On the Discrimination Risk of Mean Aggregation Feature Imputation in Graphs

Anonymous Author(s)
Affiliation
Address
email

Abstract

While machine learning methods have demonstrated success on graph-structured data, many methods rely on fully-observed node features. This has led to an increase in research on imputing unknown or missing node features. However, in human networks, nodes belonging to a marginalized group have a disproportionate rate of unknown features. Human networks also contain graph structure and known feature biases. All these factors can cause graph feature imputation algorithms to predict values for unknown features that make the feature values of the marginalized group to be more distinct on average from the feature values of the dominant group than they are in reality. We call this distinction the discrimination risk. We prove that a higher discrimination risk can amplify the unfairness of a machine learning model trained on the imputed data. We then formalize a general graph feature imputation framework called mean aggregation imputation and theoretically and empirically characterize graphs in which applying this framework can yield imputed features with a high discrimination risk. We propose a simple and effective solution to ensure mean aggregation-imputed features provably have a low discrimination risk (while minimally sacrificing reconstruction error) and improve the fairness of models. We evaluate the fairness and accuracy of our solution on synthetic and real-world credit network datasets.

1 Introduction

Machine learning methods [1, 2, 3, 4, 5] have been successfully applied to graph-structured data such as social networks, product graphs, and molecules [6, 7] to aid in important problems like content recommendation, product recommendation, and molecular property prediction [8, 9, 6, 10, 11]. However, many methods rely on fully-observed features for each node, which are not available for privacy reasons, as a consequence of exclusionary data collection practices, or due to the high expenses involved in feature annotation [12, 13, 14]. As a result, the development of algorithms to leverage a graph's structure and known node feature values to impute unknown or missing features has emerged as an important research area [15, 16].

In human networks, nodes belonging to a marginalized group (e.g. on the basis of race, gender, disability, etc.) have a disproportionate rate of unknown features compared to the dominant group because marginalized communities are more reluctant to share their data, annotators erase their data, or they are sidelined in data collection [17, 18, 19, 20]. Furthermore, graph structure and node neighborhoods are correlated with group membership [21, 22], especially in homophilic graphs where nodes belonging to the same group have a higher likelihood of being connected [23]. This can be the result of social stratification [24] or the limited collection of inter-links, i.e. edges between nodes belonging to different groups [23, 6]. Moreover, known feature values are proxies for group membership [18, 25]. Hence, even if graph feature imputation algorithms do not have direct access to

Submitted to 36th Conference on Neural Information Processing Systems (NeurIPS 2022). Do not distribute.

the group membership of a node, these algorithms are influenced by unknown feature rate disparities, graph structure, and known feature values. Thus, they can predict values for unknown features that cause the feature values of the marginalized group to be more distinct on average from the feature values of the dominant group than they are in reality.

As an illustrative example, let's consider an automated candidate screening system based on the job applicant network shown in Figure 1, where nodes represent applicants and edges between applicants indicate that they have similar past work experiences. Each node has one feature: the number of years that the applicant has previously worked. Furthermore, each node belongs to one of two groups, the disabled community (group Q) or the able-bodied community (group R). (In reality, disability is a fluid and complex identity that cannot be easily reduced to a binary [26].) All the nodes in group R have a known feature value of 5 years, while all the nodes in group Q have unknown feature values; however, in reality, all the nodes in group Q also have a feature value of 5 years. Additionally, all the nodes in group Q are connected to each other but have few links (if any) to nodes in group R because of systemic barriers including hiring discrimination and a lack of accommodations [27]. Consequently, after applying the graph feature imputation algorithm Feature Propagation [16], because of the disparate rates of unknown features between the groups and structure of the graph, the nodes in Q will have, on average, feature values that are more distinct from the feature values of the nodes in R than the ground truth.

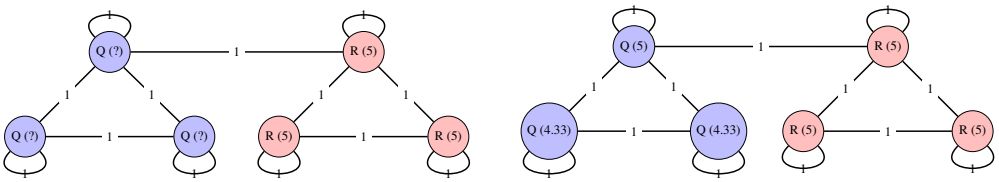

Figure 1: A job applicant network. After applying Feature Propagation [16], the nodes in Q will have feature values that are more distinct from the feature values of the nodes in R than the ground truth.

We call this distinction in imputed feature values between the marginalized and dominant groups the **discrimination risk**. In this paper, we present a theoretically-justified formulation of the discrimination risk of imputed features. We further prove that a higher discrimination risk can amplify the unfairness of a machine learning model (regardless of architecture) trained on the imputed data, which is especially dangerous in high-stakes applications like automated candidate screening and loan approval [28, 29, 30]. For instance, in the automated candidate screening example from above, a model trained on the imputed data may more easily learn to identify and reject disabled job applicants because, on average, they appear to have fewer years of work experience than able-bodied applicants; this would reinforce systemic discrimination against the disabled community [27].

We also formalize a general graph feature imputation framework called **mean aggregation imputation** that encompasses common, diffusion-based graph feature imputation algorithms in the literature. Subsequently, we theoretically and empirically characterize graphs in which applying mean aggregation feature imputation can yield a high discrimination risk, without making any assumptions about underlying distributions or models for unknown feature rates or graph structure. To the best of our knowledge, we are the first to study the effect of graph feature imputation on the fairness of models. This is challenging because we must consider biases stemming from graph structure.

Furthermore, we propose a simple and effective solution to ensure mean aggregation-imputed features provably have a low discrimination risk (while minimally sacrificing reconstruction error) and improve the fairness of models. We do so by viewing mean aggregation imputation through the lens of gradient descent and projecting imputed features into the feasible space of features with low discrimination risk. We empirically evaluate the fairness and accuracy of our solution on synthetic and real-world datasets, finding that it improves fairness without significant loss in reconstruction error on the synthetic datasets but doesn't improve fairness on the real-world datasets. We close by discussing the limitations of our solution.

2 Related work

Feature imputation Feature imputation algorithms utilize known feature values to predict unknown feature values. For example, unknown feature values may be filled as the mean of known values

[16]. However, more intricate feature imputation methods have been proposed in the machine learning, statistics, and epidemiology literature, with popular approaches including matrix completion [31, 32, 33, 34], nearest neighbors [35, 36], multiple imputation via conditional models [37, 38, 39], and causal inference [40, 41]. Notably, while feature imputation may be applied to data with unknown feature values prior to the data being passed to a machine learning model, feature imputation is distinct from label prediction with missing data, wherein models work directly with unknown feature values [42, 43, 44, 45, 46, 47, 48, 49]; we do not consider the latter paradigm in this paper. Works have extended feature imputation approaches for tabular data to incorporate graph structure [50, 51]. Graph feature imputation using deep learning methods is also gaining traction [52, 53, 15]. However, recently, [16] proposed a diffusion-based approach to impute graph features that minimizes the graph's Dirichlet energy (Feature Propagation). In this paper, we focus on a broader class of mean aggregation feature imputation algorithms (formalized in Section 4).

Fairness of missing data and feature imputation Recently, works have theoretically and empirically investigated the impact of missing data [54, 55, 19, 56, 57] and feature imputation on the fairness of machine learning models [55, 58, 59, 60, 30, 61]. These works consistently find that missing data can amplify algorithmic biases, and some show that in practice, feature imputation can yield less unfair (relative to excluding missing data) but nevertheless discriminatory model outcomes. However, these works only study tabular data and do not consider biases that emerge from graph structure [20, 22, 62]. Furthermore, they either do not provide concrete solutions, or they adapt models to directly work with missing data rather than mitigate the unfairness of feature imputation itself. Despite the prevalence of graph feature imputation methods, to the best of our knowledge, there is no research on their influence on the fairness of models that considers graph structure. Some works have explored fairness constraints in semi-supervised settings [63, 64], but they assume that node features are entirely available, which is not the case in feature imputation.

Fair graph machine learning We focus on group fairness, which ensures model predictions exhibit some form of parity between different groups [65, 21, 66, 29, 67, 68]. Works have studied statistical parity, wherein models predict the positive outcome at the same rate for different groups, and equal opportunity, in which the accuracy of model predictions is equivalent across different groups [69]. While our theoretical study of discrimination risk is aligned with statistical parity, we empirically explore the effect of mean aggregation imputation with a lower discrimination risk on both the demographic parity and equal opportunity of models. Mechanisms for improving group fairness have been categorized into pre-processing [22], training-time [21, 23, 70], and post-processing [71, 72]. Our work is similar to pre-processing, as we seek to lower the discrimination risk of imputed training data towards improving model fairness. Recently, there has been a surge of works on modifying graph structure to mitigate topology-induced biases [72, 73, 22, 70, 74, 75]. However, because graph semantics (especially for large graphs) are difficult to interpret, it is unclear if the solutions that these papers propose preserve the semantics of the original graph. On the other hand, our work does not modify graph structure and instead optimally transforms imputed features to have a low discrimination risk. Furthermore, some of these works theoretically characterize graphs with high structural bias [6, 76], but differ from our paper in that we analyze topology bias in the setting of feature imputation. [77] investigates the fairness of graph neural networks in the presence of limited group membership information but does not consider imputation; in contrast, our work assumes group membership is fully available but that features are not.

3 Discrimination risk and model unfairness

As machine learning is increasingly used in consequential applications like loan approval and automated candidate screening [28, 29, 30], ensuring its fairness is critical. To understand how feature imputation could amplify the unfairness of a machine learning model, we present a theoretically-justified metric called the discrimination risk, which applies beyond the setting of graphs and is agnostic to model architecture. We explore discrimination risk in the context of graphs in Section 5.

Suppose we have a data distribution $\mathcal{D}$. Furthermore, we have two groups: a marginalized group Q and a dominant group R. For any data instance $(x, y, s) \sim \mathcal{D}$, let $x \in \mathcal{X}$ be the d-dimensional feature values of the instance (where x_i denotes the i-th entry of x), let $y \in \mathcal{Y}$ be the label of the instance, and let $s \in \{Q, R\}$ be the group membership of the instance. We will assume that we can observe

the group membership of any data instance and that no instance can belong to both the marginalized group and dominant group.

Definition 1 (Discrimination Risk) We define the discrimination risk of $\mathcal{D}$ as:

$$\mathcal{R}_{\mathcal{D}} = \max_{i \in [d]} \left| \mathbb{E}_{(x,y,s)\sim\mathcal{D}}[x_i | s = Q] - \mathbb{E}_{(x,y,s)\sim\mathcal{D}}[x_i | s = R] \right|, \tag{1}$$

where $[d]$ is the set $\{1, \ldots, d\}$.

We now explore the relevance of discrimination risk to model unfairness. Let $\mathcal{D}'$ be the data distribution with the ground-truth features and $\mathcal{D}$ be the distribution with imputed features. We will show that if $\mathcal{R}_{\mathcal{D}} > \mathcal{R}_{\mathcal{D}'}$, imputation may amplify model unfairness.

To be concrete, let's again consider the example of an automated candidate screening system. Let $S \in \{Q, R\}$ be the marginal distribution over the group membership of job applicants. Furthermore, let $X' \in \mathcal{X}$ be the marginal distribution over the ground-truth feature values of applicants (e.g. number of years previously worked, highest degree, etc.) In contrast, let $X \in \mathcal{X}$ be the distribution over imputed feature values of applicants. Let $Y \in \mathcal{Y}$ be the marginal distribution over applicant labels (e.g. whether an applicant should be hired, a screening score for an applicant, etc.) Now, let h' be a model trained on samples from $\mathcal{D}'$, and h be another model trained on samples from $\mathcal{D}$. Additionally, let $Z' \in \mathcal{Y}$ be the distribution over the predictions of h' on instances sampled from X, and let $Z \in \mathcal{Y}$ be the distribution over predictions of h on instances sampled from X.

We have the dependencies $S \to X'$ and $S \to X$ because disability affects the number of years previously worked by a job applicant. $S \to X$ may be additionally necessary because S can influence the feature imputation algorithm. Furthermore, we assume that h' and h have access to the feature values of an applicant, but not the applicant's group membership, and that the association of S with Z' through Y can be fully explained by X'. Thus, Z' is conditionally independent of S given X'. Similarly, we assume that the association of S with Z through Y can be fully explained by X, so Z is conditionally independent of S given X.

Because we are interested in how feature imputation may amplify model unfairness, we investigate when the statistical parity or total variation distance $d_{TV}(Z|S = Q, Z|S = R) > d_{TV}(Z'|S = Q, Z'|S = R)$ [78], where $Z|S = Q$ is the conditional prediction distribution given group-Q membership. d_{TV} measures the distance between two probability distributions A and B as $d_{TV}(A, B) = \sup_{x\in\mathcal{F}} |A(x) - B(x)|$. Intuitively, $d_{TV}(Z|S = Q, Z|S = R)$ captures how much the prediction distribution of h absolutely differs between Q and R, and thus it quantifies the (statistical parity) unfairness of h. We now discuss the relationships of $d_{TV}(Z'|S = Q, Z'|S = R)$ to $d_{TV}(X'|S = Q, X'|S = R)$ and $d_{TV}(Z|S = Q, Z|S = R)$ to $d_{TV}(X|S = Q, X|S = R)$. We begin with the following lemma from [79].

Lemma 1 (Corollary 17 from [79]) By the Data Processing Inequality, $d_{TV}(Z'|S = Q, Z'|S = R) \leq d_{TV}(X'|S = Q, X'|S = R)$ and $d_{TV}(Z|S = Q, Z|S = R) \leq d_{TV}(X|S = Q, X|S = R)$.

Please refer to Section A.1 for the proof of Lemma 1. At a high level, Lemma 1 states that the unfairness of any model is bounded above by the statistical parity distance of the features between the groups. We now use Lemma 1 to prove the following theorem that connects $d_{TV}(Z'|S = Q, Z'|S = R)$ to $\mathcal{R}_{\mathcal{D}'}$ and $d_{TV}(Z|S = Q, Z|S = R)$ to $\mathcal{R}_{\mathcal{D}}$.

Theorem 1 Suppose $X'|S = Q \sim \mathcal{N}(\mu'_Q, \Sigma'_Q)$; $X'|S = R \sim \mathcal{N}(\mu'_R, \Sigma'_R)$; $X|S = Q \sim \mathcal{N}(\mu_Q, \Sigma_Q)$; and $X|S = Q \sim \mathcal{N}(\mu_Q, \Sigma_Q)$. We then get the following bounds:

$$\mathrm{d}_{TV}(Z'|S = Q, Z'|S = R) \in \left[\frac{1}{\frac{4\cdot\max\{\lambda_{max}(\Sigma'_Q), \lambda_{max}(\Sigma'_R)\}}{C'\cdot\mathcal{R}^2_{\mathcal{D}'}} + 1}, \sqrt{1 - \sqrt{\frac{\det\Sigma'_Q}{\det\Sigma'_R} \cdot e^{-\frac{C'\cdot\mathcal{R}^2_{\mathcal{D}'}}{\lambda_{min}(\Sigma'_R)} - tr(\Sigma'^{-1}_R\Sigma'_Q) + d}}} \right]$$

$$\mathrm{d}_{TV}(Z|S = Q, Z|S = R) \in \left[\frac{1}{\frac{4\cdot\max\{\lambda_{max}(\Sigma_Q), \lambda_{max}(\Sigma_R)\}}{C\cdot\mathcal{R}^2_{\mathcal{D}}} + 1}, \sqrt{1 - \sqrt{\frac{\det\Sigma_Q}{\det\Sigma_R} \cdot e^{-\frac{C\cdot\mathcal{R}^2_{\mathcal{D}}}{\lambda_{min}(\Sigma_R)} - tr(\Sigma_R^{-1}\Sigma_Q) + d}}} \right]$$

where $0 \leq C' \leq d$ and $0 \leq C \leq d$. Please refer to Section A.2 for the proof of Theorem 1. This result suggests that minimizing $\mathcal{R}_{\mathcal{D}}$ can minimize the unfairness of the model trained on the imputed data. Furthermore, it is possible that $\mathcal{R}_{\mathcal{D}} > \mathcal{R}_{\mathcal{D}'}$, in which case feature imputation may amplify the unfairness of a model. While our definition of discrimination risk applies beyond the setting of graphs

and is agnostic to the model architecture, in practice, it is important to consider model complexity and the context of the task. We also add that our definition of discrimination risk bears resemblance to the Average Treatment Effect studied in causality [80]. Furthermore, for clarity, we note that [58] has previously proposed a metric also called discrimination risk which quantifies how much the deviation of imputed feature values from the ground-truth feature values differs across groups; this quantity is related to the equal opportunity of a model trained on the imputed data. In contrast, our definition of discrimination risk simply measures how much imputed features differ across groups and is more aligned with the statistical parity of a model. Statistical parity and equal opportunity are mutually exclusive, except in degenerate cases [18]. We leave extending our definition of discrimination risk to other notions of fairness for future work [69].

4 Overview of graph feature imputation

Prior to investigating the discrimination risk of graph feature imputation, we first present a general framework for mean aggregation feature imputation that encompasses common, diffusion-based graph feature imputation algorithms in the literature.

Suppose we have an undirected, possibly weighted homogeneous graph $G = (V, E)$. Each node has d features, hence the node feature matrix $X \in \mathbb{R}^{N \times d}$, where $N = |V|$, the cardinality of the set. For simplicity, we will assume that $d = 1$ in our analyses and extend our results to the case $d > 1$ afterwards. Feature values are unknown for some nodes in G (denoted as the set U), and known for others (denoted as the set K). The feature value of each node is either known or unknown, i.e. $U \cup K = V$ and $U \cap K = \emptyset$. Let X_S refer to the feature values of the nodes in set S. Assume without loss of generality that $X = \begin{bmatrix} X_K \\ X_U \end{bmatrix}$. Furthermore, let $A \in \mathbb{R}^{N \times N}$ denote the weighted adjacency matrix of G, where A_{ij} is the nonnegative weight corresponding to the edge from node j to node i. Additionally, let $A_{S_1 S_2}$ denote the submatrix of A with rows belonging to the nodes in set S_1 and columns belonging to the nodes in set S_2. Let $A := \begin{bmatrix} A_{KK} & A_{KU} \\ A_{UK} & A_{UU} \end{bmatrix}$. D is the diagonal degree matrix, i.e. $D_{ii} = \sum_{j=1}^{N} A_{ij}$ and $D := \begin{bmatrix} D_K & 0 \\ 0 & D_U \end{bmatrix}$.

Definition 2 (Mean Aggregation Feature Imputation) Denote the feature values at iteration t of mean aggregation feature imputation as $X^{(t)}$. Furthermore, let $X_S^{(t)}$ refer to the feature values of the nodes in set S at iteration t. Then, at each iteration t:

$$MX^{(t+1)} := \phi(MX^{(t)}) = \begin{bmatrix} \beta I_{|K|} & 0 \\ 0 & I_{|U|} \end{bmatrix} TMX^{(t)} + \begin{bmatrix} (1-\beta) I_{|K|} & 0 \\ 0 & 0 \end{bmatrix} MX^{(0)}, \tag{2}$$

where $M : \mathbb{R}^N \to \mathbb{R}^N$ is a diagonal invertible map, $T \in \mathbb{R}^{N \times N}$ is a right-stochastic matrix, and $\beta \in [0, 1]$ is a regularization hyperparameter.

We can see that mean aggregation feature imputation treats channels independently (i.e. does not support channel mixing), and only works with continuous (not discrete) features. Mean aggregation encompasses many common graph-agnostic and graph-aware feature imputation methods, including **Global Mean** (sets the unknown features to the uniform mean of all the known features), **Neighbor Mean** (sets the unknown features to the degree-weighted mean of the known features for neighboring nodes), **Feature Propagation** (predicts the unknown features to minimize the Dirichlet energy of the graph while preserving the known feature values), and **Graph Regularization** (predicts the unknown features via a smoothness constraint and a fitting constraint for the known features). For proofs, refer to Section A.3. Despite Neighbor Mean, Feature Propagation, and Graph Regularization being intended for homophilic graphs [16], mean aggregation feature imputation encompasses algorithms that could perform well on heterophilic graphs as well, with an appropriate choice of T [16]. We also note that T cannot be A, as this might cause feature values to explode over multiple iterations.

5 Discrimination risk of mean aggregation feature imputation

To better understand how mean aggregation feature imputation amplifies the unfairness of a machine learning model, we theoretically characterize graphs in which mean aggregation imputation increases

the discrimination risk, without making any assumptions about underlying distributions or models for unknown feature rates or graph structure.

We begin by defining new notation. In particular, we first focus on the case of a single feature (i.e. $d = 1$), and extend our analysis to the case $d > 1$ in Section A.6. Let X_v be the feature of a node v. Let Q denote the set of nodes that belong to the marginalized group, and R denote the set of nodes that belong to the dominant group. We will assume that $Q \cup R = V$ and $Q \cap R = \emptyset$. We define the discrimination risk after t iterations of mean aggregation imputation as:

$$\mathcal{R}^{(t)} := \left| \mathbb{E}_{q \sim Q}[X_q^{(t)}] - \mathbb{E}_{r \sim R}[X_r^{(t)}] \right| \tag{3}$$

where the expectations are taken uniformly over the nodes in each set. Now, define $\tilde{X} := MX$. Then, a modified version of the discrimination risk after t iterations of mean aggregation imputation is $\tilde{\mathcal{R}}^{(t)} := \left| \mathbb{E}_{q \sim Q}[\tilde{X}_q^{(t)}] - \mathbb{E}_{r \sim R}[\tilde{X}_r^{(t)}] \right|$. We now bound the discrimination risk $\tilde{\mathcal{R}}^{(t)}$ of the imputed features with respect to $\tilde{\mathcal{R}}^{(0)}$. We bound $\tilde{\mathcal{R}}^{(t)}$ rather than $\mathcal{R}^{(t)}$ for simplicity; however, we empirically validate that the bound properties also hold for $\mathcal{R}^{(t)}$ in Section 7.

We begin with Theorem 2. Define $\tilde{\mu}_Q^{(t)} := \mathbb{E}_{q \sim Q}[\tilde{X}_q^{(t)}]$ and $\tilde{\mu}_R^{(t)} := \mathbb{E}_{r \sim R}[\tilde{X}_r^{(t)}]$. Furthermore, let $\tilde{\sigma}^{(t)}$ denote the maximal deviation of the feature values at iteration t, i.e. $\forall q_1 \in Q, |\tilde{X}_{q_1}^{(t)} - \tilde{\mu}_Q^{(t)}| \leq \max_{q_2 \in Q} |\tilde{X}_{q_1}^{(t)} - \tilde{X}_{q_2}^{(t)}| \leq \tilde{\sigma}^{(t)}$ and $\forall r_1 \in R, |\tilde{X}_{r_1}^{(t)} - \tilde{\mu}_R^{(t)}| \leq \max_{r_2 \in R} |\tilde{X}_{r_1}^{(t)} - \tilde{X}_{r_2}^{(t)}| \leq \tilde{\sigma}^{(t)}$. Additionally, define $T_{S_1 \to S_2} := \sum_{b \in S_2} \sum_{a \in S_1} T_{ba}$.

Theorem 2 Let the contraction coefficient $\alpha := \left| 1 - \frac{T_{R \to Q \cap U} + \beta T_{R \to Q \cap K}}{|Q|} - \frac{T_{Q \to R \cap U} + \beta T_{Q \to R \cap K}}{|R|} \right|$. Then, $\alpha \leq 1$, and:

$$\max \left\{ \alpha^t \tilde{\mathcal{R}}^{(0)} - 2 \left(\sum_{j=0}^{t-1} \alpha^j \right) \tilde{\sigma}^{(0)}, 0 \right\} \leq \tilde{\mathcal{R}}^{(t)} \leq \alpha^t \tilde{\mathcal{R}}^{(0)} + 2 \left(\sum_{j=0}^{t-1} \alpha^j \right) \tilde{\sigma}^{(0)}$$

$$\alpha < 1 \implies \lim_{t \to \infty} \tilde{\mathcal{R}}^{(t)} \leq \frac{2\tilde{\sigma}^{(0)}}{1 - \alpha}.$$

Please refer to Section A.4 for a proof of Theorem 2. Theorem 2 shows that the bounds on the discrimination risk contract more slowly (with more iterations of mean aggregation feature imputation) with a larger α. Furthermore, the upper bound on the discrimination risk is larger with a larger α and may depend on the initial unknown node features. Theorem 2 allows for interesting interpretations of how graph properties like the rate of unknown features, group size, and graph structure affect the discrimination risk of mean aggregation feature imputation. In Section A.5, we successively vary each property (holding all other properties constant) and investigate its impact on α, and in turn the discrimination risk. We find that a low unknown feature rate for both groups or disparate unknown feature rates across the groups and a low inter-link to intra-link ratio can increase α, and thus the discrimination risk of mean aggregation-imputed features. Additionally, group size alone may not affect α or the discrimination risk.

6 Fair graph feature imputation

We propose a simple and effective solution to ensure mean aggregation feature imputation provably has a low discrimination risk while minimally sacrificing reconstruction error. At a high level, we want to constrain the discrimination risk at every iteration t of imputation to be at most ϵ, i.e. $\forall t \in [0, \infty), \mathcal{R}^{(t)} \leq \epsilon$. We do this by viewing mean aggregation imputation through a gradient descent lens and projecting imputed features into the feasible space of features with discrimination risk at most ϵ at each iteration [81]. We focus on a single feature i, but our algorithms can be extended to all features by applying them to each feature separately.

We begin with the case where the known feature values remain fixed, i.e. $\beta = 0$. Recall the iterative algorithm for mean aggregation feature imputation when $\beta = 0$:

$$MX^{(t+1)} := \phi(MX^{(t)}) = \begin{bmatrix} 0 & 0 \\ 0 & I_{|U|} \end{bmatrix} TMX^{(t)} + \begin{bmatrix} I_{|K|} & 0 \\ 0 & 0 \end{bmatrix} MX^{(0)}.$$

We see that $\forall t \in [0, \infty), X_K^{(t)} = X_K$. Furthermore, define $\Delta := I_N - M^{-1}TM$. In the case of Feature Propagation, $\Delta = I_N - D^{\frac{1}{2}}(D^{-1}A)D^{-\frac{1}{2}} = I_N - D^{-\frac{1}{2}}AD^{-\frac{1}{2}}$ is the symmetric normalized Laplacian of G [16]. We see that $X_U^{(t+1)} = (I_N - \Delta)_{UU}X_U^{(t)} - \Delta_{UK}X_K$. As discussed in [16], we can view the update $X_U^{(t+1)} := X_U^{(t)} - \gamma(\Delta_{UU}X_U^{(t)} + \Delta_{UK}X_K)$ as an iteration of gradient descent (with step size $\gamma = 1$) on the objective function $\ell(x) = \frac{1}{2}x^T\Delta_{UU}x + X_K^T\Delta_{KU}x + \frac{1}{2}X_K^T\Delta_{KK}X_K$, where X_K is constant. For Feature Propagation, ℓ is the Dirichlet energy of G [16]. We now present a theorem that shows how to perform mean aggregation feature imputation with a discrimination risk of at most ϵ when the known feature values remain fixed.

Theorem 3 (ϵ-Fair Imputation, $\beta = 0$) Vanilla mean aggregation feature imputation updates $X_U^{(t+1)} := X_U^{(t)} - \gamma(\Delta_{UU}X_U^{(t)} + \Delta_{UK}X_K) = Z_U^{(t)}$, where $\gamma = 1$. Let ϵ-fair mean aggregation feature imputation instead update $X_U^{(t+1)} := P_W Z_U^{(t)} + P_B$, where:

$$P_W = \begin{cases} I_{|U|}, & \mathcal{R}_K - \epsilon \leq c^T Z_U^{(t)} \leq \mathcal{R}_K + \epsilon \\ I_{|U|} - \frac{cc^T}{c^Tc}, & \text{otherwise} \end{cases}, P_B = \frac{cc^T}{c^Tc} \begin{cases} \mathcal{R}_K - \epsilon, & c^T Z_U^{(t)} < \mathcal{R}_K - \epsilon \\ \mathcal{R}_K + \epsilon, & c^T Z_U^{(t)} > \mathcal{R}_K + \epsilon \\ 0, & \text{otherwise} \end{cases}$$

$$\mathcal{R}_K = \frac{1}{|R|}\sum_{r \in R \cap K} X_r - \frac{1}{|Q|}\sum_{q \in Q \cap K} X_q$$

$$c \in \mathbb{R}^{|U|}, c^T Z_U^{(t)} = \frac{1}{|Q|}\sum_{q \in Q \cap U} Z_q^{(t)} - \frac{1}{|R|}\sum_{r \in R \cap U} Z_r^{(t)}$$

Then, assuming $0 \leq \lambda_{min}(\Delta_{UU}) \leq \lambda_{max}(\Delta_{UU}) < 1$ (where λ_{min} and λ_{max} are the minimum and maximum eigenvalues, respectively): 1) a unique optimal (with respect to ℓ) feasible solution X_U^* exists; 2) for fixed step size $\gamma = \frac{1}{\lambda_{max}(\Delta_{UU})}$, ϵ-fair imputation converges as $\|X_U^{(t)} - X_U^*\|_2^2 \leq \left(1 - \frac{\lambda_{min}(\Delta_{UU})}{\lambda_{max}(\Delta_{UU})}\right)^t \|X_U^{(0)} - X_U^*\|_2^2$; 3) for fixed step size $\gamma = 1$, ϵ-fair imputation converges to X_U^*.

Please refer to Section A.7 for a proof of Theorem 3. The convergence of our solution to the unique optimal (with respect to ℓ) feasible solution implies that our solution provably has a discrimination risk of at most ϵ while minimally sacrificing reconstruction error. Furthermore, because our solution simply interleaves projections into the mean aggregation imputation framework, it preserves the framework's speed and scalability [16]. We similarly have a solution when $\beta > 0$, i.e. when the known node feature values do not remain fixed, which we present in Section A.8.

7 Experimental results and discussion

We empirically evaluate the fairness and reconstruction error of our solution on various mean aggregation feature imputation algorithms and synthetic and real-world datasets. We find that while our solution yields improved fairness without significant loss in reconstruction error on the synthetic datasets, there is not an improvement in fairness on the real-world datasets.

Datasets We construct undirected two-block synthetic networks (`SBM`) using `StochasticBlockModelDataset` from PyTorch Geometric [82] (where one block corresponds to the marginalized group Q and the other block to the dominant group R) with various (relative) group sizes and inter- and intra-link rates (more information in Section B.1). `SBM` does not have a corresponding task, i.e. the nodes do not have labels. We also use the real-world `Credit defaulter` and `German credit` networks from [29]. The `Credit defaulter` network consists of 30,000 nodes representing individuals, with edges between them indicating similar spending and payment patterns. The corresponding task is to predict whether an individual will default on their credit card payment or not, and the groups are those 25 years old or younger and those above the age of 25 (more information in Section B.1). The `German credit` network comprises 1,000 nodes representing clients in a German bank who are connected if they have similar credit accounts. The corresponding task is to predict whether a client has good or bad credit risk, and the groups are men and women (more information in Section B.1). (In reality, gender is neither binary nor static, and treating it as such can produce harms [83].) We refrain from using the `Recidivism graph` from [29] so as not to support the development of carceral technology [84].

Protocols and performance evaluation By default, none of the datasets contain unknown or missing features. To simulate diverse scenarios with unknown features, for each group, we independently at random mark node feature values as unknown with a different probability. We experiment with all 25 combinations of unknown feature rates of $\{0.1, 0.3, 0.5, 0.7, 0.9\}$ for the groups. Nodes, even within the same group, may have different unknown features. We choose this scheme to study the effect of disparate unknown feature rates across the groups, which reflects the real world [17, 18, 19, 20]. We encourage future empirical work on other unknown feature schemes, including missingness based on node degree or marking all or none of the features for each node as unknown.

To impute unknown features, we use the regular mean aggregation imputation algorithms overviewed in Section 4: Global Mean (GM), Neighbor Mean (NM), Feature Propagation (FP), and Graph Regularization (GR) (with $\beta = 0.25$), and their ϵ-fair counterparts (for $\epsilon \in \{0.0, 0.025, 0.05\}$). For models, we use a simple linear classifier ($linear$), two-layer MLP (mlp), and Graph Convolutional Network (gcn) [2] (more information in Section B.3). We train all models on the imputed data, but validate and test on fully-observed data. Because there are no previous works (to the best of our knowledge) that directly address the unfairness of graph feature imputation, we do not have baselines against which to compare.

To evaluate imputed features for `SBM`, since we don't have labels, we employ relative reconstruction error $\mathbf{RE}$ [16]. For the real-world datasets, we consider the test accuracy ($\mathbf{Acc}$) of models trained on the imputed data. To evaluate group fairness, we compute the discrimination risk ($\mathbf{DR}$) of the imputed data. For `SBM`, we also train models on the imputed data to predict group membership and calculate the test accuracy of the models on identifying group membership (which we refer to as $\mathbf{MI}$) [85, 21]. To evaluate group fairness for the real-world datasets, we use the test statistical parity ($\mathbf{SP}$) of the models, defined as $|P(Z = 1|S = Q) - P(Z = 1|S = R)|$ [78], and test equal opportunity ($\mathbf{EO}$), defined as $|P(Z = 1|S = Q, Y = 1) - P(Z = 1|S = R, Y = 1)|$ [86]. Please refer to Section B.4 for more details on the metrics. For all metrics, we report the mean and standard error over 5 runs using different random seeds. On each run, a new dataset (in the case of `SBM`) is generated, new splits are created, and a new model is trained.

Q1. Does the contraction coefficient α align with the discrimination risk of mean aggregation imputation across graphs with different properties? Figures 2 to 12 in the Appendix show that for `SBM`, discrimination risk and α generally have a strong positive association over unknown feature rates, group sizes, and inter-link rate to intra-link rate ratios, which substantiates Theorem 2. This association is weaker for Global Mean and Neighbor Mean. Refer to Section B.5 for more details.

Q2. Does ϵ-fair mean aggregation imputation (compared to regular mean aggregation imputation) improve the group fairness of a model trained on the imputed data? Table 1 shows that, for `SBM`, ϵ-fair mean aggregation imputation achieves comparable reconstruction error to its regular counterpart while greatly reducing the discrimination risk and test group membership identification accuracy for all models. As expected, we see that the discrimination risk of ϵ-fair imputation is at most ϵ, and discrimination risk and test group membership identification accuracy are positively correlated, which substantiates Theorem 1. Furthermore, the reconstruction error for ϵ-fair FP and GR (which leverage graph structure and are thus more susceptible to graph structural bias) are much lower than that of the naïve ϵ-fair GM (which is graph-agnostic), but fair FP and GR reduce the discrimination risk and test group membership identification accuracy for all models to similar levels as fair GM. However, the test group membership identification accuracy generally decreases less as ϵ decreases for mlp and gcn than it does for $linear$, which suggests that minimizing the discrimination risk of imputed features is more effective at removing linearly-encoded group membership information than non-linearly encoded information. Furthermore, ϵ-fair feature imputation does not guard against group membership information that gcn learns via graph structure during training. We have similar findings when averaging over different relative group sizes (refer to Table 3) and combinations of inter- and intra-link rates (refer to Table 4).

In contrast, Tables 2 and 6 (in the Appendix) show that, for the real-world datasets, regular mean aggregation imputation and its ϵ-fair counterpart yield comparable test accuracy and statistical parity fairness for all models. In the case of `Credit defaulter`, our solution even appears to exacerbate the unfairness of gcn. We suspect this is because the datasets already produce models with low fairness, upon which it is difficult for our ϵ-fairness solution to improve. We were unable to reproduce similar unfairness results to those in [29], even when all features are known. We find similar results for equal opportunity, as shown in Tables 5 and 7.

Table 1: Reconstruction error (**RE**), discrimination risk (**DR**), and test group membership identification accuracy (**MI**) of all models averaged over all 25 combinations of unknown feature rates of $\{0.1, 0.3, 0.5, 0.7, 0.9\}$ for each group in `SBM`. We use 0.5 relative group sizes and 0.5 inter- and intra-link rates.

Method	RE ↓	DR ↓	$\mathbf{MI}_{linear}$ ↓	$\mathbf{MI}_{mlp}$ ↓	$\mathbf{MI}_{gcn}$ ↓
0-Fair GM	1.21 ± 0.021	$\mathbf{0 \pm 0}$	$\mathbf{0.602 \pm 0.098}$	$\mathbf{0.669 \pm 0.019}$	$\mathbf{0.504 \pm 0.038}$
0.025-Fair GM	1.204 ± 0.021	0.021 ± 0.002	0.72 ± 0.087	0.683 ± 0.01	0.551 ± 0.069
0.05-Fair GM	1.196 ± 0.02	0.034 ± 0.005	0.736 ± 0.037	0.69 ± 0.014	0.535 ± 0.058
Regular GM	$\mathbf{1 \pm 0}$	0.051 ± 0.015	0.817 ± 0.02	0.817 ± 0.013	0.651 ± 0.089
0-Fair NM	1.19 ± 0.02	$\mathbf{0 \pm 0}$	$\mathbf{0.599 \pm 0.094}$	$\mathbf{0.686 \pm 0.021}$	$\mathbf{0.507 \pm 0.04}$
0.025-Fair NM	1.183 ± 0.02	0.02 ± 0.002	0.72 ± 0.084	0.706 ± 0.013	0.552 ± 0.059
0.05-Fair NM	1.175 ± 0.019	0.033 ± 0.004	0.734 ± 0.037	0.706 ± 0.02	0.539 ± 0.052
Regular NM	$\mathbf{0.977 \pm 0.002}$	0.048 ± 0.014	0.828 ± 0.021	0.818 ± 0.013	0.631 ± 0.094
0-Fair FP	1.184 ± 0.020	$\mathbf{0 \pm 0}$	$\mathbf{0.6 \pm 0.096}$	$\mathbf{0.702 \pm 0.02}$	$\mathbf{0.505 \pm 0.034}$
0.025-Fair FP	1.176 ± 0.020	0.018 ± 0.003	0.716 ± 0.076	0.724 ± 0.014	0.562 ± 0.058
0.05-Fair FP	1.169 ± 0.019	0.025 ± 0.006	0.72 ± 0.03	0.723 ± 0.018	0.531 ± 0.058
Regular FP	$\mathbf{0.977 \pm 0.003}$	0.028 ± 0.009	0.814 ± 0.023	0.817 ± 0.012	0.612 ± 0.079
0-Fair GR	1.006 ± 0.004	$\mathbf{0 \pm 0}$	$\mathbf{0.588 \pm 0.093}$	$\mathbf{0.713 \pm 0.022}$	$\mathbf{0.511 \pm 0.039}$
0.025-Fair GR	1.005 ± 0.004	0.023 ± 0.002	0.757 ± 0.055	0.741 ± 0.012	0.577 ± 0.078
0.05-Fair GR	1.003 ± 0.004	0.039 ± 0.006	0.772 ± 0.027	0.744 ± 0.016	0.538 ± 0.066
Regular GR	$\mathbf{0.977 \pm 0.003}$	0.021 ± 0.007	0.814 ± 0.024	0.821 ± 0.01	0.604 ± 0.08

Table 2: Test accuracy (**Acc**) and statistical parity (**SP**) of all models averaged over all 25 combinations of unknown feature rates of $\{0.1, 0.3, 0.5, 0.7, 0.9\}$ for each group in `German credit`.

Method	$\mathbf{Acc}_{linear}$ ↑	$\mathbf{Acc}_{mlp}$ ↑	$\mathbf{Acc}_{gcn}$ ↑	$\mathbf{SP}_{linear}$ ↓	$\mathbf{SP}_{mlp}$ ↓	$\mathbf{SP}_{gcn}$ ↓
0.0-Fair GM	0.700 ± 0.006	0.707 ± 0.003	$\mathbf{0.699 \pm 0.002}$	0.051 ± 0.016	0.028 ± 0.004	0.011 ± 0.01
0.025-Fair GM	$\mathbf{0.705 \pm 0.003}$	0.707 ± 0.003	0.698 ± 0.002	0.044 ± 0.012	0.028 ± 0.007	0.02 ± 0.026
0.05-Fair GM	0.704 ± 0.007	$\mathbf{0.708 \pm 0.004}$	0.697 ± 0.002	$\mathbf{0.034 \pm 0.009}$	0.029 ± 0.003	0.013 ± 0.005
Regular GM	0.701 ± 0.002	0.708 ± 0.004	0.699 ± 0.001	0.043 ± 0.01	$\mathbf{0.025 \pm 0.005}$	$\mathbf{0.006 \pm 0.005}$
0.0-Fair NM	0.699 ± 0.005	0.706 ± 0.003	0.697 ± 0.003	0.053 ± 0.015	$\mathbf{0.033 \pm 0.007}$	$\mathbf{0.007 \pm 0.006}$
0.025-Fair NM	$\mathbf{0.7 \pm 0.006}$	0.706 ± 0.003	0.697 ± 0.002	$\mathbf{0.041 \pm 0.009}$	0.037 ± 0.007	0.015 ± 0.013
0.05-Fair NM	0.7 ± 0.006	0.706 ± 0.003	0.697 ± 0.002	0.046 ± 0.013	0.033 ± 0.005	0.01 ± 0.003
Regular NM	0.7 ± 0.003	$\mathbf{0.708 \pm 0.001}$	$\mathbf{0.698 \pm 0.001}$	0.044 ± 0.02	0.034 ± 0.007	0.016 ± 0.007
0.0-Fair FP	0.694 ± 0.021	$\mathbf{0.713 \pm 0.011}$	$\mathbf{0.704 \pm 0.007}$	$\mathbf{0.012 \pm 0.012}$	0.025 ± 0.025	0.019 ± 0.039
0.025-Fair FP	$\mathbf{0.708 \pm 0.012}$	0.706 ± 0.012	0.689 ± 0.027	0.024 ± 0.028	0.026 ± 0.026	0.026 ± 0.057
0.05-Fair FP	0.702 ± 0.03	0.706 ± 0.011	0.708 ± 0.046	0.078 ± 0.01	$\mathbf{0.023 \pm 0.026}$	$\mathbf{0 \pm 0}$
Regular FP	0.7 ± 0.024	0.708 ± 0.012	0.698 ± 0.01	0.063 ± 0.069	0.03 ± 0.02	0.007 ± 0.01
0.0-Fair GR	0.698 ± 0.005	$\mathbf{0.703 \pm 0.004}$	0.698 ± 0.001	0.04 ± 0.02	$\mathbf{0.021 \pm 0.003}$	0.006 ± 0.007
0.025-Fair GR	$\mathbf{0.702 \pm 0.004}$	0.702 ± 0.002	$\mathbf{0.7 \pm 0.001}$	0.041 ± 0.014	0.025 ± 0.002	0.008 ± 0.01
0.05-Fair GR	0.699 ± 0.004	0.703 ± 0.003	0.699 ± 0.003	$\mathbf{0.034 \pm 0.01}$	0.024 ± 0.004	$\mathbf{0.005 \pm 0.005}$
Regular GR	0.697 ± 0.003	0.703 ± 0.003	0.7 ± 0.001	0.038 ± 0.017	0.027 ± 0.005	0.01 ± 0.009

8 Conclusion

We prove that a higher discrimination risk can amplify the unfairness of a machine learning model trained on imputed data. We formalize a general graph feature imputation framework called mean aggregation imputation and theoretically and empirically characterize graphs in which applying the framework can yield a high discrimination risk. We propose a simple and effective solution to ensure mean aggregation-imputed features provably have a low discrimination risk (while minimally sacrificing reconstruction error) and improve the fairness of models.

Our analysis and solution, like many fair machine learning algorithms, assume that groups are discrete and that group membership is known and static, which is not true in reality [81, 83, 26]. Furthermore, we don't consider fairness at the intersections of different groups [87, 88], and operationalizations of fairness beyond parity between two groups [89]; we encourage future work in these directions. Furthermore, while fairness is often framed as sufficient for the creation of ethical systems, this is not necessarily the case. For instance, ϵ-fair mean aggregation feature imputation may be used to train a more fair model that diversifies news recommendations to social media users [6], but if this model recommends hostile or intolerant news sources to LGBTQIA+ users, this could lead to psychological harm [81]. We remind readers to carefully consider the ethics of downstream model use cases.

References

[1] Franco Scarselli, Marco Gori, Ah Chung Tsoi, Markus Hagenbuchner, and Gabriele Monfardini. The graph neural network model. *IEEE Transactions on Neural Networks*, 20(1):61–80, 2009.

[2] Thomas N. Kipf and Max Welling. Semi-Supervised Classification with Graph Convolutional Networks. In *Proceedings of the 5th International Conference on Learning Representations*, ICLR '17, 2017.

[3] William L. Hamilton, Rex Ying, and Jure Leskovec. Inductive representation learning on large graphs. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS'17, page 1025–1035, Red Hook, NY, USA, 2017. Curran Associates Inc.

[4] Petar Velickovic, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio', and Yoshua Bengio. Graph attention networks. *ArXiv*, abs/1710.10903, 2018.

[5] Hanqing Zeng, Hongkuan Zhou, Ajitesh Srivastava, Rajgopal Kannan, and Viktor K. Prasanna. Graphsaint: Graph sampling based inductive learning method. *ArXiv*, abs/1907.04931, 2020.

[6] Peizhao Li, Yifei Wang, Han Zhao, Pengyu Hong, and Hongfu Liu. On dyadic fairness: Exploring and mitigating bias in graph connections. In *International Conference on Learning Representations*, 2021.

[7] Weihua Hu, Matthias Fey, Marinka Zitnik, Yuxiao Dong, Hongyu Ren, Bowen Liu, Michele Catasta, and Jure Leskovec. Open graph benchmark: Datasets for machine learning on graphs. *ArXiv*, abs/2005.00687, 2020.

[8] Wenqi Fan, Yao Ma, Qing Li, Yuan He, Eric Zhao, Jiliang Tang, and Dawei Yin. Graph neural networks for social recommendation, 2019.

[9] Shiwen Wu, Wentao Zhang, Fei Sun, and Bin Cui. Graph neural networks in recommender systems: A survey. *ArXiv*, abs/2011.02260, 2020.

[10] Shichang Zhang, Ziniu Hu, Arjun Subramonian, and Yizhou Sun. Motif-driven contrastive learning of graph representations, 2021.

[11] Oliver Wieder, Stefan Kohlbacher, Mélaine Kuenemann, Arthur Garon, Pierre Ducrot, Thomas Seidel, and Thierry Langer. A compact review of molecular property prediction with graph neural networks. *Drug Discovery Today: Technologies*, 37:1–12, 2020.

[12] Jeffrey M. Wooldridge. Inverse probability weighted estimation for general missing data problems. *Journal of Econometrics*, 141(2):1281–1301, 2007.

[13] Jonathan A. C. Sterne, Ian R. White, John B. Carlin, Michael Spratt, Patrick Royston, Michael G. Kenward, Angela M. Wood, and James R. Carpenter. Multiple imputation for missing data in epidemiological and clinical research: potential and pitfalls. *The BMJ*, 338, 2009.

[14] Preethi Lahoti, Alex Beutel, Jilin Chen, Kang Lee, Flavien Prost, Nithum Thain, Xuezhi Wang, and Ed Chi. Fairness without demographics through adversarially reweighted learning. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 728–740. Curran Associates, Inc., 2020.

[15] Indro Spinelli, Simone Scardapane, and Aurelio Uncini. Missing data imputation with adversarially-trained graph convolutional networks. *Neural networks : the official journal of the International Neural Network Society*, 129:249–260, 2020.

[16] Emanuele Rossi, Henry Kenlay, Maria I. Gorinova, Benjamin Paul Chamberlain, Xiaowen Dong, and Michael Bronstein. On the unreasonable effectiveness of feature propagation in learning on graphs with missing node features, 2021.

[17] Solon Barocas and Andrew D Selbst. Big data's disparate impact. *Calif. L. Rev.*, 104:671, 2016.

[18] Solon Barocas, Moritz Hardt, and Arvind Narayanan. *Fairness and Machine Learning*. fairmlbook.org, 2019. `http://www.fairmlbook.org`.

[19] Fernando Martínez-Plumed, C. Ferri, David Nieves, and José Hernández-Orallo. Missing the missing values: The ugly duckling of fairness in machine learning. *International Journal of Intelligent Systems*, 36:3217–3258, 2021.

[20] Dana Pessach and Erez Shmueli. A review on fairness in machine learning. *ACM Comput. Surv.*, 55(3), feb 2022.

[21] John Palowitch and Bryan Perozzi. Monet: Debiasing graph embeddings via the metadata-orthogonal training unit. *ArXiv*, abs/1909.11793, 2019.

[22] Yushun Dong, Ninghao Liu, Brian Jalaian, and Jundong Li. Edits: Modeling and mitigating data bias for graph neural networks. In *Proceedings of the ACM Web Conference 2022*, WWW '22, page 1259–1269, New York, NY, USA, 2022. Association for Computing Machinery.

[23] Donald Loveland, Jiayi Pan, Aaresh Farrokh Bhathena, and Yiyang Lu. Fairedit: Preserving fairness in graph neural networks through greedy graph editing. *ArXiv*, abs/2201.03681, 2022.

[24] Bas Hofstra, Rense Corten, Frank van Tubergen, and Nicole B. Ellison. Sources of segregation in social networks: A novel approach using facebook. *American Sociological Review*, 82(3):625–656, 2017.

[25] Tianlu Wang, Jieyu Zhao, Mark Yatskar, Kai-Wei Chang, and Vicente Ordonez. Balanced datasets are not enough: Estimating and mitigating gender bias in deep image representations. In *ICCV*, 2019.

[26] Sharon N. Barnartt. Disability as a fluid state: Introduction. 2010.

[27] Mason Ameri, Lisa A. Schur, Meera Adya, F. Scott Bentley, Patrick F. McKay, and Douglas L. Kruse. The disability employment puzzle: A field experiment on employer hiring behavior. *ILR Review*, 71:329–364, 2015.

[28] Ifeoma Ajunwa. An auditing imperative for automated hiring. *DecisionSciRN: Recruiting & Hiring (Sub-Topic)*, 2019.

[29] Chirag Agarwal, Himabindu Lakkaraju, and Marinka Zitnik. Towards a unified framework for fair and stable graph representation learning. In *UAI*, 2021.

[30] Christo Wilson, Avijit Ghosh, Shan Jiang, Alan Mislove, Lewis Baker, Janelle Szary, Kelly Trindel, and Frida Polli. Building and auditing fair algorithms: A case study in candidate screening. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, FAccT '21, page 666–677, New York, NY, USA, 2021. Association for Computing Machinery.

[31] Emmanuel J. Candès and Benjamin Recht. Exact matrix completion via convex optimization. *Foundations of Computational Mathematics*, 9:717–772, 2009.

[32] Diederik P. Kingma and Max Welling. Auto-encoding variational bayes. *CoRR*, abs/1312.6114, 2014.

[33] Trevor Hastie, Rahul Mazumder, Jason D. Lee, and Reza Zadeh. Matrix completion and low-rank svd via fast alternating least squares. *J. Mach. Learn. Res.*, 16(1):3367–3402, jan 2015.

[34] Jinsung Yoon, James Jordon, and Mihaela van der Schaar. Gain: Missing data imputation using generative adversarial nets. *ArXiv*, abs/1806.02920, 2018.

[35] LAWRENCE R. LANDERMAN, KENNETH C. LAND, and CARL F. PIEPER. An empirical evaluation of the predictive mean matching method for imputing missing values. *Sociological Methods & Research*, 26(1):3–33, 1997.

[36] Olga Troyanskaya, Michael Cantor, Gavin Sherlock, Pat Brown, Trevor Hastie, Robert Tibshirani, David Botstein, and Russ B. Altman. Missing value estimation methods for DNA microarrays . *Bioinformatics*, 17(6):520–525, 06 2001.

[37] Trivellore E. Raghunathan, James M. Lepkowski, John Van Hoewyk, and Peter W. Solenberger. A multivariate technique for multiply imputing missing values using a sequence of regression models. *Survey Methodology*, 27:85–95, 2001.

[38] Daniel J. Stekhoven and Peter Bühlmann. MissForest—non-parametric missing value imputation for mixed-type data. *Bioinformatics*, 28(1):112–118, 10 2011.

[39] B. Jafrasteh, Daniel Hern'andez-Lobato, Sim'on Pedro Lubi'an-L'opez, and Isabel Benavente-Fern'andez. Gaussian processes for missing value imputation. *ArXiv*, abs/2204.04648, 2022.

[40] Ilya Shpitser, Karthika Mohan, and Judea Pearl. Missing data as a causal and probabilistic problem. In *UAI*, 2015.

[41] Peng Ding and Fan Li. Causal inference: A missing data perspective. *arXiv: Methodology*, 2017.

[42] Zoubin Ghahramani and Michael Jordan. Supervised learning from incomplete data via an em approach. In J. Cowan, G. Tesauro, and J. Alspector, editors, *Advances in Neural Information Processing Systems*, volume 6. Morgan-Kaufmann, 1993.

[43] David Williams, X. Liao, Ya Xue, and Lawrence Carin. Incomplete-data classification using logistic regression. *Proceedings of the 22nd international conference on Machine learning*, 2005.

[44] Kristiaan Pelckmans, Jos De Brabanter, Johan A. K. Suykens, and Bart De Moor. Handling missing values in support vector machine classifiers. *Neural networks : the official journal of the International Neural Network Society*, 18 5-6:684–92, 2005.

[45] Jing Xia, Shengyu Zhang, Guolong Cai, Li Li, Qing Pan, Jing Yan, and Gangmin Ning. Adjusted weight voting algorithm for random forests in handling missing values. *Pattern Recognit.*, 69:52–60, 2017.

[46] Marek Śmieja, Lukasz Struski, Jacek Tabor, Bartosz Zieliński, and Przemysław Spurek. Processing of missing data by neural networks. In *NeurIPS*, 2018.

[47] Jiaxuan You, Xiaobai Ma, Daisy Yi Ding, Mykel J. Kochenderfer, and Jure Leskovec. Handling missing data with graph representation learning. *ArXiv*, abs/2010.16418, 2020.

[48] Hibiki Taguchi, Xin Liu, and Tsuyoshi Murata. Graph convolutional networks for graphs containing missing features. *Future Gener. Comput. Syst.*, 117:155–168, 2021.

[49] Bo Jiang and Ziyan Zhang. Incomplete graph representation and learning via partial graph neural networks, 2020.

[50] Mark Huisman. Imputation of missing network data: Some simple procedures. *J. Soc. Struct.*, 10, 2009.

[51] Vassilis Kalofolias, Xavier Bresson, Michael M. Bronstein, and Pierre Vandergheynst. Matrix completion on graphs. *ArXiv*, abs/1408.1717, 2014.

[52] Rianne van den Berg, Thomas Kipf, and Max Welling. Graph convolutional matrix completion. *ArXiv*, abs/1706.02263, 2017.

[53] Jason S. Hartford, Devon R. Graham, Kevin Leyton-Brown, and Siamak Ravanbakhsh. Deep models of interactions across sets. In *ICML*, 2018.

[54] Betsy Anne Williams, Catherine F. Brooks, and Yotam Shmargad. How Algorithms Discriminate Based on Data They Lack: Challenges, Solutions, and Policy Implications. *Journal of Information Policy*, 8(1):78–115, 03 2018.

[55] Christian Fricke. Missing Fairness: The Discriminatory Effect of Missing Values in Datasets on Fairness in Machine Learning. Master's thesis, Aalto University. School of Science, 2020.

[56] Naman Goel, Alfonso Amayuelas, Amit Deshpande, and Ajay Sharma. The importance of modeling data missingness in algorithmic fairness: A causal perspective. *ArXiv*, abs/2012.11448, 2021.

[57] Yiliang Zhang and Qi Long. Assessing fairness in the presence of missing data. In M. Ranzato, A. Beygelzimer, Y. Dauphin, P.S. Liang, and J. Wortman Vaughan, editors, *Advances in Neural Information Processing Systems*, volume 34, pages 16007–16019. Curran Associates, Inc., 2021.

[58] Haewon Jeong, Hao Wang, and Flávio du Pin Calmon. Fairness without imputation: A decision tree approach for fair prediction with missing values. *ArXiv*, abs/2109.10431, 2021.

[59] Yiliang Zhang and Qi Long. Fairness in missing data imputation, 2021.

[60] Hadis Anahideh, Nazanin Nezami, and Denisa Gándara. Auditing fairness and imputation impact in predictive analytics for higher education. *ArXiv*, abs/2109.07908, 2021.

[61] Manvi Choudhary, Charlotte Laclau, and Christine Largeron. A survey on fairness for machine learning on graphs. *ArXiv*, abs/2205.05396, 2022.

[62] Wenbin Zhang, Jeremy C. Weiss, Shuigeng Zhou, and Toby Walsh. Fairness amidst non-iid graph data: A literature review. *ArXiv*, abs/2202.07170, 2022.

[63] Tao Zhang, Tianqing Zhu, Mengde Han, Jing Li, Wanlei Zhou, and Philip S. Yu. Fairness constraints in semi-supervised learning, 2020.

[64] Joymallya Chakraborty, Quang Huy Tu, Suvodeep Majumder, and Tim Menzies. Can we achieve fairness using semi-supervised learning?, 11 2021.

[65] Tahleen Rahman, Bartlomiej Surma, Michael Backes, and Yang Zhang. Fairwalk: Towards fair graph embedding. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19*, pages 3289–3295. International Joint Conferences on Artificial Intelligence Organization, 7 2019.

[66] Maarten Buyl and Tijl De Bie. DeBayes: a Bayesian method for debiasing network embeddings. In Hal Daumé III and Aarti Singh, editors, *Proceedings of the 37th International Conference on Machine Learning*, volume 119 of *Proceedings of Machine Learning Research*, pages 1220–1229. PMLR, 13–18 Jul 2020.

[67] Jing Ma, Ruocheng Guo, Mengting Wan, Longqi Yang, Aidong Zhang, and Jundong Li. Learning fair node representations with graph counterfactual fairness. *Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining*, 2022.

[68] Jian Kang, Yan Zhu, Yinglong Xia, Jiebo Luo, and Hanghang Tong. Rawlsgcn: Towards rawlsian difference principle on graph convolutional network. In *Proceedings of the ACM Web Conference 2022*, WWW '22, page 1214–1225, New York, NY, USA, 2022. Association for Computing Machinery.

[69] Sahil Verma and Julia Rubin. Fairness definitions explained. In *Proceedings of the International Workshop on Software Fairness*, FairWare '18, page 1–7, New York, NY, USA, 2018. Association for Computing Machinery.

[70] Sean Current, Yuntian He, Saket Gurukar, and Srinivas Parthasarathy. Fairmod: Fair link prediction and recommendation via graph modification. *ArXiv*, abs/2201.11596, 2022.

[71] A. Bose and William L. Hamilton. Compositional fairness constraints for graph embeddings. In *ICML*, 2019.

[72] Farzan Masrour, Tyler Wilson, Heng Yan, Pang-Ning Tan, and Abdol Esfahanian. Bursting the filter bubble: Fairness-aware network link prediction. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(01):841–848, Apr. 2020.

[73] Indro Spinelli, Simone Scardapane, Amir Hussain, and Aurelio Uncini. Biased edge dropout for enhancing fairness in graph representation learning. *ArXiv*, abs/2104.14210, 2021.

[74] Nan Wang, Lu Lin, Jundong Li, and Hongning Wang. Unbiased graph embedding with biased graph observations. In *Proceedings of the ACM Web Conference 2022*, WWW '22, page 1423–1433, New York, NY, USA, 2022. Association for Computing Machinery.

[75] Yanying Li, Xiuling Wang, Yue Ning, and Hui Wang. Fairlp: Towards fair link prediction on social network graphs. In *Proceedings of the 16th International AAAI Conference on Web and Social Media*, 2022.

[76] Zhimeng Jiang, Xiaotian Han, Chao Fan, Zirui Liu, Na Zou, Ali Mostafavi, and Xia Hu. Fmp: Toward fair graph message passing against topology bias. *ArXiv*, abs/2202.04187, 2022.

[77] Enyan Dai and Suhang Wang. 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*, WSDM '21, page 680–688, New York, NY, USA, 2021. Association for Computing Machinery.

[78] Cynthia Dwork, Moritz Hardt, Toniann Pitassi, Omer Reingold, and Richard Zemel. Fairness through awareness. In *Proceedings of the 3rd Innovations in Theoretical Computer Science Conference*, ITCS '12, page 214–226, New York, NY, USA, 2012. Association for Computing Machinery.

[79] Han Zhao and Geoff Gordon. Inherent tradeoffs in learning fair representations. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

[80] Jasjeet S. Sekhon. The neyman— rubin model of causal inference and estimation via matching methods. 2008.

[81] Arjun Subramonian. On dyadic fairness: Exploring and mitigating bias in graph connections. In *ICLR Blog Track*, 2022. https://iclr-blog-track.github.io/2022/03/25/dyadic-fairness/.

[82] Matthias Fey and Jan E. Lenssen. Fast graph representation learning with PyTorch Geometric. In *ICLR Workshop on Representation Learning on Graphs and Manifolds*, 2019.

[83] Sunipa Dev, Masoud Monajatipoor, Anaelia Ovalle, Arjun Subramonian, J. M. Phillips, and Kai Wei Chang. Harms of gender exclusivity and challenges in non-binary representation in language technologies. *ArXiv*, abs/2108.12084, 2021.

[84] Lelia Hampton. Black feminist musings on algorithmic oppression. *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 2021.

[85] Brian Hu Zhang, Blake Lemoine, and Margaret Mitchell. Mitigating unwanted biases with adversarial learning. In *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*, AIES '18, page 335–340, New York, NY, USA, 2018. Association for Computing Machinery.

[86] Moritz Hardt, Eric Price, and Nathan Srebro. Equality of opportunity in supervised learning. *ArXiv*, abs/1610.02413, 2016.

[87] Michael Kearns, Seth Neel, Aaron Roth, and Zhiwei Steven Wu. Preventing fairness gerrymandering: Auditing and learning for subgroup fairness. In *ICML*, 2018.

[88] Joy Buolamwini and Timnit Gebru. Gender shades: Intersectional accuracy disparities in commercial gender classification. In Sorelle A. Friedler and Christo Wilson, editors, *Proceedings of the 1st Conference on Fairness, Accountability and Transparency*, volume 81 of *Proceedings of Machine Learning Research*, pages 77–91. PMLR, 23–24 Feb 2018.

[89] Abigail Z. Jacobs and Hanna Wallach. Measurement and fairness. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, FAccT '21, page 375–385, New York, NY, USA, 2021. Association for Computing Machinery.

[90] Clément L. Canonne. A short note on an inequality between kl and tv. 2022.

[91] John C. Duchi. Derivations for linear algebra and optimization. 2016.

[92] Jacob Steinhardt. Lecture notes for stat260 (robust and nonparametric statistics). 2021.

[93] Dengyong Zhou, Olivier Bousquet, Thomas Lal, Jason Weston, and Bernhard Schölkopf. Learning with local and global consistency. In S. Thrun, L. Saul, and B. Schölkopf, editors, *Advances in Neural Information Processing Systems*, volume 16. MIT Press, 2004.

[94] Amir Beck. Proximal-based methods tutorial, 2021.

[95] Lieven Vandenberghe. Ece236c - optimization methods for large-scale systems course notes, 2021.

[96] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems 32*, pages 8024–8035. Curran Associates, Inc., 2019.

[97] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980, 2015.

[98] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, 15(56):1929–1958, 2014.

[99] Organizers of QueerInAI, Ashwin S, William Agnew, Hetvi Jethwani, and Arjun Subramonian. Rebuilding trust: Queer in ai approach to artificial intelligence risk management, 2021.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] (We transparently discuss the limitations of theoretical results, formalizations, and experimental results throughout the paper, directly before or after they are presented.)
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] (We refrain from using a recidivism prediction dataset and inferring identity from data for ethical reasons in Sections 7 and B.4, and discuss potential negative societal impacts of our work in Section 8.)
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes] (We enumerate all assumptions in the theorem statements or in the paragraphs leading up to the theorems.)
   (b) Did you include complete proofs of all theoretical results? [Yes] (We do so in Section A.)
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] (All experiment code and relevant dependencies and instructions are included in the supplemental material.)
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] (All training details are specified in Sections 7, B.1, B.2, and B.3.)

(c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] (We report all metrics with their mean and standard error computed over 5 runs with different random seeds, as discussed in Section 7.)

(d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] (We do so in Section B.3.)

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...

(a) If your work uses existing assets, did you cite the creators? [Yes] (We cite the original creators of all datasets, code, and libraries in Sections 7 and B and include URLs.)

(b) Did you mention the license of the assets? [Yes] (All code and datasets are used in accordance with their license, as explained in Sections B.1, B.2, and B.3.)

(c) Did you include any new assets either in the supplemental material or as a URL? [Yes] (The code for running the experiments in Sections 7 and B are included in the supplemental material. We do not create any new datasets.)

(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes] (The real-world datasets are used in accordance with their MIT license, as explained in Section B.1.)

(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] (We do so in Section B.1.)

5. If you used crowdsourcing or conducted research with human subjects...

(a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]

(b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]

(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

A Proofs

A.1 Proof of Lemma 1 (special case of total variation distance)

We assume Z and X are continuous probability distributions, but this proof can be easily altered for other kinds of probability distributions and the result still holds. Let $\mathbb{P}(S = Q) = p$. By definition, the total variation information:

$$I_{TV}(Z;S) = d_{TV}(P_{Z,S}||P_Z \otimes P_S) = \sum_{s\in\{Q,R\}} \mathbb{P}(S=s) \int_{\mathcal{Y}} \frac{1}{2} \left| \frac{f_{Z,S}(z,s)}{f_Z(z)\mathbb{P}(S=s)} - 1 \right| f_Z(z)\,\mathrm{d}z$$

By breaking up joint probabilities into conditional probabilities and factoring:

$$
\begin{aligned}
I_{TV}(Z;S) &= \sum_{s\in\{Q,R\}} \mathbb{P}(S=s)\int_{\mathcal{Y}} \frac{1}{2}\left|\frac{f_{Z|S=s}(z)\mathbb{P}(S=s)}{f_Z(z)\mathbb{P}(S=s)} - 1\right| f_Z(z)\,\mathrm{d}z \\
&= \sum_{s\in\{Q,R\}} \mathbb{P}(S=s)\int_{\mathcal{Y}} \frac{1}{2}\left|f_{Z|S=s}(z) - f_Z(z)\right|\mathrm{d}z \\
&= \frac{p}{2}\int_{\mathcal{Y}} \left|f_{Z|S=Q}(z) - f_Z(z)\right|\mathrm{d}z + \int_{\mathcal{Y}} \frac{1-p}{2}\left|f_{Z|S=R}(z) - f_Z(z)\right|\mathrm{d}z \\
&= \frac{1}{2}\Big[p\int_{\mathcal{Y}} \left|f_{Z|S=Q}(z) - (pf_{Z|S=Q}(z) + (1-p)f_{Z|S=R}(z))\right|\mathrm{d}z \\
&\quad + (1-p)\int_{\mathcal{Y}} \left|f_{Z|S=R}(z) - (pf_{Z|S=Q}(z) + (1-p)f_{Z|S=R}(z))\right|\mathrm{d}z\Big] \\
&= \frac{1}{2}\Big[p\int_{\mathcal{Y}} \left|(1-p)f_{Z|S=Q}(z) - (1-p)f_{Z|S=R}(z)\right|\mathrm{d}z \\
&\quad + (1-p)\int_{\mathcal{Y}} \left|pf_{Z|S=R}(z) - pf_{Z|S=Q}(z)\right|\mathrm{d}z\Big] \\
&= \frac{p(1-p)}{2}\left[\int_{\mathcal{Y}} \left|f_{Z|S=Q}(z) - f_{Z|S=R}(z)\right|\mathrm{d}z + \int_{\mathcal{Y}} \left|f_{Z|S=R}(z) - f_{Z|S=Q}(z)\right|\mathrm{d}z\right] \\
&= p(1-p)\int_{\mathcal{Y}} \left|f_{Z|S=Q}(z) - f_{Z|S=R}(z)\right|\mathrm{d}z \\
&= 2p(1-p)d_{TV}(Z|S=Q, Z|S=R)
\end{aligned}
$$

It can be similarly shown that $I_{TV}(X;S) = 2p(1-p)d_{TV}(X|S=Q, X|S=R)$.

Now, by the Data Processing Inequality, $I_{TV}(Z;S) \leq I_{TV}(X;S)$. Hence:

$$
\begin{aligned}
d_{TV}(Z|S=Q, Z|S=R) &= \frac{1}{2p(1-p)} I_{TV}(Z;S) \\
&\leq \frac{1}{2p(1-p)} I_{TV}(X;S) = d_{TV}(X|S=Q, X|S=R)
\end{aligned}
$$

Similarly:

$$
\begin{aligned}
d_{TV}(Z'|S=Q, Z'|S=R) &= \frac{1}{2p(1-p)} I_{TV}(Z';S) \\
&\leq \frac{1}{2p(1-p)} I_{TV}(X';S) = d_{TV}(X'|S=Q, X'|S=R)
\end{aligned}
$$

A.2 Proof of Theorem 1

Leveraging the Bretagnolle–Huber (BH) bound[1], we can upper bound d_{TV} in terms of the KL-divergence d_{KL}:

$$
d_{TV}(X|S=Q, X|S=R) \leq \sqrt{1 - e^{-d_{KL}(X|S=Q||X|S=R)}}
$$

By Section 9 from [91], $d_{KL}(X|S=Q||X|S=R)$ admits a closed-form solution:

$$
\begin{aligned}
d_{KL}(X|S=Q||X|S=R) &= \frac{1}{2}\left(\log\frac{\det\Sigma_R}{\det\Sigma_Q} - d + tr(\Sigma_R^{-1}\Sigma_Q) + \|\mu_Q - \mu_R\|^2_{\Sigma_R^{-1}}\right) \\
&\leq \frac{1}{2}\left(\log\frac{\det\Sigma_R}{\det\Sigma_Q} - d + tr(\Sigma_R^{-1}\Sigma_Q) + \lambda_{max}(\Sigma_R^{-1})\|\mu_Q - \mu_R\|_2^2\right),
\end{aligned}
$$

[1] We use the BH bound rather than Pinsker's inequality because Pinkser's inequality becomes vacuous for KL-divergence > 2 [90]

where $\lambda_{max}(\Sigma_R^{-1})$ is the maximum eigenvalue of Σ_R^{-1}. We note that $\lambda_{max}(\Sigma_R^{-1}) = \frac{1}{\lambda_{min}(\Sigma_R)} > 0$ (where $\lambda_{min}(\Sigma_R)$ is the minimum eigenvalue of Σ_R) because Σ_R is positive semidefinite.

It is clear that $\|\mu_Q - \mu_R\|_\infty^2 = \max_{i\in[d]} |(\mu_Q)_i - (\mu_R)_i|^2 \leq \sum_{i\in[d]} |(\mu_Q)_i - (\mu_R)_i|^2 = \|\mu_Q - \mu_R\|_2^2$. Moreover, $\|\mu_Q - \mu_R\|_2^2 = \sum_{i\in[d]} |(\mu_Q)_i - (\mu_R)_i|^2 \leq \sum_{i\in[d]} \max_{j\in[d]} |(\mu_Q)_j - (\mu_R)_j|^2 = d \cdot \|\mu_Q - \mu_R\|_\infty^2$. Therefore, $\|\mu_Q - \mu_R\|_2^2 = C \cdot \|\mu_Q - \mu_R\|_\infty^2$, for $1 \leq C \leq d$.

Combining the previous observations and recognizing that $\|\mu_Q - \mu_R\|_\infty^2 = \mathcal{R}_{\mathcal{D}}^2$:

$$d_{TV}(X|S=Q, X|S=R) \leq \sqrt{1 - \sqrt{\frac{\det \Sigma_Q}{\det \Sigma_R} \cdot e^{-\frac{C\cdot\mathcal{R}_{\mathcal{D}}^2}{\lambda_{min}(\Sigma_R)} - tr(\Sigma_R^{-1}\Sigma_Q) + d}}}$$

Now, by Lemma 2.7 from [92]:

$$\begin{aligned}\|\mu_Q - \mu_R\|_2^2 &\leq 4 \cdot \max\{\lambda_{max}(\Sigma_Q), \lambda_{max}(\Sigma_R)\} \left(\frac{d_{TV}(X|S=Q, X|S=R)}{1 - d_{TV}(X|S=Q, X|S=R)}\right) \\ &\leq \frac{4 \cdot \max\{\lambda_{max}(\Sigma_Q), \lambda_{max}(\Sigma_R)\}}{\frac{1}{d_{TV}(X|S=Q, X|S=R)} - 1}\end{aligned}$$

Using $\|\mu_Q - \mu_R\|_2^2 = C \cdot \|\mu_Q - \mu_R\|_\infty^2 = C \cdot \mathcal{R}_{\mathcal{D}}^2$, we can derive:

$$\frac{1}{\frac{4\cdot\max\{\lambda_{max}(\Sigma_Q), \lambda_{max}(\Sigma_R)\}}{C\cdot\mathcal{R}_{\mathcal{D}}^2} + 1} \leq d_{TV}(X|S=Q, X|S=R)$$

Similarly:

$$\mathrm{d}_{TV}(X'|S=Q, X'|S=R) \in \left[\frac{1}{\frac{4\cdot\max\{\lambda_{max}(\Sigma'_Q), \lambda_{max}(\Sigma'_R)\}}{C'\cdot\mathcal{R}_{\mathcal{D}'}^2} + 1}, \sqrt{1 - \sqrt{\frac{\det \Sigma'_Q}{\det \Sigma'_R} \cdot e^{-\frac{C'\cdot\mathcal{R}_{\mathcal{D}'}^2}{\lambda_{min}(\Sigma'_R)} - tr(\Sigma'^{-1}_R\Sigma'_Q) + d}}}\right]$$

Then, the theorem is proved by application of Lemma 1.

A.3 Example Mean Aggregation Imputation Algorithms

Global Mean This method sets the unknown features to the uniform mean of all the known features. To achieve this, we can choose $M := I_N$, $T := \begin{bmatrix} I_{|K|} & 0 \\ \frac{1}{|K|}\mathbb{1}_{|U|\times|K|} & 0 \end{bmatrix}$ (where $\mathbb{1}$ is the all-ones matrix), $\beta := 0$, $X_K^{(0)} := X_K$, and $X_U^{(0)} := 0$. We only need to complete one iteration.

Neighbor Mean This method sets the unknown features to the degree-weighted mean of the known features for neighboring nodes. We can choose $M := I_N$, $T := D^{-1}A$, $\beta := 0$, $X_K^{(0)} := X_K$, and $X_U^{(0)} := 0$. We only need to complete one iteration.

Feature Propagation This method proposed by [16] predicts the unknown features to minimize the Dirichlet energy of the graph while preserving the known feature values. [16] shows that this is equivalent to iteratively computing until convergence:

$$X_K^{(t+1)} := X_K^{(t)}$$

$$X_U^{(t+1)} := (D_U^{-\frac{1}{2}} A_{UK} D_K^{-\frac{1}{2}}) X_K^{(t)} + (D_U^{-\frac{1}{2}} A_{UU} D_U^{-\frac{1}{2}}) X_U^{(t)}$$

Multiplying both sides by $D_U^{-\frac{1}{2}}$, we can re-express the second update rule as:

$$D_U^{-\frac{1}{2}} X_U^{(t+1)} = (D_U^{-1} A_{UK})(D_K^{-\frac{1}{2}} X_K^{(t)}) + (D_U^{-1} A_{UU})(D_U^{-\frac{1}{2}} X_U^{(t)})$$

Therefore, to achieve Feature Propagation, we can choose $M := D^{-\frac{1}{2}}$, $T := D^{-1}A$, $\beta := 0$, and $X_K^{(0)} := X_K$. Per [16], we can choose $X_U^{(0)}$ arbitrarily, and we need to iterate till convergence.

Graph Regularization This method inspired by [93] predicts the unknown features via a smoothness constraint and a fitting constraint for the known features. [93] shows that this is equivalent to iteratively computing until convergence:

$$X_K^{(t+1)} := \beta(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}X^{(t)})_K + (1-\beta)X_K$$

$$X_U^{(t+1)} := (D^{-\frac{1}{2}}AD^{-\frac{1}{2}}X^{(t)})_U,$$

where the hyperparameter $\beta \in (0, 1]$. Therefore, similar to Feature Propagation, to achieve Graph Regularization, we can choose $M := D^{-\frac{1}{2}}$, $T := D^{-1}A$, and $X_K^{(0)} := X_K$. Per [93], we can choose $X_U^{(0)}$ arbitrarily, and we need to iterate till convergence.

A.4 Proof of Theorem 2

The following proof is partially inspired by the proof of Theorem 4.1 in [6]. Fix t to be an arbitrary iteration of feature imputation. Recall we use the following iterative update rule to impute features:

$$\tilde{X}^{(t+1)} := \begin{bmatrix} \beta I_{|K|} & 0 \\ 0 & I_{|U|} \end{bmatrix} T\tilde{X}^{(t)} + \begin{bmatrix} (1-\beta)I_{|K|} & 0 \\ 0 & 0 \end{bmatrix} \tilde{X}$$

For a node $q \in Q \cap U$, after one iteration of feature imputation:

$$\tilde{X}_q^{(t+1)} := \sum_{s \in Q} T_{qs}\tilde{X}_s^{(t)} + \sum_{s \in R} T_{qs}\tilde{X}_s^{(t)}$$

Similarly, for a node $r \in R \cap U$, after one iteration of feature imputation:

$$\tilde{X}_r^{(t+1)} := \sum_{s \in Q} T_{rs}\tilde{X}_s^{(t)} + \sum_{s \in R} T_{rs}\tilde{X}_s^{(t)}$$

In contrast, for a node $q \in Q \cap K$, after one iteration of feature imputation:

$$\tilde{X}_q^{(t+1)} := \beta\left(\sum_{s \in Q} T_{qs}\tilde{X}_s^{(t)} + \sum_{s \in R} T_{qs}\tilde{X}_s^{(t)}\right) + (1-\beta)\tilde{X}_q^{(t)}$$

Similarly, for a node $r \in R \cap K$, after one iteration of feature imputation:

$$\tilde{X}_r^{(t+1)} := \beta\left(\sum_{s \in Q} T_{rs}\tilde{X}_s^{(t)} + \sum_{s \in R} T_{rs}\tilde{X}_s^{(t)}\right) + (1-\beta)\tilde{X}_r^{(t)}$$

We say $v \in [\mu \pm \sigma] \iff \mu - \sigma \preceq v \preceq \mu + \sigma$. Then, for a node $q \in Q \cap U$, by the right-stochastic nature of T:

$$\begin{aligned} \tilde{X}_q^{(t+1)} &\in \left[\left(\sum_{s \in Q} T_{qs}\tilde{\mu}_Q^{(t)} + \sum_{s \in R} T_{qs}\tilde{\mu}_R^{(t)}\right) \pm \tilde{\sigma}^{(t)}\right] \\ &\in \left[\left(\tilde{\mu}_Q^{(t)} + \sum_{s \in R} T_{qs}\left(\tilde{\mu}_R^{(t)} - \tilde{\mu}_Q^{(t)}\right)\right) \pm \tilde{\sigma}^{(t)}\right] \end{aligned}$$

Similarly, for a node $r \in R \cap U$:

$$\begin{aligned} \tilde{X}_r^{(t+1)} &\in \left[\left(\sum_{s \in Q} T_{rs}\tilde{\mu}_Q^{(t)} + \sum_{s \in R} T_{rs}\tilde{\mu}_R^{(t)}\right) \pm \tilde{\sigma}^{(t)}\right] \\ &\in \left[\left(\tilde{\mu}_R^{(t)} + \sum_{s \in Q} T_{rs}\left(\tilde{\mu}_Q^{(t)} - \tilde{\mu}_R^{(t)}\right)\right) \pm \tilde{\sigma}^{(t)}\right] \end{aligned}$$

In contrast, for a node $q \in Q \cap K$:

$$\tilde{X}_q^{(t+1)} \in \left[\left(\beta \left(\sum_{s \in Q} T_{qs} \tilde{\mu}_Q^{(t)} + \sum_{s \in R} T_{qs} \tilde{\mu}_R^{(t)} \right) + (1-\beta) \tilde{\mu}_Q^{(t)} \right) \pm \tilde{\sigma}^{(t)} \right]$$
$$\in \left[\left(\tilde{\mu}_Q^{(t)} + \beta \sum_{s \in R} T_{qs} \left(\tilde{\mu}_R^{(t)} - \tilde{\mu}_Q^{(t)} \right) \right) \pm \tilde{\sigma}^{(t)} \right]$$

Similarly, for a node $r \in R \cap K$:

$$\tilde{X}_r^{(t+1)} \in \left[\left(\beta \left(\sum_{s \in Q} T_{rs} \tilde{\mu}_Q^{(t)} + \sum_{s \in R} T_{rs} \tilde{\mu}_R^{(t)} \right) + (1-\beta) \tilde{\mu}_R^{(t)} \right) \pm \tilde{\sigma}^{(t)} \right]$$
$$\in \left[\left(\tilde{\mu}_R^{(t)} + \beta \sum_{s \in Q} T_{rs} \left(\tilde{\mu}_Q^{(t)} - \tilde{\mu}_R^{(t)} \right) \right) \pm \tilde{\sigma}^{(t)} \right]$$

By the Law of Total Expectation:

$$\mathbb{E}_{q \sim Q}[\tilde{X}_q^{(t+1)}] = \mathbb{P}(q \in U | q \in Q) \mathbb{E}_{q \sim Q \cap U}[\tilde{X}_q^{(t+1)}] + \mathbb{P}(q \in K | q \in Q) \mathbb{E}_{q \sim Q \cap K}[\tilde{X}_q^{(t+1)}]$$
$$\in \Big[\left(\frac{1}{|Q|} \Big(\sum_{q \in Q \cap U} \tilde{\mu}_Q^{(t)} + \sum_{s \in R} T_{qs} \left(\tilde{\mu}_R^{(t)} - \tilde{\mu}_Q^{(t)} \right) \right)$$
$$+ \frac{1}{|Q|} \left(\sum_{q \in Q \cap K} \tilde{\mu}_Q^{(t)} + \beta \sum_{s \in R} T_{qs} \left(\tilde{\mu}_R^{(t)} - \tilde{\mu}_Q^{(t)} \right) \right) \Big) \pm \tilde{\sigma}^{(t)} \Big]$$
$$\in \Big[\Big(\tilde{\mu}_Q^{(t)} + \frac{1}{|Q|} \sum_{q \in Q \cap U} \sum_{s \in R} T_{qs} \left(\tilde{\mu}_R^{(t)} - \tilde{\mu}_Q^{(t)} \right)$$
$$+ \frac{\beta}{|Q|} \sum_{q \in Q \cap K} \sum_{s \in R} T_{qs} \left(\tilde{\mu}_R^{(t)} - \tilde{\mu}_Q^{(t)} \right) \Big) \pm \tilde{\sigma}^{(t)} \Big]$$

Similarly, $\mathbb{E}_{r \sim R}[\tilde{X}_r^{(t+1)}]$:

$$\in \left[\left(\tilde{\mu}_R^{(t)} + \frac{1}{|R|} \sum_{r \in R \cap U} \sum_{s \in Q} T_{rs} \left(\tilde{\mu}_Q^{(t)} - \tilde{\mu}_R^{(t)} \right) + \frac{\beta}{|R|} \sum_{r \in R \cap K} \sum_{s \in Q} T_{rs} \left(\tilde{\mu}_Q^{(t)} - \tilde{\mu}_R^{(t)} \right) \right) \pm \tilde{\sigma}^{(t)} \right]$$

Thus, the gap in expectation of the features of the nodes in Q and R after one iteration of feature imputation is:

$$\mathbb{E}_{q \sim Q}[\tilde{X}_q^{(t+1)}] - \mathbb{E}_{r \sim R}[\tilde{X}_r^{(t+1)}] \in \Bigg[\Bigg(1 - \Bigg(\frac{1}{|Q|} \sum_{q \in Q \cap U} \sum_{s \in R} T_{qs} + \frac{1}{|R|} \sum_{r \in R \cap U} \sum_{s \in Q} T_{qs} \Bigg)$$
$$- \beta \Bigg(\frac{1}{|Q|} \sum_{q \in Q \cap K} \sum_{s \in R} T_{qs} + \frac{1}{|R|} \sum_{r \in R \cap K} \sum_{s \in Q} T_{qs} \Bigg) \Bigg) \cdot \left(\tilde{\mu}_Q^{(t)} - \tilde{\mu}_R^{(t)} \right) \Bigg) \pm 2\tilde{\sigma}^{(t)} \Bigg]$$

Define the contraction coefficient:

$$\alpha := \left| 1 - \frac{T_{R \to Q \cap U} + \beta T_{R \to Q \cap K}}{|Q|} - \frac{T_{Q \to R \cap U} + \beta T_{Q \to R \cap K}}{|R|} \right|$$

Because $0 \leq \frac{T_{R \to Q \cap U} + \beta T_{R \to Q \cap K}}{|Q|} \leq \frac{T_{R \to Q \cap U} + T_{R \to Q \cap K}}{|Q|} = \frac{T_{R \to Q}}{|Q|} < \frac{T_{V \to Q}}{|Q|} = 1$, and similarly, $0 \leq \frac{T_{Q \to R \cap U} + \beta T_{Q \to R \cap K}}{|R|} < 1$, it must be that $0 \leq \alpha \leq 1$.

Then:

$$\max\{\alpha|\mathbb{E}_{q\sim Q}[\tilde{X}_q^{(t)}] - \mathbb{E}_{r\sim R}[\tilde{X}_r^{(t)}]| - 2\tilde{\sigma}^{(t)}, 0\} \leq |\mathbb{E}_{q\sim Q}[\tilde{X}_q^{(t+1)}] - \mathbb{E}_{r\sim R}[\tilde{X}_r^{(t+1)}]|$$
$$|\mathbb{E}_{q\sim Q}[\tilde{X}_q^{(t+1)}] - \mathbb{E}_{r\sim R}[\tilde{X}_r^{(t+1)}]| \leq \alpha|\mathbb{E}_{q\sim Q}[\tilde{X}_q^{(t)}] - \mathbb{E}_{r\sim R}[\tilde{X}_r^{(t)}]| + 2\tilde{\sigma}^{(t)}$$

$$\max\{\alpha\tilde{\mathcal{R}}^{(t)} - 2\tilde{\sigma}^{(t)}, 0\} \leq \tilde{\mathcal{R}}^{(t+1)} \leq \alpha\tilde{\mathcal{R}}^{(t)} + 2\tilde{\sigma}^{(t)}$$

Inductively, the discrimination risk $\tilde{\mathcal{R}}^{(t)}$ after t iterations of feature imputation is bounded by:

$$\max\left\{\alpha^t\tilde{\mathcal{R}}^{(0)} - 2\left(\sum_{j=0}^{t-1}\alpha^j\tilde{\sigma}^{(j)}\right), 0\right\} \leq \tilde{\mathcal{R}}^{(t)} \leq \alpha^t\tilde{\mathcal{R}}^{(0)} + 2\left(\sum_{j=0}^{t-1}\alpha^j\tilde{\sigma}^{(j)}\right)$$

$\forall v \in V$, $\tilde{X}_v^{(t+1)}$ is a convex combination of $\bigcup_{u\in V}\{\tilde{X}_u^{(t)}\}$. This is because each row of T and $\beta T + (1-\beta)I_{|K|}$ contains nonnegative entries that sum to 1. Therefore, $\tilde{X}_v^{(t+1)}$ must be in the (closed) convex hull of $\bigcup_{u\in V}\{\tilde{X}_u^{(t)}\}$. Thus, $\bigcup_{u\in V}\{\tilde{X}_u^{(t)}\}$ inductively must be contained within the (closed) convex hull of $\bigcup_{u\in V}\{\tilde{X}_u^{(0)}\}$, which has extreme points $\subseteq \bigcup_{u\in V}\{\tilde{X}_u^{(0)}\}$. Consequently, $\forall t \in [0,\infty), \tilde{\sigma}^{(t)} \leq \tilde{\sigma}^{(0)}$.

Hence:

$$\max\left\{\alpha^t\tilde{\mathcal{R}}^{(0)} - 2\left(\sum_{j=0}^{t-1}\alpha^j\right)\tilde{\sigma}^{(0)}, 0\right\} \leq \tilde{\mathcal{R}}^{(t)} \leq \alpha^t\tilde{\mathcal{R}}^{(0)} + 2\left(\sum_{j=0}^{t-1}\alpha^j\right)\tilde{\sigma}^{(0)}$$

If $\alpha < 1$:

$$\max\left\{\alpha^t\tilde{\mathcal{R}}^{(0)} - 2\left(\frac{1-\alpha^t}{1-\alpha}\right)\tilde{\sigma}^{(0)}, 0\right\} \leq \tilde{\mathcal{R}}^{(t)} \leq \alpha^t\tilde{\mathcal{R}}^{(0)} + 2\left(\frac{1-\alpha^t}{1-\alpha}\right)\tilde{\sigma}^{(0)}$$

Moreover, upon convergence:

$$0 \leq \lim_{t\to\infty}\tilde{\mathcal{R}}^{(t)} \leq \frac{2\tilde{\sigma}^{(0)}}{1-\alpha}$$

A.5 Analysis of Theorem 2

We focus on Feature Propagation [16], but our analysis may be easily extended to other mean aggregation feature imputation algorithms. We assume for simplicity that all edges have a weight of 1.

Unknown feature rates Suppose the intra-link rate $\mathbb{P}((u,v) \in E|u \in Q, v \in Q) = \mathbb{P}((u,v) \in E|u \in R, v \in R) = \frac{1}{2}$ and inter-link rate $\mathbb{P}((u,v) \in E|u \in Q, v \in R) = \mathbb{P}((u,v) \in E|u \in R, v \in Q) = \frac{1}{2}$. Furthermore, assume equal (relative) group sizes, i.e. $\frac{|Q|}{N} = \frac{|R|}{N} = \frac{1}{2}$. $\frac{T_{R\to Q\cap U}+\beta T_{R\to Q\cap K}}{|Q|} = \frac{T_{R\to Q\cap U}}{N/2} = \frac{\sum_{q\in Q\cap U}\sum_{r\in R}T_{qr}}{N/2} = \frac{\sum_{q\in Q\cap U}\sum_{r\in R}D_{qq}^{-1}A_{qr}}{N/2}$. By decomposition, $D_{qq} = \sum_{u\in Q}A_{qu} + \sum_{v\in R}A_{qv} = \frac{1}{2}|Q| + \frac{1}{2}|R| = \frac{N}{2}$. Therefore, $\frac{T_{R\to Q\cap U}+\beta T_{R\to Q\cap K}}{|Q|} = \frac{\sum_{q\in Q\cap U}\sum_{r\in R}A_{qr}}{N^2/4} = \frac{\frac{1}{2}(|Q\cap U|\times|R|)}{N^2/4} = \frac{\frac{1}{2}(\mathbb{P}(v\in U|v\in Q)\cdot|Q|\times|R|)}{N^2/4} = \frac{1}{2}\mathbb{P}(v \in U|v \in Q)$, where $\mathbb{P}(v \in U|v \in Q)$ is the unknown feature rate for group Q. Similarly, $\frac{T_{Q\to R\cap U}+\beta T_{Q\to R\cap K}}{|R|} = \frac{1}{2}\mathbb{P}(v \in U|v \in R)$. Thus, $\alpha = |1 - \frac{1}{2}\mathbb{P}(v \in U|v \in Q) - \frac{1}{2}\mathbb{P}(v \in U|v \in R)|$. This reveals that a low unknown feature rate for both groups or disparate unknown feature rates across the groups can increase α, and thus the discrimination risk of mean aggregation-imputed features. This aligns with [59]'s finding that imputation fairness can be influenced by the imbalance of feature missingness across groups, although [59] studies equal opportunity rather than statistical parity fairness.

Group sizes Now, suppose the intra-link rate $\mathbb{P}((u,v) \in E | u \in Q, v \in Q) = \mathbb{P}((u,v) \in E | u \in R, v \in R) = \frac{1}{2}$ and inter-link rate $\mathbb{P}((u,v) \in E | u \in Q, v \in R) = \mathbb{P}((u,v) \in E | u \in R, v \in Q) = \frac{1}{2}$. Furthermore, assume equal unknown feature rates, i.e. $\mathbb{P}(v \in U | v \in Q) = \mathbb{P}(v \in U | v \in R) = \frac{1}{2}$. $\frac{T_{R\to Q\cap U} + \beta T_{R\to Q\cap K}}{|Q|} = \frac{\sum_{q\in Q\cap U}\sum_{r\in R} T_{qr}}{|Q|} = \frac{\sum_{q\in Q\cap U}\sum_{r\in R} D_{qq}^{-1} A_{qr}}{|Q|}$. $D_{qq} = \frac{N}{2}$. Therefore, $\frac{T_{R\to Q\cap U} + \beta T_{R\to Q\cap K}}{|Q|} = \frac{\sum_{q\in Q\cap U}\sum_{r\in R} A_{qr}}{|Q|\cdot N/2} = \frac{\frac{1}{2}(|Q\cap U|\times|R|)}{|Q|\cdot N/2} = \frac{\frac{1}{2}(\frac{1}{2}|Q|\times|R|)}{|Q|\cdot N/2} = \frac{1}{2}\cdot\frac{|R|}{N}$. Similarly, $\frac{T_{Q\to R\cap U} + \beta T_{Q\to R\cap K}}{|R|} = \frac{1}{2}\cdot\frac{|Q|}{N}$. Thus, $\alpha = |1 - \frac{1}{2}\cdot\frac{|R|}{N} - \frac{1}{2}\cdot\frac{|Q|}{N}| = \frac{1}{2}$. This demonstrates that group size alone may not affect α or the discrimination risk of mean aggregation-imputed features.

Graph structure Finally, suppose we have equal unknown feature rates, i.e. $\mathbb{P}(v \in U | v \in Q) = \mathbb{P}(v \in U | v \in R) = \frac{1}{2}$. Furthermore, assume equal (relative) group sizes, i.e. $\frac{|Q|}{N} = \frac{|R|}{N} = \frac{1}{2}$. $\frac{T_{R\to Q\cap U} + \beta T_{R\to Q\cap K}}{|Q|} = \frac{\sum_{q\in Q\cap U}\sum_{r\in R} T_{qr}}{N/2} = \frac{\sum_{q\in Q\cap U}\sum_{r\in R} D_{qq}^{-1} A_{qr}}{N/2}$. $D_{qq} = \sum_{u\in Q} A_{qu} + \sum_{v\in R} A_{qv} = \mathbb{P}((u,v) \in E | u \in Q, v \in Q)|Q| + \mathbb{P}((u,v) \in E | u \in R, v \in Q)|R| = \frac{N}{2}[\mathbb{P}((u,v) \in E | u \in Q, v \in Q) + \mathbb{P}((u,v) \in E | u \in R, v \in Q)]$. Therefore, $\frac{T_{R\to Q\cap U} + \beta T_{R\to Q\cap K}}{|Q|} = \frac{\mathbb{P}((u,v)\in E|u\in R, v\in Q)(|Q\cap U|\times|R|)}{[\mathbb{P}((u,v)\in E|u\in Q, v\in Q) + \mathbb{P}((u,v)\in E|u\in R, v\in Q)]\cdot N^2/4} = \frac{\frac{1}{2}|Q|\times|R|}{\left[1 + \frac{\mathbb{P}((u,v)\in E|u\in R, v\in Q)}{\mathbb{P}((u,v)\in E|u\in Q, v\in Q)}\right]\cdot N^2/4} = \frac{1}{2}\cdot\frac{1}{1 + \frac{\mathbb{P}((u,v)\in E|u\in R, v\in Q)}{\mathbb{P}((u,v)\in E|u\in Q, v\in Q)}}$. Similarly, $\frac{T_{Q\to R\cap U} + \beta T_{Q\to R\cap K}}{|R|} = \frac{1}{2}\cdot\frac{1}{1 + \frac{\mathbb{P}((u,v)\in E|u\in Q, v\in R)}{\mathbb{P}((u,v)\in E|u\in R, v\in R)}}$. Thus, $\alpha = \left|1 - \frac{1}{2}\cdot\frac{1}{1 + \frac{\mathbb{P}((u,v)\in E|u\in R, v\in Q)}{\mathbb{P}((u,v)\in E|u\in Q, v\in Q)}} - \frac{1}{2}\cdot\frac{1}{1 + \frac{\mathbb{P}((u,v)\in E|u\in Q, v\in R)}{\mathbb{P}((u,v)\in E|u\in R, v\in R)}}\right|$. Because G is undirected, $\mathbb{P}((u,v) \in E | u \in R, v \in Q) = \mathbb{P}((u,v) \in E | u \in Q, v \in R)$ and $\mathbb{P}((u,v) \in E | u \in Q, v \in Q) = \mathbb{P}((u,v) \in E | u \in R, v \in R)$. Therefore, a low inter-link to intra-link ratio can increase α and the discrimination risk of mean aggregation-imputed features.

A.6 Extending Theorem 2

We can extend Theorem 2 to the case the number of features $d > 1$. By Theorem 1, the modified discrimination risk at iteration t (including all features) is:

$$\max\left\{\min_{i\in[d]} \alpha_i^t \tilde{\mathcal{R}}_i^{(0)} - 2\left(\sum_{j=0}^{t-1}\alpha_i^j\right)\tilde{\sigma}_i^{(0)}, 0\right\} \le \max_{i\in[d]} \tilde{\mathcal{R}}_i^{(t)} \le \max_{i\in[d]} \alpha_i^t \tilde{\mathcal{R}}_i^{(0)} + 2\left(\sum_{j=0}^{t-1}\alpha_i^j\right)\tilde{\sigma}_i^{(0)}$$

Moreover, assuming $\forall i \in [d], \alpha_i < 1$, upon convergence, the discrimination risk is: $\max_{i\in[d]} \lim_{t\to\infty} \tilde{\mathcal{R}}_i^{(t)} \le \max_{i\in[d]} \frac{2\tilde{\sigma}_i^{(0)}}{1-\alpha_i}$.

A.7 Proof of Theorem 3

We want to constrain the discrimination risk of mean aggregation feature imputation to be at most ϵ. To this end, we can modify mean aggregation feature imputation to update $X_U^{(t+1)} := P_W Z_U^{(t)} + P_B$ such that $X^{(t+1)}$ has a discrimination risk of at most ϵ for all t. $|\mathbb{E}_{q\sim Q}[X_q^{(t+1)}] - \mathbb{E}_{r\sim R}[X_r^{(t+1)}]| = |\frac{1}{|Q|}\sum_{q\in Q\cap K} X_q + \frac{1}{|Q|}\sum_{q\in Q\cap U} Z_q^{(t)} - (\frac{1}{|R|}\sum_{r\in R\cap K} X_r + \frac{1}{|R|}\sum_{r\in R\cap U} Z_r^{(t)})|$. Hence, we have a closed convex polytope wherein unknown feature values yield discrimination risk of at most ϵ:

$$\mathcal{R}_K - \epsilon \le \frac{1}{|Q|}\sum_{q\in Q\cap U} Z_q^{(t)} - \frac{1}{|R|}\sum_{r\in R\cap U} Z_r^{(t)} = c^T Z_U^{(t)} \le \mathcal{R}_K + \epsilon$$

If $\mathcal{R}_K - \epsilon \le c^T Z_U^{(t)} \le \mathcal{R}_K + \epsilon$, then $P_W = I_{|U|}$ and $P_B = 0$. Otherwise, we must project onto the closer of the two boundaries of the polytope. In this case, $P_W = I_{|U|} - \frac{cc^T}{c^T c}$ and $P_B = \frac{cc^T}{c^T c}\begin{cases}\mathcal{R}_K - \epsilon, & c^T Z_U^{(t)} < \mathcal{R}_K - \epsilon \\ \mathcal{R}_K + \epsilon, & c^T Z_U^{(t)} > \mathcal{R}_K + \epsilon\end{cases}$.

The affine projection we perform at each step is closed and convex. Furthermore, ℓ is $\lambda_{max}(\Delta_{UU})$-smooth for the Euclidean norm (where λ_{max} is the maximum eigenvalue) because for $x_1, x_2 \in \mathbb{R}^{|U|}$:

$$\begin{aligned}\|\nabla\ell(x_1) - \nabla\ell(x_2)\|_2 &= \|(\Delta_{UU}x_1 + \Delta_{UK}X_K) - (\Delta_{UU}x_2 + \Delta_{UK}X_K)\|_2 \\ &= \sqrt{(x_1 - x_2)^T\Delta_{UU}^2(x_1 - x_2)} \\ &\leq \sqrt{\lambda_{max}^2(\Delta_{UU})\|x_1 - x_2\|_2^2} \\ &= \lambda_{max}(\Delta_{UU})\|x_1 - x_2\|_2\end{aligned}$$

In the case of Feature Propagation, $\lambda_{max}(\Delta_{UU}) < 1$ due to properties of the symmetric normalized Laplacian [16].

Additionally, for $m \geq 0$, when $m \leq \lambda_{min}(\Delta_{UU})$, $\ell(x) - \frac{m}{2}x^Tx$ is convex because:

$$\begin{aligned}\ell(x) - \frac{m}{2}x^Tx &= \frac{1}{2}x^T\Delta_{UU}x + X_K^T\Delta_{KU}x + \frac{1}{2}X_K^T\Delta_{KK}X_K - \frac{m}{2}x^Tx \\ &= \frac{1}{2}x^T(\Delta_{UU} - mI)x + X_K^T\Delta_{KU}x + \frac{1}{2}X_K^T\Delta_{KK}X_K\end{aligned}$$

This expression is convex if and only if its Hessian $\Delta_{UU} - mI$ has nonnegative eigenvalues. Therefore, m can be at most $\lambda_{min}(\Delta_{UU})$.

Then, by [94] and [95]:

1. a unique optimal (with respect to ℓ) feasible solution X_U^* exists
2. for fixed step size $\gamma = \frac{1}{\lambda_{max}(\Delta_{UU})}$, ϵ-fair imputation converges as $\|X_U^{(t)} - X_U^*\|_2^2 \leq \left(1 - \frac{\lambda_{min}(\Delta_{UU})}{\lambda_{max}(\Delta_{UU})}\right)^t \|X_U^{(0)} - X_U^*\|_2^2$
3. for fixed step size $\gamma = 1 < \frac{1}{\lambda_{max}(\Delta_{UU})}$, ϵ-fair imputation converges to X_U^*

A.8 Theorem 4

We have a solution when $\beta > 0$, i.e. when the known node feature values do not remain fixed. We can view the update of $X^{(t+1)} := \begin{bmatrix}\beta I_{|K|} & 0 \\ 0 & I_{|U|}\end{bmatrix} M^{-1}TMX^{(t)} + \begin{bmatrix}(1-\beta)I_{|K|} & 0 \\ 0 & 0\end{bmatrix} X$ as an iteration of gradient descent (with step size $\gamma = 1$) for the objective function $\ell(x) = \frac{1}{2}x^T\Delta x + \frac{1}{2}(\frac{1-\beta}{\beta})\|x_K - X_K\|_2^2$ [93].

Theorem 4 (ϵ-Fair Imputation, $\beta > 0$) Vanilla mean aggregation feature imputation updates $X^{(t+1)} := \begin{bmatrix}\beta I_{|K|} & 0 \\ 0 & I_{|U|}\end{bmatrix}(I_N - \Delta)X^{(t)} + \begin{bmatrix}(1-\beta)I_{|K|} & 0 \\ 0 & 0\end{bmatrix} X = Z^{(t)}$. Let ϵ-fair mean aggregation feature imputation instead update $X^{(t+1)} := P_W Z^{(t)} + P_B$, where:

$$P_W = \begin{cases} I_N, & -\epsilon \leq c^TZ^{(t)} \leq \epsilon \\ I_N - \frac{cc^T}{c^Tc}, & \text{otherwise}\end{cases}, P_B = \frac{cc^T}{c^Tc}\begin{cases} -\epsilon, & c^TZ^{(t)} < -\epsilon \\ \epsilon, & c^TZ^{(t)} > \epsilon \\ 0, & \text{otherwise}\end{cases}$$

$$c \in \mathbb{R}^N, c^TZ^{(t)} = \frac{1}{|Q|}\sum_{q\in Q} Z_q^{(t)} - \frac{1}{|R|}\sum_{r\in R} Z_r^{(t)}$$

Then, assuming $0 \leq \lambda_{min}(\Delta) + \frac{1-\beta}{\beta} \leq \lambda_{max}(\Delta) + \frac{1-\beta}{\beta} < 1$: 1) a unique optimal (with respect to ℓ) feasible solution X^* exists; 2) for fixed step size $\gamma = \frac{1}{\lambda_{max}(\Delta)+\frac{1-\beta}{\beta}}$, ϵ-fair imputation converges as $\|X^{(t)} - X^*\|_2^2 \leq \left(1 - \frac{\lambda_{min}(\Delta)+\frac{1-\beta}{\beta}}{\lambda_{max}(\Delta)+\frac{1-\beta}{\beta}}\right)^t \|X^{(0)} - X^*\|_2^2$; 3) for fixed step size $\gamma = 1$, ϵ-fair imputation converges to X^*.

Proof of Theorem 4 We want to constrain the discrimination risk of mean aggregation feature imputation to be at most ϵ. To this end, we can modify mean aggregation feature imputation to update $X^{(t+1)} := P_W Z^{(t)} + P_B$ such that $X^{(t+1)}$ has a discrimination risk of at most ϵ for all t.

$|\mathbb{E}_{q\sim Q}[X_q^{(t+1)}] - \mathbb{E}_{r\sim R}[X_r^{(t+1)}]| = \frac{1}{|Q|}\sum_{q\in Q} Z_q^{(t)} - \frac{1}{|R|}\sum_{r\in R} Z_r^{(t)}$. Hence, we have a closed convex polytope wherein feature values have discrimination risk of at most ϵ:

$$-\epsilon \leq \frac{1}{|Q|}\sum_{q\in Q} Z_q^{(t)} - \frac{1}{|R|}\sum_{r\in R} Z_r^{(t)} = c^T Z^{(t)} \leq \epsilon$$

If $-\epsilon \leq c^T Z^{(t)} \leq \epsilon$, then $P_W = I_N$ and $P_B = 0$. Otherwise, we must project onto the closer of the two boundaries of the polytope. In this case, $P_W = I_N - \frac{cc^T}{c^T c}$ and $P_B = \frac{cc^T}{c^T c}\begin{cases} -\epsilon, & c^T Z^{(t)} < -\epsilon \\ \epsilon, & c^T Z^{(t)} > \epsilon \end{cases}$.

The affine projection we perform at each step is closed and convex. Furthermore, ℓ is $\left(\lambda_{max}(\Delta) + \frac{1-\beta}{\beta}\right)$-smooth for the Euclidean norm because for $x_1, x_2 \in \mathbb{R}^N$:

$$\begin{aligned}
\|\nabla\ell(x_1) - \nabla\ell(x_2)\|_2 &= \left\|\left(\Delta x_1 + \frac{1-\beta}{\beta}\left((x_1)_K - X_K\right)\right) - \left(\Delta x_2 + \frac{1-\beta}{\beta}\left((x_2)_K - X_K\right)\right)\right\|_2 \\
&\leq \sqrt{(x_1-x_2)^T\Delta^2(x_1-x_2)} + \frac{1-\beta}{\beta}\sqrt{(x_1-x_2)^T\left(\begin{bmatrix} I_{|K|} & 0 \\ 0 & 0\end{bmatrix}\right)^2(x_1-x_2)} \\
&\leq \left(\lambda_{max}(\Delta) + \frac{1-\beta}{\beta}\right)\|x_1 - x_2\|_2
\end{aligned}$$

Additionally, for $m \geq 0$, when $m \leq \lambda_{min}(\Delta) + \frac{1-\beta}{\beta}$, $\ell(x) - \frac{m}{2}x^T x$ is convex because:

$$\begin{aligned}
\ell(x) - \frac{m}{2}x^T x &= \frac{1}{2}x^T\Delta x + \frac{1}{2}\left(\frac{1-\beta}{\beta}\right)\|x_K - X_K\|_2^2 - \frac{m}{2}x^T x \\
&= \frac{1}{2}x^T(\Delta - mI)x + \frac{1}{2}\left(\frac{1-\beta}{\beta}\right)\|x_K - X_K\|_2^2
\end{aligned}$$

This expression is convex if and only if its Hessian $\Delta - mI + \frac{1-\beta}{\beta}\begin{bmatrix} I_{|K|} & 0 \\ 0 & 0\end{bmatrix}$ has nonnegative eigenvalues. Therefore, m can be at most $\lambda_{min}(\Delta) + \frac{1-\beta}{\beta}$.

Then, by [94] and [95]:

1. a unique optimal (with respect to ℓ) feasible solution X^* exists
2. for fixed step size $\gamma = \frac{1}{\lambda_{max}(\Delta)+\frac{1-\beta}{\beta}}$, ϵ-fair imputation converges as $\|X^{(t)} - X^*\|_2^2 \leq \left(1 - \frac{\lambda_{min}(\Delta)+\frac{1-\beta}{\beta}}{\lambda_{max}(\Delta)+\frac{1-\beta}{\beta}}\right)^t \|X^{(0)} - X^*\|_2^2$
3. for fixed step size $\gamma = 1 < \frac{1}{\lambda_{max}(\Delta)+\frac{1-\beta}{\beta}}$, ϵ-fair imputation converges to X^*

B Additional experimental results

B.1 Datasets

SBM synthetic datasets Each network has 500 train nodes, 250 validation nodes, and 250 test nodes, split uniformly at random. Each node has a 10-dimensional feature vector sampled as described in the documentation[2]. All edges have a weight of 1. PyTorch Geometric is used in accordance with its MIT license.

[2] `https://pytorch-geometric.readthedocs.io/en/latest/modules/datasets.html#torch_geometric.datasets.StochasticBlockModelDataset`

Real-world datasets In the `Credit defaulter` dataset, each node has 13 features (e.g. education, credit history, etc.), with an average degree of 95.79 ± 85.88 [29]. In the `German credit` dataset, each node has 27 features (e.g. loan amount, account-related features, etc.), with an average degree of 44.48 ± 26.51. For both datasets, we use a 50/25/25 train/validation/test split, with each split comprising an equal portion of each label, and we do not include group membership as a feature. To the best of our knowledge (via manual sampling and inspection), neither dataset contains personally identifiable information or offensive content. We use [29]'s data and data loading code[3] in accordance with the MIT license.

B.2 Imputation algorithms

We run GM and NM for 1 iteration each, and FP and GR for 40 iterations. We adapted the code for data utilities, Feature Propagation, and model training from [16][4] in accordance with its Apache-2.0 license. We state all changes in this paper. We implement all algorithms using PyTorch, in accordance with its license [96].

B.3 Models and training

For mlp and gcn, we use a hidden dimension of 64. We train all models full-batch using the Adam optimizer with a learning rate of 0.005 and Dropout rate of 0.5 [97, 98]. We also use early stopping with a patience of 200 epochs, i.e. we stop training when the best validation accuracy has not changed for 200 epochs, and train for a maximum of 10000 epochs. We do not do any hyperparameter tuning. We implement and train all models using PyTorch and PyTorch Geometric [96, 82]. We train all models on a single `tesla v100-sxm2-16gb` GPU on an internal cluster.

B.4 Performance Evaluation

To evaluate imputed features for `SBM`, since we don't have labels, we employ relative reconstruction error $\mathbf{RE}$ (calculated as $\|X_{true} - X_{pred}\|_2 / \|X_{true}\|_2$, where X_{true} and X_{pred} are the ground-truth and imputed features, respectively [16]. A lower reconstruction error is better, and we would like regular mean aggregation imputation and its ϵ-fair counterparts to have comparable reconstruction errors. To measure performance on the real-world datasets, we consider the test accuracy ($\mathbf{Acc}$) of models trained on the imputed data. A higher test accuracy is preferable, and we again would like comparable accuracies for regular and ϵ-fair imputation.

To evaluate group fairness, we compute the discrimination risk ($\mathbf{DR}$) of the imputed data. A lower discrimination risk is preferable. For the `SBM` synthetic datasets, we also measure how much information the imputed features contain about group membership. We do this by training the models on the imputed data to predict group membership and calculate the test accuracy of the models on identifying group membership (which we refer to as $\mathbf{MI}$) [85, 21]. The models may be conceptualized as adversaries attempting to recover group membership from the imputed features. Thus, we would like $\mathbf{MI}$ to be closer to 0.5 (i.e. the imputed features contain no information about group membership). We do not compute $\mathbf{MI}$ for the real-world datasets, as inferring group membership or identity from real-world data is invasive, invalid, and can be weaponized against marginalized communities (e.g. to find and incarcerate LGBTQIA+ individuals) [99]. To evaluate group fairness for the real-world datasets, we use the test statistical parity ($\mathbf{SP}$) of the models, defined as $|P(Z = 1|S = Q) - P(Z = 1|S = R)|$ (disparity in positive outcome rate for the groups) [78], and test equal opportunity ($\mathbf{EO}$), defined as $|P(Z = 1|S = Q, Y = 1) - P(Z = 1|S = R, Y = 1)|$ (disparity in accuracy of predicting positive outcome for the groups) [86].

B.5 Contraction coefficient

As we analyzed, Figures 2 to 12 show that, for `SBM`: 1) a low unknown feature rate for both groups or disparate unknown feature rates across the groups increases α and the discrimination risk (Figures 2, 5, 8, 11); 2) group size alone does not affect α or the discrimination risk (Figures 3, 6, 9, 12); 3) a lower inter-link to intra-link ratio increases α and the discrimination risk (Figures 4, 7, 10).

[3] `https://github.com/chirag126/nifty`

[4] `https://github.com/twitter-research/feature-propagation`

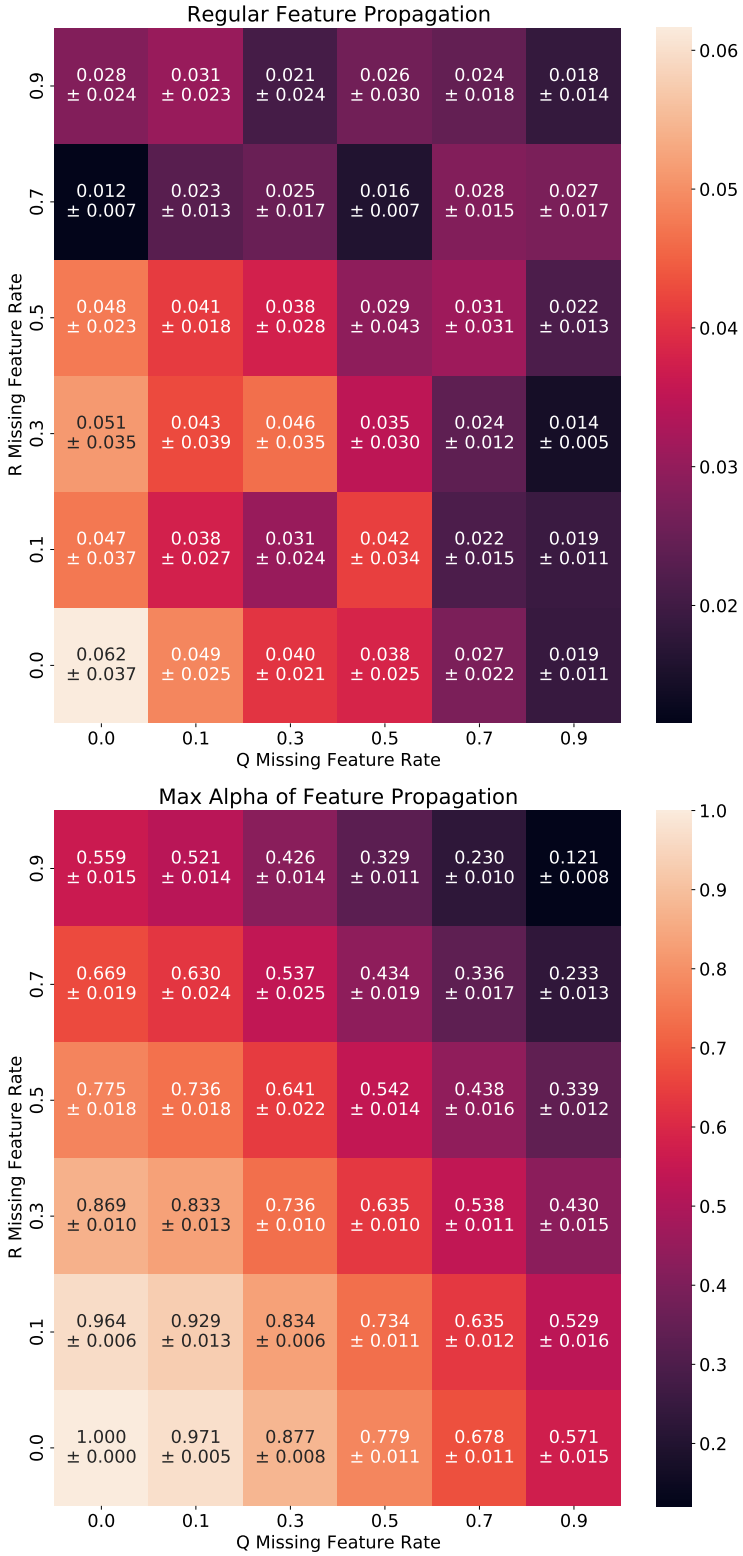

Figure 2: Heatmap of discrimination risks and maximum α (over all channels) of Feature Propagation for 36 combinations of unknown feature rates for each group in SBM. We use 0.5 relative group sizes and 0.5 inter- and intra-link rates.

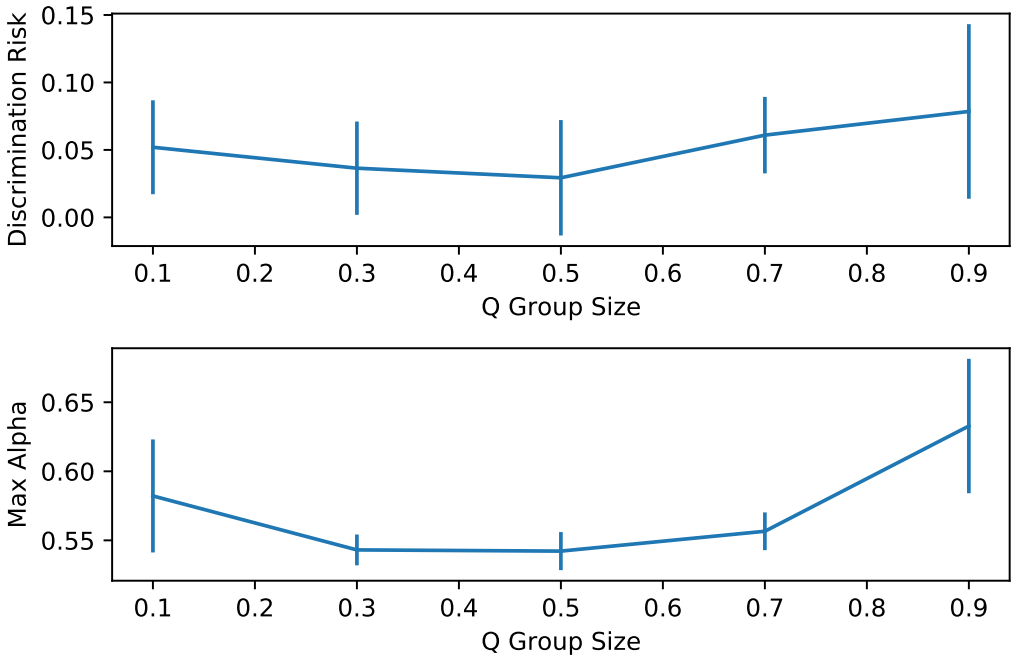

Figure 3: Plots of discrimination risk and maximum α (over all channels) of Feature Propagation vs. relative size of group Q in SBM. We use 0.5 unknown feature rates for both groups and 0.5 inter- and intra-link rates.

Table 3: Reconstruction error (**RE**), discrimination risk (**DR**), and test group membership identification accuracy (**MI**) of all models averaged over relative sizes of group Q of $\{0.1, 0.3, 0.5, 0.7, 0.9\}$ in SBM. We use 0.5 unknown feature rates for both groups and 0.5 inter- and intra-link rates.

Method	**RE** $\downarrow$	**DR** $\downarrow$	**MI**$_{linear}$ $\downarrow$	**MI**$_{mlp}$ $\downarrow$	**MI**$_{gcn}$ $\downarrow$
0-Fair GM	1.054 ± 0.004	$\mathbf{0 \pm 0}$	$\mathbf{0.758 \pm 0.025}$	$\mathbf{0.78 \pm 0.014}$	0.742 ± 0.018
0.025-Fair GM	1.051 ± 0.004	0.022 ± 0.004	0.79 ± 0.012	0.787 ± 0.012	$\mathbf{0.74 \pm 0.014}$
0.05-Fair GM	1.048 ± 0.003	0.032 ± 0.003	0.791 ± 0.018	0.794 ± 0.013	0.747 ± 0.019
Regular GM	$\mathbf{1 \pm 0}$	0.041 ± 0.008	0.835 ± 0.01	0.845 ± 0.011	0.771 ± 0.027
0-Fair NM	1.015 ± 0.003	$\mathbf{0 \pm 0}$	$\mathbf{0.757 \pm 0.023}$	$\mathbf{0.792 \pm 0.015}$	$\mathbf{0.738 \pm 0.016}$
0.025-Fair NM	1.012 ± 0.003	0.019 ± 0.003	0.791 ± 0.022	0.8 ± 0.014	0.744 ± 0.011
0.05-Fair NM	1.009 ± 0.003	0.029 ± 0.006	0.787 ± 0.017	0.807 ± 0.011	0.746 ± 0.017
Regular NM	$\mathbf{0.959 \pm 0.003}$	0.038 ± 0.013	0.835 ± 0.011	0.843 ± 0.015	0.763 ± 0.024
0-Fair FP	1.003 ± 0.005	$\mathbf{0 \pm 0}$	$\mathbf{0.757 \pm 0.019}$	$\mathbf{0.799 \pm 0.014}$	$\mathbf{0.736 \pm 0.013}$
0.025-Fair FP	1 ± 0.005	0.021 ± 0.002	0.785 ± 0.021	0.801 ± 0.014	0.754 ± 0.017
0.05-Fair FP	0.997 ± 0.005	0.033 ± 0.005	0.789 ± 0.016	0.806 ± 0.012	0.738 ± 0.016
Regular FP	$\mathbf{0.947 \pm 0.005}$	0.051 ± 0.017	0.829 ± 0.006	0.841 ± 0.02	0.760 ± 0.022
0-Fair GR	0.962 ± 0.005	$\mathbf{0 \pm 0}$	$\mathbf{0.752 \pm 0.024}$	$\mathbf{0.788 \pm 0.019}$	0.742 ± 0.013
0.025-Fair GR	0.961 ± 0.005	0.023 ± 0.003	0.797 ± 0.015	0.797 ± 0.02	0.752 ± 0.016
0.05-Fair GR	0.96 ± 0.005	0.036 ± 0.005	0.799 ± 0.009	0.805 ± 0.014	$\mathbf{0.739 \pm 0.017}$
Regular GR	$\mathbf{0.945 \pm 0.006}$	0.036 ± 0.012	0.821 ± 0.015	0.82 ± 0.014	0.759 ± 0.021

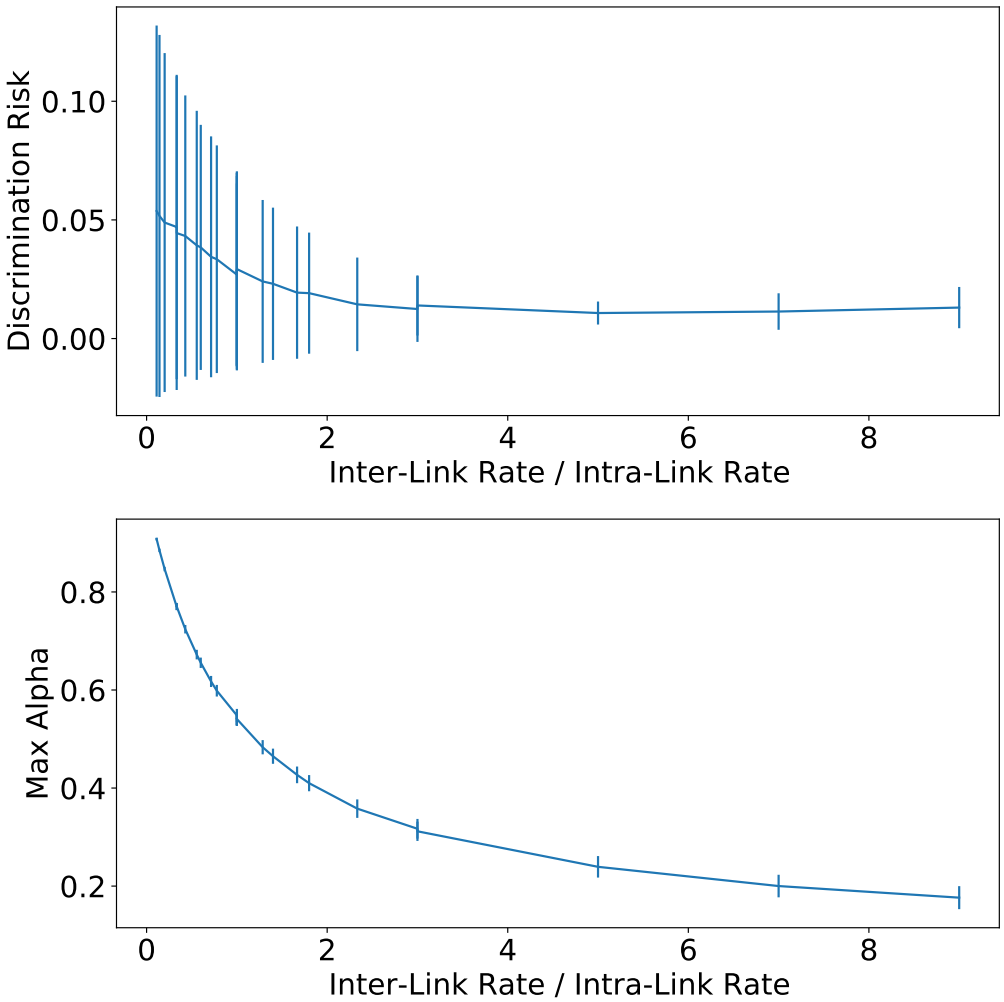

Figure 4: Plots of discrimination risk and maximum α (over all channels) of Feature Propagation vs. ratio of inter-link rate to intra-link rate in `SBM`. We use 0.5 relative group sizes and 0.5 unknown feature rates for both groups.

Table 4: Reconstruction error (**RE**), discrimination risk (**DR**), and test group membership identification accuracy (**MI**) of all models averaged over all 25 combinations of inter- and intra-link rates of $\{0.1, 0.3, 0.5, 0.7, 0.9\}$ in `SBM`. We use 0.5 relative group sizes and 0.5 unknown feature rates for both groups.

Method	**RE** $\downarrow$	**DR** $\downarrow$	$\mathbf{MI}_{linear}$ $\downarrow$	$\mathbf{MI}_{mlp}$ $\downarrow$	$\mathbf{MI}_{gcn}$ $\downarrow$
0-Fair NM	1.028 ± 0.009	$\mathbf{0 \pm 0}$	$\mathbf{0.609 \pm 0.102}$	$\mathbf{0.729 \pm 0.046}$	$\mathbf{0.905 \pm 0.003}$
0.025-Fair NM	1.023 ± 0.008	0.014 ± 0.011	0.724 ± 0.09	0.749 ± 0.035	0.911 ± 0.008
0.05-Fair NM	1.019 ± 0.008	0.02 ± 0.02	0.74 ± 0.046	0.768 ± 0.036	0.911 ± 0.01
Regular NM	$\mathbf{0.931 \pm 0.003}$	0.022 ± 0.024	0.845 ± 0.026	0.866 ± 0.027	0.924 ± 0.008
0-Fair FP	1.022 ± 0.012	$\mathbf{0 \pm 0}$	$\mathbf{0.64 \pm 0.064}$	$\mathbf{0.742 \pm 0.038}$	$\mathbf{0.905 \pm 0.003}$
0.025-Fair FP	1.017 ± 0.012	0.014 ± 0.012	0.697 ± 0.095	0.753 ± 0.039	0.912 ± 0.007
0.05-Fair FP	1.013 ± 0.012	0.023 ± 0.022	0.740 ± 0.040	0.762 ± 0.04	0.909 ± 0.008
Regular FP	$\mathbf{0.918 \pm 0.004}$	0.034 ± 0.043	0.844 ± 0.025	0.853 ± 0.035	0.922 ± 0.009
0-Fair GR	0.948 ± 0.043	$\mathbf{0 \pm 0}$	$\mathbf{0.578 \pm 0.105}$	$\mathbf{0.773 \pm 0.038}$	$\mathbf{0.905 \pm 0.004}$
0.025-Fair GR	0.946 ± 0.004	0.016 ± 0.013	0.779 ± 0.036	0.793 ± 0.038	0.915 ± 0.005
0.05-Fair GR	0.945 ± 0.004	0.02 ± 0.02	0.769 ± 0.018	0.797 ± 0.0366	0.912 ± 0.009
Regular GR	$\mathbf{0.916 \pm 0.005}$	0.023 ± 0.032	0.846 ± 0.023	0.864 ± 0.023	0.921 ± 0.009

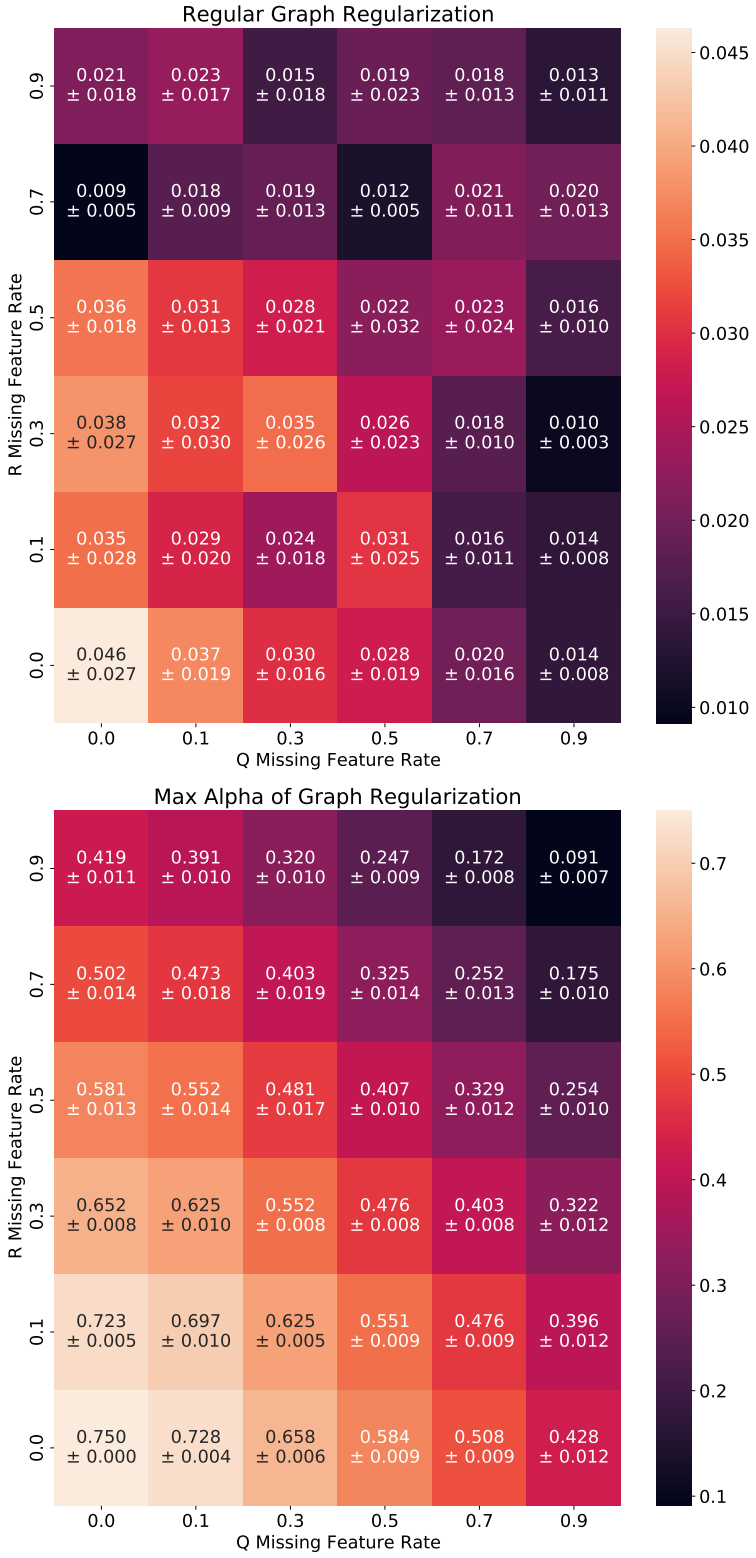

Figure 5: Heatmap of discrimination risks and maximum α (over all channels) of Graph Regularization for 36 combinations of unknown feature rates for each group in SBM. We use 0.5 relative group sizes and 0.5 inter- and intra-link rates.

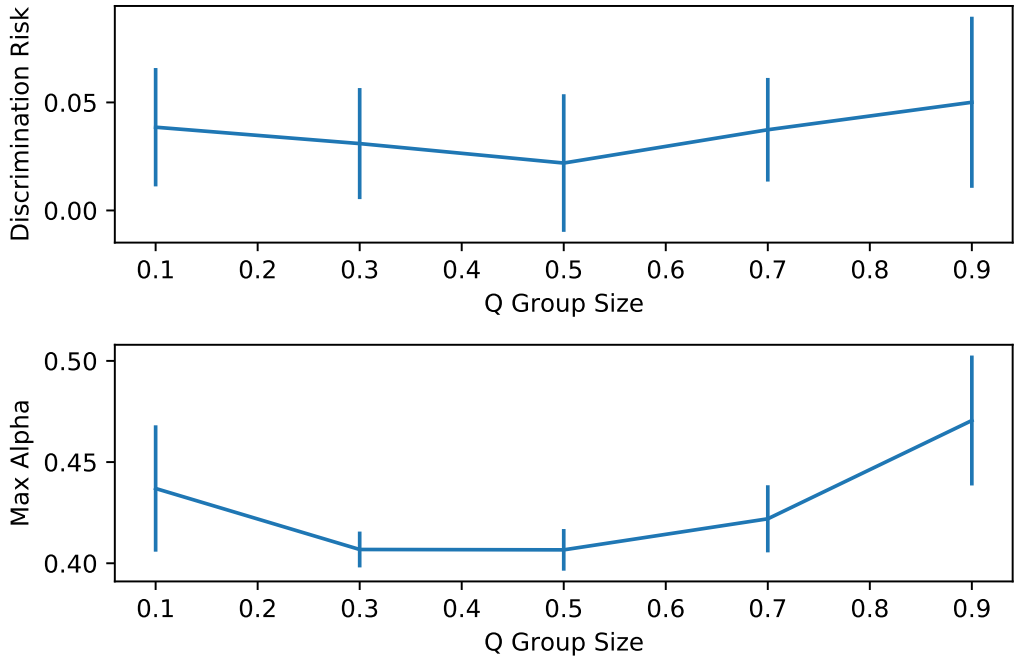

Figure 6: Plots of discrimination risk and maximum α (over all channels) of Graph Regularization vs. relative size of group Q in `SBM`. We use 0.5 unknown feature rates for both groups and 0.5 inter- and intra-link rates.

Table 5: Equal opportunity (**EO**) averaged over all 25 combinations of unknown feature rates of $\{0.1, 0.3, 0.5, 0.7, 0.9\}$ for each group in `German credit`.

Method	$\mathbf{EO}_{linear} \downarrow$	$\mathbf{EO}_{mlp} \downarrow$	$\mathbf{EO}_{gcn} \downarrow$
0.0-Fair GM	0.037 ± 0.01	0.029 ± 0.004	0.009 ± 0.008
0.025-Fair GM	0.031 ± 0.007	0.029 ± 0.008	0.018 ± 0.021
0.05-Fair GM	$\mathbf{0.026 \pm 0.003}$	0.03 ± 0.003	0.013 ± 0.005
Regular GM	0.033 ± 0.008	$\mathbf{0.023 \pm 0.003}$	$\mathbf{0.006 \pm 0.005}$
0.0-Fair NM	0.038 ± 0.009	0.037 ± 0.006	$\mathbf{0.007 \pm 0.006}$
0.025-Fair NM	$\mathbf{0.035 \pm 0.008}$	0.038 ± 0.007	0.013 ± 0.012
0.05-Fair NM	0.04 ± 0.006	0.035 ± 0.006	0.009 ± 0.003
Regular NM	0.038 ± 0.012	$\mathbf{0.032 \pm 0.006}$	0.012 ± 0.006
0.0-Fair FP	$\mathbf{0.01 \pm 0.011}$	0.034 ± 0.018	0.024 ± 0.041
0.025-Fair FP	0.028 ± 0.031	0.031 ± 0.018	0.023 ± 0.051
0.05-Fair FP	0.043 ± 0.07	$\mathbf{0.029 \pm 0.028}$	$\mathbf{0 \pm 0}$
Regular FP	0.042 ± 0.046	0.038 ± 0.02	0.004 ± 0.006
0.0-Fair GR	0.029 ± 0.012	$\mathbf{0.022 \pm 0.003}$	0.005 ± 0.006
0.025-Fair GR	0.031 ± 0.011	0.024 ± 0.005	0.007 ± 0.007
0.05-Fair GR	$\mathbf{0.027 \pm 0.007}$	0.024 ± 0.006	$\mathbf{0.004 \pm 0.004}$
Regular GR	0.032 ± 0.01	0.025 ± 0.007	0.009 ± 0.01

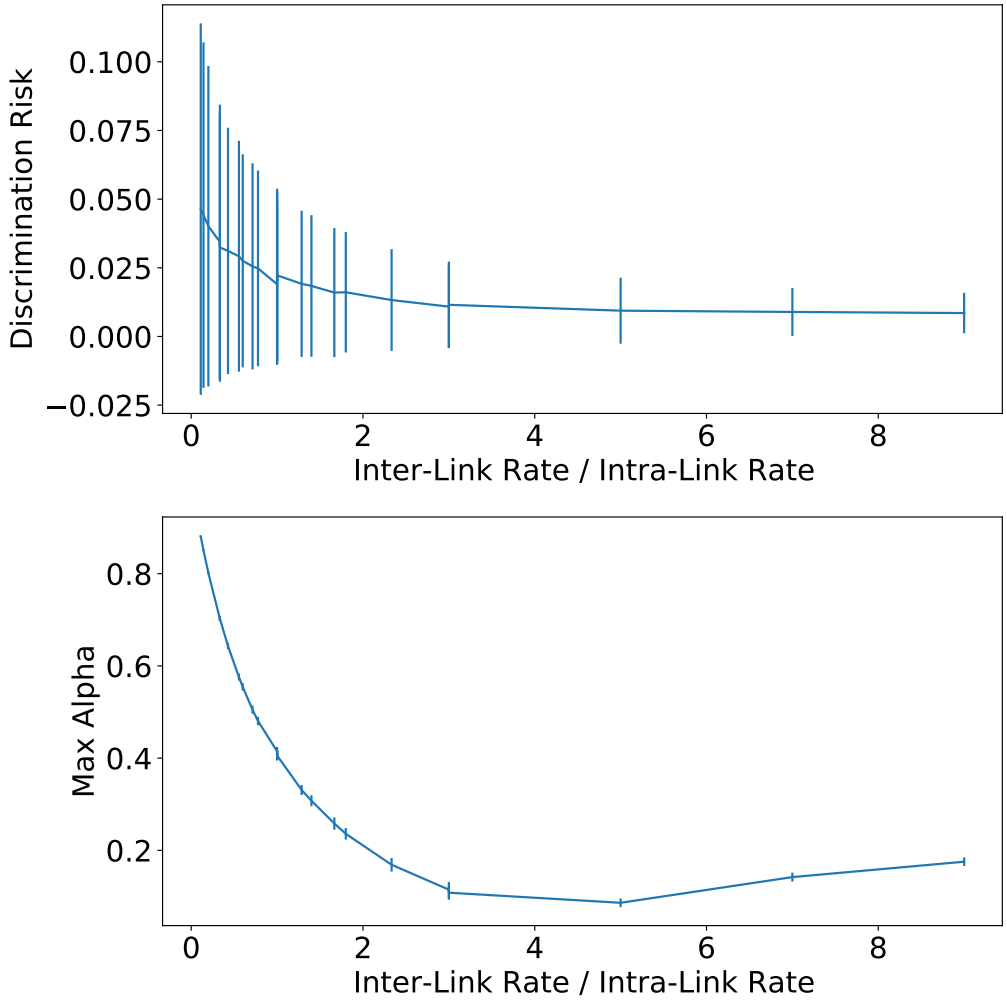

Figure 7: Plots of discrimination risk and maximum α (over all channels) of Graph Regularization vs. ratio of inter-link rate to intra-link rate in `SBM`. We use 0.5 relative group sizes and 0.5 unknown feature rates for both groups.

Table 6: Test accuracy (**Acc**) and statistical parity (**SP**) of all models averaged over all 25 combinations of unknown feature rates of $\{0.1, 0.3, 0.5, 0.7, 0.9\}$ for each group in `Credit defaulter`.

Method	$\mathbf{Acc}_{linear} \uparrow$	$\mathbf{Acc}_{mlp} \uparrow$	$\mathbf{Acc}_{gcn} \uparrow$	$\mathbf{SP}_{linear} \downarrow$	$\mathbf{SP}_{mlp} \downarrow$	$\mathbf{SP}_{gcn} \downarrow$
0.0-Fair GM	0.781 ± 0.002	$\mathbf{0.764 \pm 0.012}$	0.771 ± 0.007	0.063 ± 0.015	0.08 ± 0.024	0.016 ± 0.009
0.025-Fair GM	0.78 ± 0.006	0.757 ± 0.008	0.774 ± 0.002	0.059 ± 0.021	0.083 ± 0.012	0.015 ± 0.004
0.05-Fair GM	0.78 ± 0.003	0.759 ± 0.013	$\mathbf{0.775 \pm 0.002}$	0.076 ± 0.015	0.08 ± 0.017	0.015 ± 0.003
Regular GM	$\mathbf{0.782 \pm 0.006}$	0.76 ± 0.018	0.775 ± 0.006	$\mathbf{0.055 \pm 0.031}$	$\mathbf{0.056 \pm 0.012}$	$\mathbf{0.005 \pm 0.006}$
0.0-Fair NM	$\mathbf{0.781 \pm 0.002}$	0.765 ± 0.006	0.771 ± 0.007	0.063 ± 0.017	0.085 ± 0.013	0.015 ± 0.013
0.025-Fair NM	0.78 ± 0.005	$\mathbf{0.766 \pm 0.005}$	0.774 ± 0.002	0.057 ± 0.025	0.088 ± 0.008	0.015 ± 0.005
0.05-Fair GM	0.781 ± 0.003	0.769 ± 0.01	$\mathbf{0.775 \pm 0.002}$	0.082 ± 0.011	0.082 ± 0.018	0.016 ± 0.003
Regular GM	0.781 ± 0.007	0.762 ± 0.014	0.773 ± 0.008	$\mathbf{0.054 \pm 0.031}$	$\mathbf{0.061 \pm 0.011}$	$\mathbf{0.005 \pm 0.007}$
0.0-Fair FP	0.779 ± 0.005	0.757 ± 0.022	$\mathbf{0.77 \pm 0.008}$	0.06 ± 0.022	0.085 ± 0.014	0.016 ± 0.014
0.025-Fair FP	0.78 ± 0.002	0.764 ± 0.004	0.774 ± 0.002	0.056 ± 0.027	0.092 ± 0.008	0.016 ± 0.005
0.05-Fair FP	0.78 ± 0.001	$\mathbf{0.768 \pm 0.008}$	0.774 ± 0.002	0.076 ± 0.005	0.084 ± 0.014	0.017 ± 0.004
Regular FP	$\mathbf{0.781 \pm 0.005}$	0.764 ± 0.01	0.775 ± 0.006	$\mathbf{0.051 \pm 0.029}$	$\mathbf{0.075 \pm 0.011}$	$\mathbf{0.005 \pm 0.006}$
0.0-Fair GR	0.773 ± 0.009	$\mathbf{0.796 \pm 0.006}$	0.771 ± 0.011	0.072 ± 0.044	0.098 ± 0.032	0.011 ± 0.012
0.025-Fair GR	0.779 ± 0.005	0.792 ± 0.007	0.772 ± 0.003	0.052 ± 0.032	0.091 ± 0.02	0.017 ± 0.012
0.05-Fair GR	0.78 ± 0.003	0.792 ± 0.007	$\mathbf{0.773 \pm 0.004}$	0.078 ± 0.0314	0.094 ± 0.028	0.023 ± 0.01
Regular GR	$\mathbf{0.781 \pm 0.005}$	0.785 ± 0.004	0.773 ± 0.008	$\mathbf{0.049 \pm 0.043}$	$\mathbf{0.073 \pm 0.038}$	$\mathbf{0.008 \pm 0.01}$

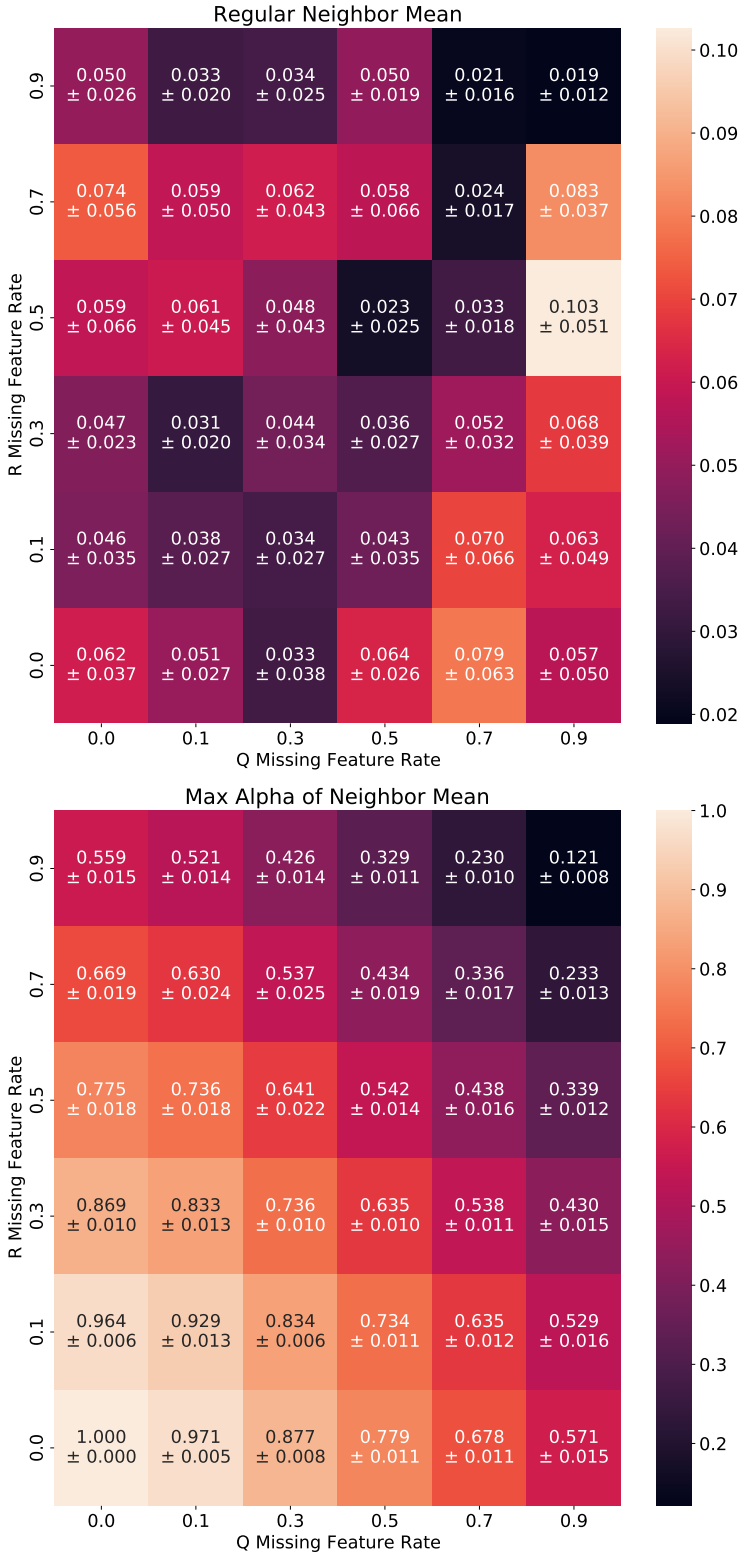

Figure 8: Heatmap of discrimination risks and maximum α (over all channels) of Neighbor Mean for 36 combinations of unknown feature rates for each group in SBM. We use 0.5 relative group sizes and 0.5 inter- and intra-link rates.

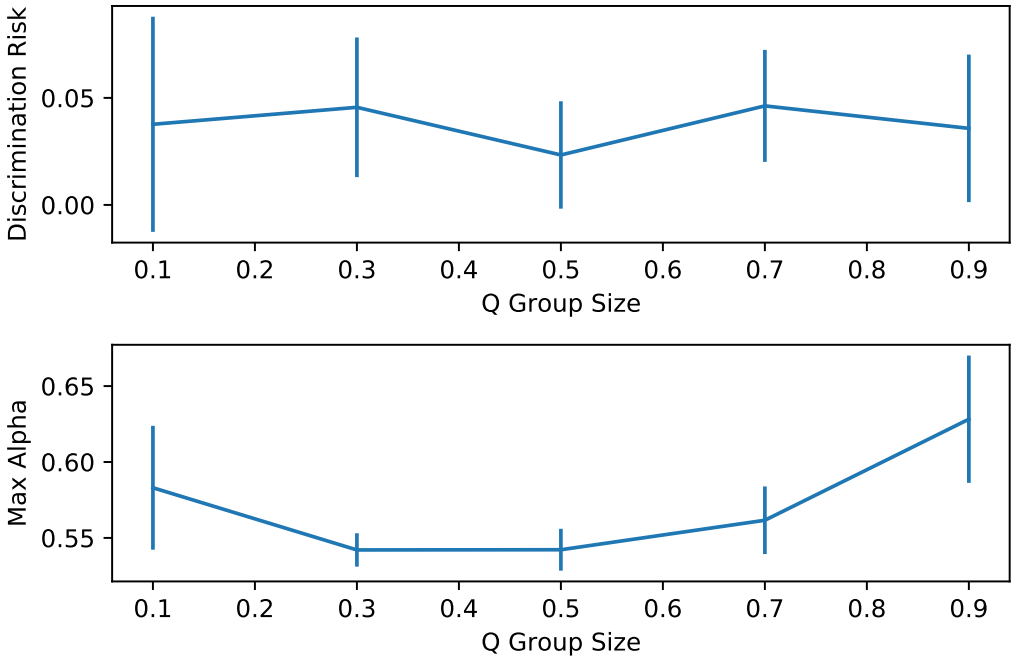

Figure 9: Plots of discrimination risk and maximum α (over all channels) of Neighbor Mean vs. relative size of group Q in `SBM`. We use 0.5 unknown feature rates for both groups and 0.5 inter- and intra-link rates.

Table 7: Equal opportunity (**EO**) of all models averaged over all 25 combinations of unknown feature rates of $\{0.1, 0.3, 0.5, 0.7, 0.9\}$ for each group in `Credit defaulter`.

Method	$\mathbf{EO}_{linear} \downarrow$	$\mathbf{EO}_{mlp} \downarrow$	$\mathbf{EO}_{gcn} \downarrow$
0.0-Fair GM	0.039 ± 0.008	0.056 ± 0.019	0.013 ± 0.007
0.025-Fair GM	0.035 ± 0.014	0.058 ± 0.009	0.012 ± 0.003
0.05-Fair GM	0.048 ± 0.010	0.057 ± 0.016	0.012 ± 0.002
Regular GM	$\mathbf{0.031 \pm 0.017}$	$\mathbf{0.038 \pm 0.011}$	$\mathbf{0.004 \pm 0.005}$
0.0-Fair NM	0.039 ± 0.01	0.06 ± 0.009	0.013 ± 0.007
0.025-Fair NM	0.033 ± 0.015	0.06 ± 0.007	0.011 ± 0.004
0.05-Fair NM	0.05 ± 0.007	0.057 ± 0.014	0.012 ± 0.002
Regular NM	$\mathbf{0.031 \pm 0.018}$	$\mathbf{0.041 \pm 0.007}$	$\mathbf{0.005 \pm 0.006}$
0.0-Fair FP	0.035 ± 0.013	0.059 ± 0.013	0.013 ± 0.008
0.025-Fair FP	0.031 ± 0.016	0.062 ± 0.007	0.013 ± 0.004
0.05-Fair FP	0.043 ± 0.005	0.057 ± 0.011	0.014 ± 0.002
Regular FP	$\mathbf{0.028 \pm 0.016}$	$\mathbf{0.05 \pm 0.01}$	$\mathbf{0.004 \pm 0.005}$
0.0-Fair GR	0.051 ± 0.036	0.07 ± 0.029	0.008 ± 0.011
0.025-Fair GR	$\mathbf{0.03 \pm 0.02}$	0.06 ± 0.025	0.012 ± 0.011
0.05-Fair GR	0.048 ± 0.03	0.067 ± 0.025	0.015 ± 0.009
Regular GR	0.03 ± 0.038	$\mathbf{0.051 \pm 0.038}$	$\mathbf{0.007 \pm 0.007}$

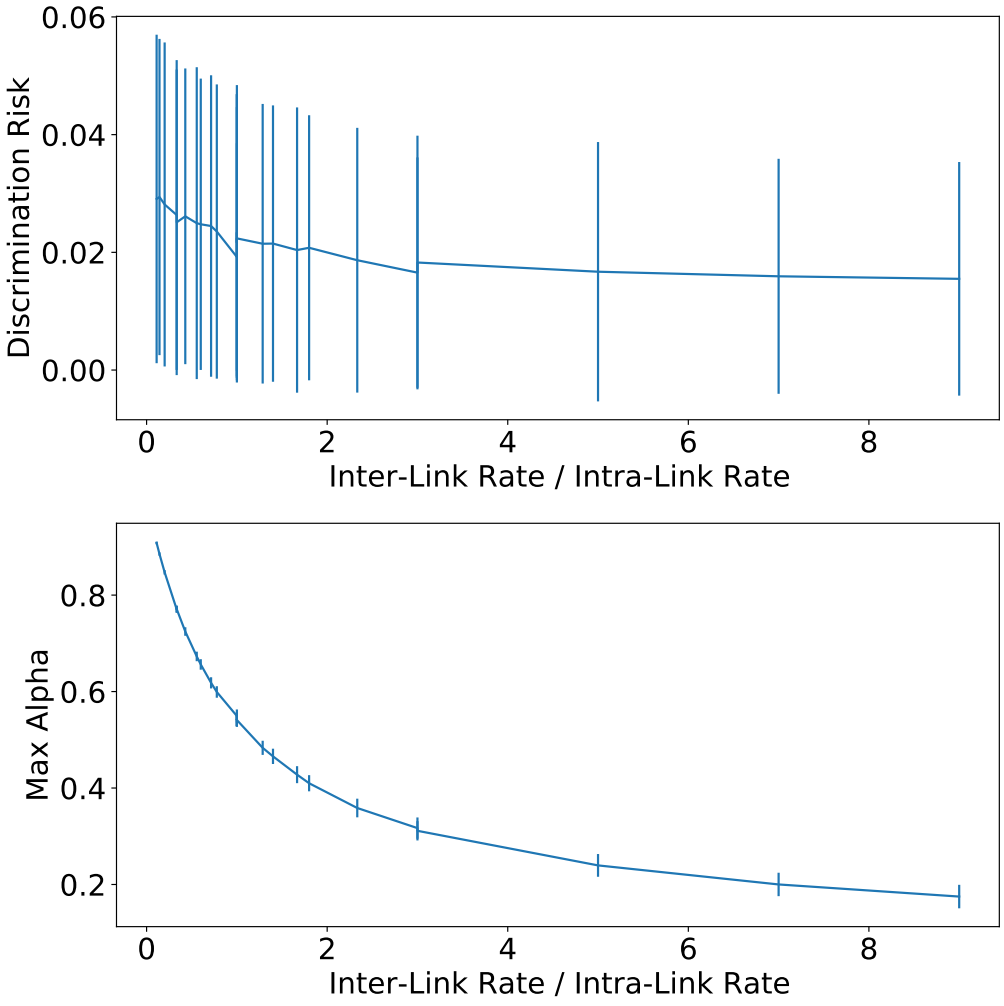

Figure 10: Plots of discrimination risk and maximum α (over all channels) of Neighbor Mean vs. ratio of inter-link rate to intra-link rate in SBM. We use 0.5 relative group sizes and 0.5 unknown feature rates for both groups.

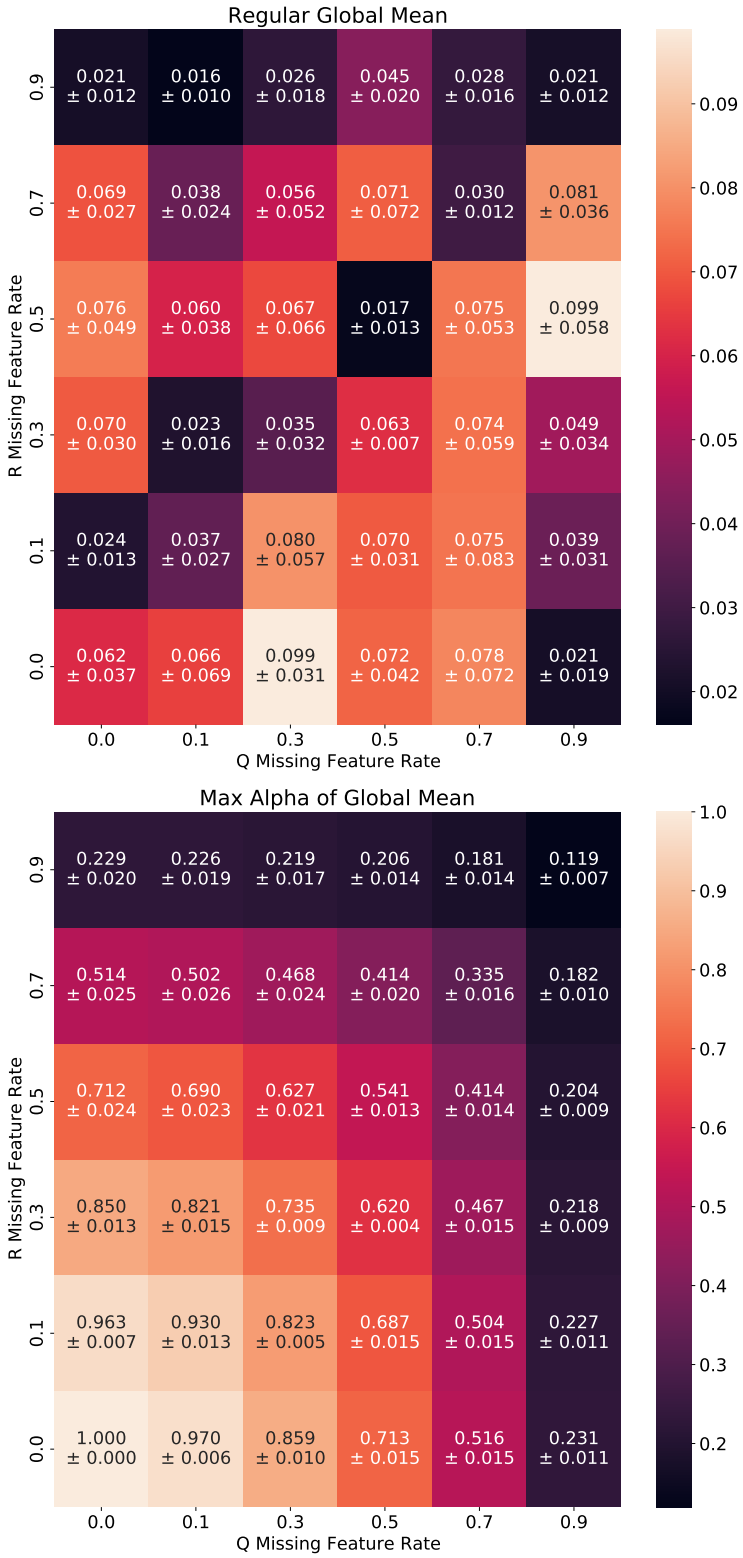

Figure 11: Heatmap of discrimination risks and maximum α (over all channels) of Global Mean for 36 combinations of unknown feature rates for each group in SBM. We use 0.5 relative group sizes. **Note:** Global Mean is not affected by graph structure.

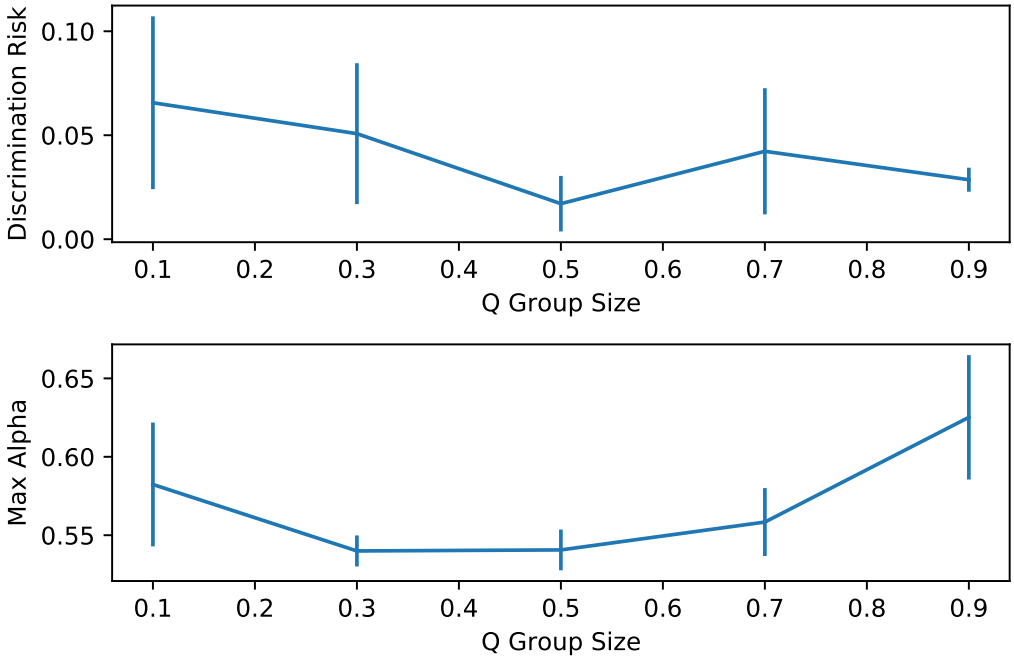

Figure 12: Plots of discrimination risk and maximum α (over all channels) of Global Mean vs. relative size of group Q in SBM. We use 0.5 unknown feature rates for both groups. **Note:** Global Mean is not affected by graph structure.