$ expect for FairGNN with $\lambda = 0.01$. All experiments used a single Nvidia P100 GPU with the average run of 5 minutes per seed for Pokec and 1 minute for NBA. Results where logged and analyzed using the [3, 9] platforms.

4.3 Metrics

4.3.1 Fairness Metrics.

Equalized odds. The definition in Eq. 2, can be formally written as:

$$\mathbb{P}(\hat{Y} = y|Y = y, A = a_1) = \mathbb{P}(\hat{Y} = y|Y = y, A = a_2) \quad \forall a_1, a_2 \in A, \forall y \in Y$$

(8)

The value of $\mathbb{P}(\hat{Y} = y|Y = y, A = a)$ can be calculated from the test-set as follows: given all samples with label $y$ and sensitive attribute $a$, we calculate the proportion of samples that where labeled $y$ by the model. As we handle a binary sensitive attribute, given a label $y \in Y$, we calculate the absolute difference between the two sensitive attribute values:

$$\Delta EO(y) = |\mathbb{P}(\hat{Y} = y|Y = y, A = 0) - \mathbb{P}(\hat{Y} = y|Y = y, A = 1)|$$

(9)

According to Eq. 8, our goal is to have both probabilities equal. Therefore, we desire $\Delta EO(y)$ to strive to 0. We finally aggregate $\Delta EO(y)$ for all labels using the max operator to get a final scalar metric:

$$\Delta EO = \max(\{\Delta EO(y)|y \in Y\})$$

(10)

As we propose an equalized odds architecture, $\Delta EO$ is our main fairness metric.

Statistical parity. The definition in Eq. 1 can be formally written as:

$$\mathbb{P}(\hat{Y} = y|A = a_1) = \mathbb{P}(\hat{Y} = y|A = a_2) \quad \forall a_1, a_2 \in A$$

(11)

The value of $\mathbb{P}(\hat{Y} = y|A = a)$ can be calculated from the test-set the following way: given all samples with sensitive attribute $a$,
we calculate the proportion of samples that where labeled y by the model. As we handle a binary sensitive attribute, given a label y ∈ Y we calculate the absolute difference between the two sensitive attribute values:

\[ ΔSP(y) = |P(\hat{Y} = y|A = 0) - P(\hat{Y} = y|A = 1)| \] (12)

According to Eq. 11, our goal is to have both probabilities equal. Therefore, we desire ΔSP(y) to strive to 0. We finally aggregate ΔSP(y) for all labels using the max operator to get a final scalar metric:

\[ ΔSP = \max(\{ΔSP(y)|y ∈ Y\}) \] (13)

4.3.2 Performance Metrics. As our main classification metric, we used the F1 score. We examined both the micro F1 score, which is computed globally based on the true and false predictions, and the macro F1 score, computed per each class and averaged across all classes. For completeness, we also report the Accuracy (ACC).

5 EXPERIMENTAL RESULTS

In this section, we report the experimental results. We start by comparing EqGNN to the baselines (Section 5.1). We then demonstrate the importance of λ to the EqGNN architecture (Section 5.2). We continue by showing the superiority of the permutation loss, compared to other loss functions, both over synthetic datasets (Section 5.3) and real datasets (Section 5.4). Finally, we explore two qualitative examples, that visualizes the importance of fairness in graphs (Section 5.5).

5.1 Main Result

Table 2 reports the results of EqGNN and baselines over the datasets with respect to the performance and fairness metrics. We can notice that, while the performance metrics are very much similar between all baselines (apart from Debias in Pokec-region), EqGNN outperforms all other baselines in both fairness metrics. An interesting observation is that Debias is the second best, after EqGNN, to improve the EO metric, without harming the performance metrics.

This can be explained as it is the only baseline to optimize with respect to EO. Additionally, Debias has gained fairness in Pokec-region, but at the cost of performance. This is a general phenomena: the lower the performance, the better the fairness. For example, when the performance is random, surely the algorithm doesn’t prefer any particular group and therefore is extremely fair. Here, EqGNN is able to both optimize the fairness metrics while keeping the performance metrics high. The particularly low performance demonstrated by FairGNN was also validated with the authors of the paper. The previously reported results were validated over a single validation step as opposed to several, to insure statistical significance.

5.2 The Discriminator for Bias Reduction

As a second analysis, we demonstrate the importance of the λ parameter with respect to the performance and fairness metrics. The λ hyper-parameter serves as a regularization for task performance as opposed to fairness. High values of λ cause the discriminator EO regulation on the classifier to be higher. While EqGNN results reported in this paper use λ = 1 for Pokec datasets, and λ = 0.1 for NBA, we show additional results for λ ∈ {0.01, 0.1, 1, 100}. In Figure 2, we can observe that the selected λs show best results over all metrics for Pokec-gender, while similar results were shown over Pokec-region and NBA. Obviously, enlarging the λ results in a more fair model but at the cost of performance. The λ hyper-parameter is an issue of priority: depending on the task, one should decide what should be the performance vs. fairness prioritization. Therefore, EqGNN can be used with any desired λ where we chose λ = 1 as it is the elbow of the curve.

5.3 Synthetic Evaluation of the Permutation Loss

In this experiment, we wish to demonstrate the power of the permutation loss over synthetic data. Going back to the notations used in Section 3.3, we generate two paired groups X₁, X₂ ⊂ ℝ² in the following ways:

- Rotation:
  \[ X₁ \sim \begin{pmatrix} Z₁ \\ Z₂ \end{pmatrix}, \quad X₂ \sim \begin{pmatrix} \cos θ & -\sin θ \\ \sin θ & \cos θ \end{pmatrix} \cdot X₁, \]

where Z₁, Z₂ ∼ N(0, 1), and θ = ± π 2. This can simply be thought of as one group is a 2-dimensional Gaussian, while the second is the exact same Gaussian but rotated by θ. As a rotation over a Gaussian resolves also with a Gaussian, X₂ is also a 2-dimensional Gaussian. Yet, it is paired to X₁, as given a sample from X₁, we can predict its pair from X₂ (simply rotate it by θ).

- Shift:
  \[ X₁ \sim \begin{pmatrix} Z₁ \\ Z₂ \end{pmatrix}, \quad X₂ \sim X₁ + \begin{pmatrix} δ \\ 0 \end{pmatrix}, \]

where Z₁, Z₂ ∼ N(0, 1), and δ = 0.1. This can simply be thought of as one group is a 2-dimensional Gaussian, while the second is the exact same Gaussian but shifted by δ on the first axis. As shifting a Gaussian by a small value, X₂ overlaps X₁ and therefore, it is hard to distinguish between the two. Yet, it is paired to X₁, as given a sample from X₁, we can predict its pair from X₂ (simply add δ).

Over these two synthetic datasets, we train four classifiers.
Figure 2: The comparisons of different $\lambda$ values over the Pokec-gender dataset. Lower-right is better.

| Model  | Shift | Rotation |
|--------|-------|----------|
| T-test | 0.24  | 0.47     |
| Paired T-test | 0 | 0.36 |
| C2ST   | 0.5   | 0.5      |
| Permutation | 0 | 0 |

- **T-test** - adapted: As the original unpaired t-test requires a one dimensional data, we first map the samples into a single scalar using a fully connected layer and train it using the the t-statistic defined in Section 3.1.

- **Paired T-test** - adapted: Similar to T-test, but using the paired t-statistic defined in Section 3.3.

- **C2ST** [18]: A linear classifier that given a sample, tries to predict to which group it belongs to.

- **Permutation** (Section 3.3): A linear classifier that given a randomly shuffled pair, predicts if it was shuffled or not. For detailed implementation please refer to Algorithm 1.

We sample 10000 pairs for train and an additional 10000 for test, and average results over 5 runs. In Table 4 we report the p-value of the classifiers over the different generated datasets.

We can observe that, the permutation classifier captures the difference between the pairs perfectly in both datasets. This does not hold for the Paired T-test that captures the difference only for the Shift dataset. The reason it classifies well only over the Shift dataset is because it is a linear transformation, which is easier to learn. We can further notice that both unpaired classifiers (T-test and C2ST) perform poorly over both datasets. The promising results of the permutation classifier on our synthetic datasets, drive us to choose it as the potential discriminator in the EqGNN architecture. We validate this choice over real-datasets next section.

### 5.4 The Importance of the Permutation Loss

As an ablation study, we compare different loss functions for the discriminator. We choose to compare the permutation loss with three different loss functions: (1) Unpaired: Inspired by [24], an unpaired binary cross-entropy loss as presented in Eq. 4. The loss is estimated by a classifier that predicts if a sample represents a real sensitive attribute or a dummy. (2) Permutation/h: A permutation loss without concatenating the hidden representation $h_i$ to the discriminator samples, while leaving the sample to be $(Y_i, A_i, \tilde{A}_i, \tilde{Y}_i)$. (3) Paired: A paired loss:

$$\min_{\theta_Y} \max_{\theta_D} \min_{\theta_A} L_{\text{adv}} = E_{A \sim P_{\text{syn}}(A \mid Y)} [\sigma(D(Y \mid A \mid F(X, G) \mid h))] - \sigma(D(Y \mid \tilde{A} \mid F(X, G) \mid h)) \quad (14)$$

where $\sigma$ is the Sigmoid activation. This loss is the known paired student t-test with a neural network version of it (as demonstrated by
We end this section with a few qualitative examples over the Pokec-statistical parity which optimize the equalized odds. In the Pokec datasets, the performance metrics are not impacted apart from the paired loss. We hypothesize this is caused due to its non-convexity in adversarial settings. Additionally, the paired loss demonstrates the same phenomena again: the lower the performance, the better the fairness. In the NBA dataset we do not see much difference between the loss functions. This can be explained due to the size of the graph. However, we do see that the permutation loss is the only one to improve fairness metrics while not hurting the performance metrics. Finally, we can notice that, paired loss functions (the permutation loss and the paired loss) perform better than the unpaired loss (apart from NBA, where the unpaired loss hurts the performance metrics). This can be explained by our paired problem, where we check for the difference between two scenarios of a node (real and fake). This illustrates the general importance of a paired loss function for paired problems.

5.5 Qualitative Example

We end this section with a few qualitative examples over the Pokec-gender test-set. Specifically, we present two qualitative examples, where the central node has the same sensitive attribute as over 80% of its 2-hop neighbors, but holds a different label from most of them. We consider 2-hops, as our classifier includes 2 GCN layers. Figure 3a presents the example for a sensitive attribute being a male where in Figure 3b being a female; i.e., nodes in Figure 3a are mostly males and in Figure 3b mostly females. A biased approach would be to be inclined to predict the same label for the central node as its same-gender neighbors. Above the central node we observe the prediction distribution for $\lambda = 0$ and $\lambda = 1$. In Figure 3a we observe that, when no discriminator is applied ($\lambda = 0$), and therefore there is no regularization for bias, the probability is 52.55% towards most neighbors label. On the other hand, when applying the discriminator ($\lambda = 1$), the probability for that class drops to 31.04%, and rises to 47.34% for the correct label. Similarly, in Figure 3b, we observe that, when no discriminator is applied ($\lambda = 0$), the probability is 54.55% towards most neighbors label. Again, this in comparison to the case when applying the discriminator ($\lambda = 1$), the probability for that class drops to 45.23%, and rises to 54.42% for the correct label. These qualitative examples show that, a equalized odds regulator over graphs can help make less biased predictions, even when the neighbours at the graphs might cause bias.

6 CONCLUSIONS

In this work, we explored fairness in graphs. Unlike previous work which optimize the statistical parity (SP) fairness criterion, we present a method that learns to optimize equalized odds (EO). While SP promises equal chances between groups, it might cripple the utility of the prediction task as it does not give equalized opportunity as EO. We propose a method that trains a GNN model to neglect information regarding the sensitive attribute only with respect to its label. Our method pretrains a sampler to learn the distribution of the sensitive attributes of the nodes given their labels. We then continue training a GNN classifier while regularizing it with a discriminator that discriminates between true and sampled sensitive attributes using a novel loss function – the “permutation loss”. This loss allows comparison of pairs. For the unique setup of adversarial learning over graphs, we show it brings performance gains both in utility and in EO. While this work uses the loss for the specific case of nodes in two scenarios: fake and true, this loss is general and can be used for any paired problem.

For future work, we wish to test the novel loss over additional architectures and tasks. We draw the reader attention that the C2ST discriminator is the commonly used discriminator for many architectures that work over paired data. For instance, the pix2pix architecture [13] is a classic architecture that inspired many works. Although the pix2pix discriminator receives paired samples, it is still just an advanced C2ST discriminator. Alternatively, using a paired discriminator instead, can create a much powerful discriminator and therefore a much powerful generator. Observing many works that apply over paired samples, we haven’t found any architectures
that are designed to work over paired samples. We believe that, although this work uses the permutation loss for a specific use-case, it is a general architecture that can be used for any paired problem. We empirically show that our method outperforms different baselines in the combined fairness-performance metrics, over datasets with different attributes and sizes. To the best of our knowledge, we are the first to optimize GNNs for the EO criteria and hope it will serve as a beacon for works to come.

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