A Stochastic Optimization Framework for Fair Risk Minimization

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Abstract

Despite the success of large-scale empirical risk minimization (ERM) at achieving high accuracy across a variety of machine learning tasks, *fair* ERM is hindered by the incompatibility of fairness constraints with stochastic optimization. We consider the problem of fair classification with discrete sensitive attributes and potentially large models and data sets, requiring stochastic solvers. Existing in-processing fairness algorithms are either impractical in the large-scale setting because they require large batches of data at each iteration or they are not guaranteed to converge. In this paper, we develop *the first stochastic in-processing fairness algorithm with guaranteed convergence*. For demographic parity, equalized odds, and equal opportunity notions of fairness, we provide slight variations of our algorithm–called FERMI–and prove that each of these variations converges in stochastic optimization with any batch size. Empirically, we show that FERMI is amenable to stochastic solvers with multiple (non-binary) sensitive attributes and non-binary targets, performing well even with minibatch size as small as one. Extensive experiments show that FERMI achieves the most favorable tradeoffs between fairness violation and test accuracy across all tested setups compared with state-of-the-art baselines for demographic parity, equalized odds, equal opportunity. These benefits are especially significant with small batch sizes and for non-binary classification with large number of sensitive attributes, making FERMI a practical, scalable fairness algorithm.

1 Introduction

Ensuring that decisions made using machine learning (ML) algorithms are fair to different subgroups is of utmost importance. Without any mitigation strategy, learning algorithms may result in discrimination against certain subgroups based on sensitive attributes, such as gender or race, even if such discrimination is absent in the training data [Mehrabi et al., 2021], and algorithmic fairness literature aims to remedy such discrimination issues [Sweeney, 2013, Datta et al., 2015, Feldman et al., 2015, Bolukbasi et al., 2016, Angwin et al., 2016, Calmon et al., 2017a, Hardt et al., 2016, Fish et al., 2016, Woodworth et al., 2017, Zafar et al., 2017, Bechavod and Ligett, 2017, Agarwal et al., 2018, Kearns et al., 2018, Prost et al., 2019, Lahoti et al., 2020]. Modern ML problems often involve large-scale models with hundreds of millions or even billions of parameters, e.g., BART [Lewis et al., 2019], ViT [Dosovitskiy et al., 2020], GPT-2 [Radford et al., 2019]. In such cases, during fine-tuning, the available memory on a node constrains us to use stochastic optimization with (small) minibatches in each training iteration. In this paper, we address the dual challenges of *fair* and *stochastic* ML, providing *the first stochastic fairness algorithm that provably converges with any batch size*.

A machine learning algorithm satisfies the *demographic parity* fairness notion if the predicted target is independent of the sensitive attributes [Dwork et al., 2012]. Promoting demographic parity can lead to poor performance, especially if the true outcome is not independent of the sensitive attributes.

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Reference	NB target	NB attrib.	NB code	Beyond logistic	Stoch. alg. (unbiased**)	Converg. (stoch.)
FERMI (this work)	✓	✓	✓	✓	✓ (✓)	✓ (✓)
[Cho et al., 2020a]	✓	✓	✓	✓	✓ (✗)	✗
[Cho et al., 2020b]	✓	✓	✗	✓	✓ (✓)	✗
[Baharlouei et al., 2020]	✓	✓	✓	✓	✗	✓ (✗)
[Rezaei et al., 2020]	✗	✗	✗	✗	✗	✗
[Jiang et al., 2020]*	✗	✓	✗	✗	✗	✗
[Mary et al., 2019]	✓	✓	✓	✓	✓ (✗)	✗
[Prost et al., 2019]	✗	✗	✗	✓	✓ (✗)	✗
[Donini et al., 2018]	✗	✓	✗	✓	✗	✗
[Zhang et al., 2018]	✓	✓	✗	✓	✓ (✗)	✗
[Agarwal et al., 2018]	✗	✓	✗	✓	✗	✓ (✗)

Table 1: Comparison of state-of-the-art in-processing methods (**NB = non-binary**) on whether they (a) handle non-binary targets (beyond binary classification), (b) handle non-binary sensitive attributes, (c) release code that applies to non-binary targets/attributes, (d) extend to arbitrary models, (e) provide code for stochastic optimization (and whether the gradients are unbiased), (f) provide convergence guarantees (for stochastic optimization). FERMI is the only method compatible with stochastic optimization and guaranteed convergence. The only existing baselines for non-binary classification with non-binary sensitive attributes are [Mary et al., 2019, Baharlouei et al., 2020, Cho et al., 2020a] (NB code). *We refer to the in-processing method of [Jiang et al., 2020], not their post-processing method. **We use the term "unbiased" in statistical estimation sense; not to be confused with bias in the fairness sense.

To remedy this, Hardt et al. [2016] proposed *equalized odds* to ensure that the predicted target is conditionally independent of the sensitive attributes given the true label. A further relaxed version of this notion is *equal opportunity* which is satisfied if predicted target is conditionally independent of sensitive attributes given that the true label is in an advantaged class [Hardt et al., 2016]. Equal opportunity ensures that false positive rates are equal across different demographics, where negative outcome is considered an advantaged class, e.g., extending a loan.

2 Fair Risk Minimization through ERMI Regularization

In this section, we propose a fair learning objective (Eq. (FRMI obj.)) and derive an empirical variation (Eq. (FERMI obj.)) of this objective. We then develop a stochastic optimization algorithm (Algorithm 1) that we use to solve these objectives, and prove that our algorithm converges to an approximate solution of the two objectives.

Consider a learner who trains a model to make a prediction, $\widehat{Y}$, e.g., whether or not to extend a loan, supported on $[m] := \{1, \ldots, m\}$. The prediction is made using a set of features, $\mathbf{X}$, e.g., financial history features. Assume that there is a set of discrete sensitive attributes, S, e.g., race and sex, supported on $[k]$.

Definition 1 (ERMI – exponential Rényi mutual information)**.** *The exponential Rényi mutual information between $\widehat{Y}$ and S with joint distribution $p_{\widehat{Y},S}$ and marginals $p_{\widehat{Y}}$, p_S is:*

$$D_R(\widehat{Y}; S) := \mathbb{E}\left\{\frac{p_{\widehat{Y},S}(\widehat{Y}, S)}{p_{\widehat{Y}}(\widehat{Y})p_S(S)}\right\} - 1 = \sum_{j\in[m]}\sum_{r\in[k]} \frac{p_{\widehat{Y},S}(j,r)^2}{p_{\widehat{Y}}(j)p_S(r)} - 1. \tag{ERMI}$$

Definition 1 is what we would use if *demographic parity* were the fairness notion of interest. If instead one wanted to promote fairness with respect to equalized odds or equal opportunity, then it is straightforward to modify the definition by substituting appropriate conditional probabilities for $p_{\widehat{Y},S}$, $p_{\widehat{Y}}$, and p_S in Eq. (ERMI): see Appendix B. In Appendix B, we also discuss that ERMI is the χ^2-divergence (which is an f-divergence) between the joint distribution, $p_{\widehat{Y},S}$, and the Kronecker product of marginals, $p_{\widehat{Y}} \otimes p_S$ [Calmon et al., 2017b]. In particular, ERMI is non-negative, and zero if and only if demographic parity (or equalized odds or equal opportunity, for the conditional version of ERMI) is satisfied. Additionally, we show in Appendix C that ERMI provides an upper bound on other commonly used measures of fairness violation. Therefore, any algorithm that makes ERMI small will also have small fairness violation with respect to these other notions.

We can now define our fair risk minimization through ERMI framework:[1]

$$\min_{\boldsymbol{\theta}} \left\{\text{FRMI}(\boldsymbol{\theta}) := \mathcal{L}(\boldsymbol{\theta}) + \lambda D_R\big(\widehat{Y}_{\boldsymbol{\theta}}(\mathbf{X}); S\big)\right\}, \tag{FRMI obj.}$$

[1]In this section, we present all results in the context of demographic parity, leaving off all conditional expectations for clarity of presentation. The algorithm/results are readily extended to equalized odds and equal opportunity by using the conditional version of Eq. (ERMI) (which is described in Appendix B); we use these resulting algorithms for numerical experiments.

where $\mathcal{L}(\boldsymbol{\theta}) := \mathbb{E}_{(\mathbf{X},Y)}[\ell(\mathbf{X}, Y; \boldsymbol{\theta})]$ for a given loss function ℓ (e.g. L_2 loss or cross entropy loss); $\lambda > 0$ is a scalar balancing the accuracy versus fairness objectives; and $\widehat{Y}_{\boldsymbol{\theta}}(\mathbf{X})$ is the output of the learned model (i.e. the predicted label in a classification task). While $\widehat{Y}_{\boldsymbol{\theta}}(\mathbf{X}) = \widehat{Y}(\mathbf{X}; \boldsymbol{\theta})$ inherently depends on $\mathbf{X}$ and $\boldsymbol{\theta}$, in the rest of this paper, we sometimes leave the dependence of $\widehat{Y}$ on $\mathbf{X}$ and/or $\boldsymbol{\theta}$ implicit for brevity of notation. Notice that we have also left the dependence of the loss on the predicted outcome $\widehat{Y} = \widehat{Y}_{\boldsymbol{\theta}}(\mathbf{X})$ implicit. As is standard, we assume that the prediction function satisfies $\mathbb{P}(\widehat{Y}(\boldsymbol{\theta}, \mathbf{X}) = j|\mathbf{X}) = \mathcal{F}_j(\boldsymbol{\theta}, \mathbf{X})$, where $\mathcal{F}(\boldsymbol{\theta}, \mathbf{X}) = (\mathcal{F}_1(\boldsymbol{\theta}, \mathbf{X}), \ldots, \mathcal{F}_m(\boldsymbol{\theta}, \mathbf{X}))^T \in [0,1]^m$ is differentiable in $\boldsymbol{\theta}$ and $\sum_{j=1}^m \mathcal{F}_j(\boldsymbol{\theta}, \mathbf{X}) = 1$. For example, $\mathcal{F}(\boldsymbol{\theta}, \mathbf{X})$ could represent the probability label given by a logistic regression model or the output of a neural network after softmax layer.

2.1 FERMI: A Stochastic Fair Learning Algorithm

In practice, the true joint distribution of $(\mathbf{X}, S, Y, \widehat{Y})$ is unknown and we only have N samples at our disposal. Let $\mathbf{D} = \{\mathbf{x}_i, s_i, y_i, \widehat{y}(\mathbf{x}_i; \boldsymbol{\theta})\}_{i \in [N]}$ denote the features, sensitive attributes, targets, and the predictions of the model parameterized by $\boldsymbol{\theta}$ for these given samples. For now, we consider the empirical risk minimization (ERM) problem and do not require any assumptions on the data set (e.g. we allow for different samples in $\mathbf{D}$ to be drawn from different, heterogeneous distributions). Consider the empirical objective

$$\min_{\boldsymbol{\theta}} \left\{ \text{FERMI}(\boldsymbol{\theta}) := \widehat{\mathcal{L}}(\boldsymbol{\theta}) + \lambda \widehat{D}_R(\widehat{Y}_{\boldsymbol{\theta}}(\mathbf{X}), S) \right\}, \tag{FERMI obj.}$$

where $\widehat{\mathcal{L}}(\boldsymbol{\theta}) := \frac{1}{N} \sum_{i=1}^N \ell(\mathbf{x}_i, y_i; \boldsymbol{\theta})$ is the empirical loss and $\widehat{D}_R(\widehat{Y}, S)$ is defined by replacing p in Eq. (ERMI) with $\hat{p}$ denoting empirical probabilities with respect to $\mathbf{D}$: $\hat{p}_S(r) = \frac{1}{N} \sum_{i=1}^N \mathbb{1}_{\{s_i = r\}}$; $\widehat{p}_{\widehat{y}}(j) = \frac{1}{N} \sum_{i=1}^N \mathcal{F}_j(\boldsymbol{\theta}, \mathbf{x}_i)$; and $\hat{p}_{\widehat{Y},S}(j, r) = \frac{1}{N} \sum_{i=1}^N \mathcal{F}_j(\boldsymbol{\theta}, \mathbf{x}_i) \mathbf{s}_{i,r}$ for $j \in [m], r \in [k]$. Now, it is straightforward to derive an unbiased estimate for $\widehat{\mathcal{L}}(\boldsymbol{\theta})$ via $\frac{1}{|B|} \sum_{i \in B} \ell\big(\mathbf{x}_i, y_i; \boldsymbol{\theta}\big)$ where $B \subseteq [N]$ is a random minibatch of data points drawn from $\mathbf{D}$. However, unbiasedly estimating $\widehat{D}_R(\widehat{Y}, S)$ in the objective function Eq. (FERMI obj.) with $|B| < N$ samples is more difficult. In what follows, we present our approach to deriving statistically *unbiased stochastic estimators* of the gradients of $\widehat{D}_R(\widehat{Y}, S)$ given a random batch of data points B. This stochastic estimator is key to developing a stochastic convergent algorithm for solving Eq. (FERMI obj.). The key novel observation that allows us to derive this estimator is that Equation FERMI obj. can be written as a *min-max* optimization problem (see Proposition 1):

Proposition 1. *Let $\widehat{\mathbf{y}}(\mathbf{x}_i, \boldsymbol{\theta}) \in \{0,1\}^m$ and $\mathbf{s}_i = (\mathbf{s}_{i,1}, \ldots, \mathbf{s}_{i,k})^T \in \{0,1\}^k$ be the one-hot encodings of $\widehat{y}(\mathbf{x}_i, \boldsymbol{\theta})$ and s_i, respectively for $i \in [N]$. Let $(\mathbf{x}_i, s_i, y_i)$ be a random draw from $\mathbf{D}$. Then, Eq.* (FERMI obj.) *is equivalent to*

$$\min_{\boldsymbol{\theta}} \max_{W \in \mathbb{R}^{k \times m}} \left\{ \widehat{F}(\boldsymbol{\theta}, W) := \widehat{\mathcal{L}}(\boldsymbol{\theta}) + \lambda \widehat{\Psi}(\boldsymbol{\theta}, W) \right\}, \tag{1}$$

where $\widehat{\Psi}(\boldsymbol{\theta}, W) = -\operatorname{Tr}(W \widehat{P}_{\widehat{y}} W^T) + 2 \operatorname{Tr}(W \widehat{P}_{\widehat{y},s} \widehat{P}_s^{-1/2}) - 1 = \frac{1}{N} \sum_{i=1}^N \widehat{\psi}_i(\boldsymbol{\theta}, W)$ and

$$\begin{aligned}\widehat{\psi}_i(\boldsymbol{\theta}, W) &:= -\operatorname{Tr}(W \mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i, \boldsymbol{\theta}) \widehat{\mathbf{y}}(\mathbf{x}_i, \boldsymbol{\theta})^T | \mathbf{x}_i] W^T) + 2 \operatorname{Tr}(W \mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i; \boldsymbol{\theta}) \mathbf{s}_i^T | \mathbf{x}_i, s_i] \widehat{P}_s^{-1/2}) - 1 \\ &= -\operatorname{Tr}(W \operatorname{diag}(\mathcal{F}_1(\boldsymbol{\theta}, \mathbf{x}_i), \ldots, \mathcal{F}_m(\boldsymbol{\theta}, \mathbf{x}_i)) W^T) + 2 \operatorname{Tr}(W \mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i; \boldsymbol{\theta}) \mathbf{s}_i^T | \mathbf{x}_i, s_i] \widehat{P}_s^{-1/2}) - 1.\end{aligned}$$

Proposition 1 implies that for any given data set $\mathbf{D}$, the quantity $\ell(\mathbf{x}_i, y_i; \boldsymbol{\theta}) + \lambda \widehat{\psi}_i(\boldsymbol{\theta}, W)$ is an unbiased estimator of $\widehat{F}(\boldsymbol{\theta}, W)$ for all $i \in [N]$ (with respect to the empirical distribution). Thus, we can use stochastic optimization (e.g. SGDA) to solve Eq. (FERMI obj.) with any batch size $1 \leq |B| \leq N$, and the resulting algorithm will be guaranteed to converge since the stochastic gradients are unbiased. We present our proposed algorithm, which we call ***FERMI***, for solving Eq. (FERMI obj.) in Algorithm 1.

Next, we will provide our main results: Algorithm 1 converges to an approximate solution of the empirical objective Eq. (FERMI obj.) and (asymptotically) the population-level objective Eq. (FRMI obj.), for any minibatch size. Since Eq. (FERMI obj.) is potentially nonconvex in $\boldsymbol{\theta}$, a global minimum might not exist and even computing a local minimum is NP-hard in general [Murty and Kabadi, 1985]. Thus, as is standard in the nonconvex optimization literature, we aim for the milder goal of finding an approximate *stationary point* of Eq. (FERMI obj.). That is, given any $\epsilon > 0$, we aim to find a point $\boldsymbol{\theta}^*$ such that $\mathbb{E}\|\nabla \text{FERMI}(\boldsymbol{\theta}^*)\| \leq \epsilon$, where the expectation is solely with respect to the randomness of the algorithm (minibatch sampling). The following theorem guarantees that Algorithm 1 will find such a point efficiently:

Algorithm 1 FERMI Algorithm

Input: $\boldsymbol{\theta}^0 \in \mathbb{R}^{d_\theta}$, $W^0 = 0 \in \mathbb{R}^{k\times m}$, step-sizes (η_θ, η_w), fairness parameter $\lambda \geq 0$, iteration number T, minibatch sizes $|B_t|, t \in \{0, 1, \cdots, T\}$, $\mathcal{W} :=$ Frobenius norm ball of radius D around $0 \in \mathbb{R}^{k\times m}$ for D given in Appendix D, and compact neighborhood $\mathcal{N}(\boldsymbol{\theta}^*)$ of a solution $\boldsymbol{\theta}^* \in \arg\min_{\boldsymbol{\theta}} \max_W \widehat{F}(\boldsymbol{\theta}, W)$.

Compute $\widehat{P}_s^{-1/2} = \mathrm{diag}(\hat{p}_S(1)^{-1/2}, \ldots, \hat{p}_S(k)^{-1/2})$.

for $t = 0, 1, \ldots, T$ **do**

  Draw a mini-batch B_t of data points $\{(\mathbf{x}_i, s_i, y_i)\}_{i\in B_t}$

  Set $\boldsymbol{\theta}^{t+1} \leftarrow \Pi_{\mathcal{N}(\boldsymbol{\theta}^*)}\left[\boldsymbol{\theta}^t - \frac{\eta_\theta}{|B_t|}\sum_{i\in B_t}[\nabla_\theta \ell(\mathbf{x}_i, y_i; \boldsymbol{\theta}^t) + \lambda \nabla_\theta \widehat{\psi}_i(\boldsymbol{\theta}^t, W^t)]\right]$.

  Set $W^{t+1} \leftarrow \Pi_{\mathcal{W}}\Big(W^t + \frac{2\lambda\eta_w}{|B_t|}\sum_{i\in B_t}\Big[- W^t \mathrm{diag}(\mathcal{F}_1(\boldsymbol{\theta}^t, \mathbf{x}_i), \ldots, \mathcal{F}_m(\boldsymbol{\theta}^t, \mathbf{x}_i)) + \widehat{P}_s^{-1/2}\mathbb{E}[\mathbf{s}_i \widehat{\mathbf{y}}^T(\mathbf{x}_i; \boldsymbol{\theta}^t)|\mathbf{x}_i, s_i]\Big]\Big)$

end for

Pick $\hat{t}$ uniformly at random from $\{1, \ldots, T\}$ and **Return:** $\boldsymbol{\theta}^{\hat{t}}$.

Theorem 1. *(Informal statement) Let $\epsilon > 0$. Assume that $\ell(\mathbf{x}, y; \cdot)$ and $\mathcal{F}(\cdot, \mathbf{x})$ are Lipschitz continuous and differentiable with Lipschitz continuous gradient (see Appendix D for definitions), $\hat{p}_S(j) > 0$ for all sensitive attributes $j \in [k]$ and $\hat{p}_{\widehat{Y}}(l) > 0$ for all labels $l \in [m]$ and all $\boldsymbol{\theta}$ in some neighborhood of a solution $\boldsymbol{\theta}^*$. Then for any batch sizes $1 \leq |B_t| \leq N$, Algorithm 1 converges to an ϵ-first order stationary point of the Eq.* (FERMI obj.) *objective in $\mathcal{O}\left(\frac{1}{\epsilon^5}\right)$ stochastic gradient evaluations. Furthermore, there exists $N \in \mathbb{N}$ such that if $n \geq N$ and the data is drawn i.i.d. $\mathbf{D} \sim \mathcal{D}^n$, then Algorithm 1 converges to an ϵ-first order stationary point of Eq.* (FRMI obj.).

Theorem 1 implies that Algorithm 1 can efficiently achieve any tradeoff between fairness (ERMI) violation and (empirical) accuracy, depending on the choice of λ.[2] The proof of the empirical convergence in Theorem 1 follows from Proposition 1 and the observation that $\widehat{\psi}_i$ is strongly concave in W (see Appendix D). This implies that Eq. (1) is a nonconvex-strongly concave min-max problem, so the convergence guarantee of SGDA [Lin et al., 2020] yields Theorem 1.[3] To the best of our knowledge, the second (population-level) part of Theorem 1 is the first guarantee on the fairness/accuracy tradeoff that can be achieved by a non-binary classification algorithm on unseen "test data." This is important because the main goal of (fair) machine learning is to (fairly) give accurate predictions on test data, rather than merely fitting the training data well. The proof of the population-level convergence guarantee requires substantial additional work, since the empirical stochastic gradients $\nabla\widehat{\psi}_i$ are not necessarily unbiased estimators of the gradient of Eq. (FRMI obj.). Thus, we first establish asymptotic unbiasedness of these gradient estimators, using the strong law of large numbers, the continuous mapping theorem, and Lebesgue's dominated convergence theorem. To prove Theorem 1, we then use a careful argument that leverages asymptotic unbiasedness along with Danskin's theorem, Lipschitz continuity of the $\arg\max$ function for strongly concave objective, the continuous mapping theorem, and Lebesgue's dominated convergence theorem.

3 Numerical Experiments

In this section, we evaluate the performance of FERMI in terms of the fairness violation vs. test error for different notions of fairness (e.g. demographic parity, equalized odds, and equality of opportunity). To this end, we perform diverse experiments comparing FERMI to other state-of-the-art approaches on several benchmarks. In Section 3.1, we showcase the performance of FERMI applied to a logistic regression model on binary classification tasks with binary sensitive attributes on Adult, German Credit, and COMPAS datasets. In Section 3.2, we explore fairness in non-binary classification with non-binary sensitive attributes. In Appendix E, we utilize FERMI with a convolutional neural network base model for fair (to different religious groups) toxic comment detection. Furthermore, Appendix F shows how FERMI may be used beyond fair empirical risk minimization in domain generalization

[2] This sentence is accurate to the degree that an approximate stationary point of the non-convex objective Eq. (FERMI obj.) corresponds to an approximate risk minimizer.

[3] A faster convergence rate of $\mathcal{O}(\epsilon^{-3})$ could be obtained by using the (more complicated) SREDA method of Luo et al. [2020] instead of SGDA to solve FERMI objective. We omit the details here.

problems to learn a model independent of spurious features. For further experiments on datasets with missing sensitive attributes, outliers, and comparison with pre-processing and post-processing approaches see Appendix G.

3.1 Fair Binary Classification with Binary Sensitive Attributes using Logistic Regression

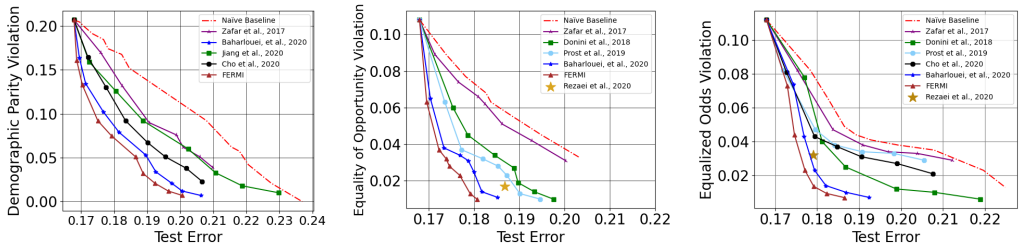

Figure 1: Accuracy/Fairness trade-off of FERMI and several state-of-the-art in-processing approaches on Adult dataset. FERMI offers the best fairness vs. accuracy tradeoff curve in all experiments against all baselines. Rezaei et al. [2020] only allow for a single output and do not yield a tradeoff curve. Further, the algorithms by Mary et al. [2019] and Baharlouei et al. [2020] are equivalent in this binary setting and shown by the red curve. In the binary/binary setting, FERMI, Mary et al. [2019] and Baharlouei et al. [2020] all try to solve the same objective Eq. (FRMI obj.). However, the empirical formulation Eq. (FERMI obj.) and FERMI algorithm that we use results in better performance, even though we are using a full-batch for all baselines in this experiment.

In the first set of experiments, we use FERMI to learn a fair logistic regression model on the Adult dataset. With the Adult data set, the task is to predict whether or not a person earns over \$50k annually without discriminating based on the sensitive attribute, gender. We compare FERMI against state-of-the-art in-processing full-batch ($|B| = N$) baselines, including [Zafar et al., 2017, Feldman et al., 2015, Kamishima et al., 2011, Jiang et al., 2020, Prost et al., 2019, Baharlouei et al., 2020, Rezaei et al., 2020, Donini et al., 2018, Cho et al., 2020a]. Since the majority of existing fair learning algorithms cannot be implemented with $|B| < N$, these experiments allow us to benchmark the performance of FERMI against a wider range of baselines. To contextualize the performance of these methods, we also include a **Naïve Baseline** that randomly replaces the model output with the majority label (0 in Adult dataset), with probability p (independent of the data), and sweep p in $[0, 1]$. At one end ($p = 1$), the output will be provably fair with performance reaching that of a naive classifier that outputs the majority class. At the other end ($p = 0$), the algorithm has no fairness mitigation and obtains the best performance (accuracy). By sweeping p, we obtain a tradeoff curve between performance and fairness violation.

In Fig. 1, we report the fairness violation (demographic parity, equalized odds, and equality of opportunity violations) vs. test error of the aforementioned in-processing approaches on the Adult dataset. The upper left corner of the tradeoff curves coincides with the unmitigated baseline, which only optimizes for performance (smallest test error). As can be seen, FERMI offers a fairness-accuracy tradeoff curve that dominates all state-of-the-art baselines in each experiment and with respect to each notion of fairness, even in the full batch setting.

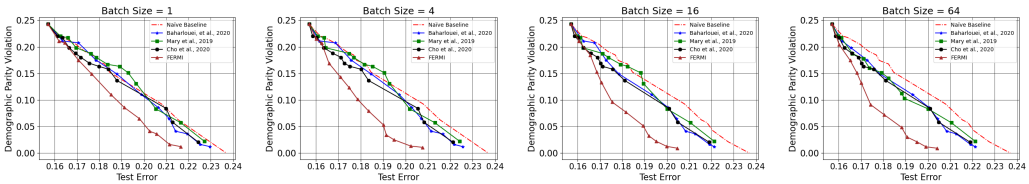

Figure 2: Performance of FERMI, Cho et al. [2020b], Mary et al. [2019], Baharlouei et al. [2020] with different batch-sizes on Adult dataset. FERMI demonstrates the best accuracy/fainess tradeoff across different batch sizes.

3.1.1 The effect of batch size on fairness/accuracy tradeoffs

Next, we evaluate the performance of FERMI on smaller batch sizes ranging from 1 to 64. To this end, we compare FERMI against several state-of-the-art in-processing algorithms that permit stochastic implementation for demographic parity: [Mary et al., 2019], [Baharlouei et al., 2020], and [Cho et al., 2020a]. Similarly to the full batch setting, for all methods, we train a logistic

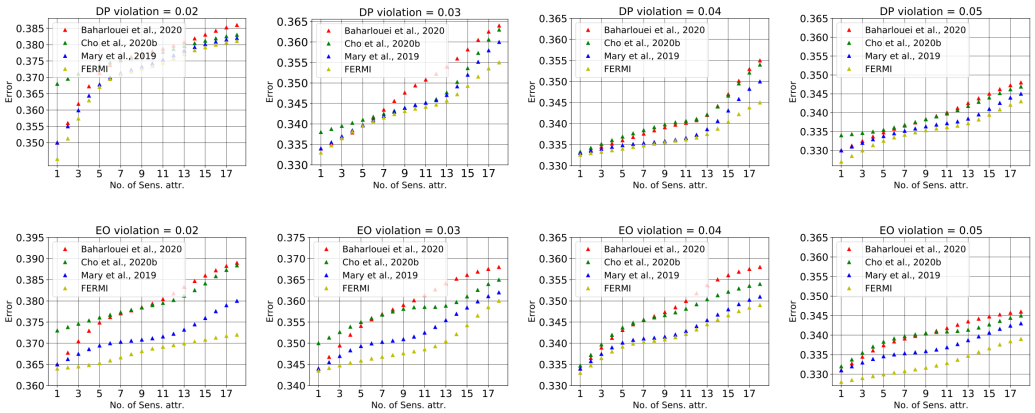

Figure 3: Comparison between FERMI, Mary et al. [2019], Baharlouei et al. [2020], and Cho et al. [2020a] on Communities dataset. [Mary et al., 2019] outperforms [Baharlouei et al., 2020, Cho et al., 2020a], which we believe could be attributed to the effectiveness of ERMI as a regularizer. FERMI outperforms Mary et al. [2019]. This can be attributed to our empirical formulation Eq. (FERMI obj.) and unbiased stochastic optimization algorithm.

regression model with a respective regularizer for each method. We use demographic parity L_∞ violation (Definition 10) to measure demographic parity violation. More details about the dataset and experiments, and additional experimental results, can be found in Appendix G. Fig. 2 shows that FERMI offers a superior fairness-accuracy tradeoff curve against all baselines, for each tested batch size, empirically confirming Theorem 1, as FERMI is the only algorithm that is guaranteed to converge for small minibatches. It is also noteworthy that all other baselines cannot beat *Naïve Baseline* when the batch size is very small, e.g., $|B| = 1$. Furthermore, FERMI with $|B| = 4$ almost achieves the same fairness-accuracy tradeoff as the full batch variant.

3.2 Fair Non-binary Classification with Multiple Sensitive Attributes

In this section, we consider a non-binary classification problem with multiple binary sensitive attributes. In this case, we consider the Communities and Crime dataset, which has 18 binary sensitive attributes in total. For our experiments, we pick a subset of $1, 2, 3, \ldots, 18$ sensitive attributes, which corresponds to $|\mathcal{S}| \in \{2, 4, 8, \ldots, 2^{18}\}$. We discretize the target into three classes $\{\text{high}, \text{medium}, \text{low}\}$. The only baselines that we are aware of that can handle non-binary classification with multiple sensitive attributes are [Mary et al., 2019], [Baharlouei et al., 2020], [Cho et al., 2020a], [Cho et al., 2020b], and [Zhang et al., 2018]. We used the publicly available implementations of [Baharlouei et al., 2020] and [Cho et al., 2020a] and extended their binary classification algorithms to the non-binary setting. The results are presented in Fig. 3, where we use conditional demographic parity L_∞ violation (Definition 10) and conditional equal opportunity L_∞ violation (Definition 11) as the fairness violation notions for the two experiments. In each panel, we compare the test error for different number of sensitive attributes for a fixed value of DP violation. It is expected that test error increases with the number of sensitive attributes, as we will have a more stringent fairness constraint to satisfy. As can be seen, compared to the baselines, FERMI offers the most favorable test error vs. fairness violation tradeoffs, particularly as the number of sensitive attributes increases and for the more stringent fairness violation levels, e.g., 0.02.

4 Discussion and Concluding Remarks

In this paper, we tackled the challenge of developing a fairness-promoting algorithm that is amenable to stochastic optimization. As discussed, algorithms for large-scale ML problems are constrained to use stochastic optimization with (small) minibatches of data in each iteration. To this end, we formulated an empirical objective (FERMI obj.) using ERMI as a regularizer, and derived unbiased stochastic gradient estimators. We proposed the stochastic FERMI algorithm (Algorithm 1) for solving this objective. We then provided the *first theoretical convergence guarantees for a stochastic in-processing fairness algorithm*, by showing that FERMI converges to stationary points of the empirical and population-level objectives. Further, these convergence results hold even for non-binary sensitive attributes and non-binary target variables, with any minibatch size.

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A Notions of Fairness

Let $(Y, \widehat{Y}, \mathcal{A}, S)$ denote the true target, predicted target, the advantaged outcome class, and the sensitive attribute, respectively. We review three major notions of fairness.

Definition 2 (demographic parity [Dwork et al., 2012])**.** *We say that a learning machine satisfies demographic parity if $\widehat{Y}$ is independent of S.*

Definition 3 (equalized odds [Hardt et al., 2016])**.** *We say that a learning machine satisfies equalized odds, if $\widehat{Y}$ is conditionally independent of S given Y.*

Definition 4 (equal opportunity [Hardt et al., 2016])**.** *We say that a learning machine satisfies equal opportunity with respect to $\mathcal{A}$, if $\widehat{Y}$ is conditionally independent of S given $Y = y$ for all $y \in \mathcal{A}$.*

Notice that the equal opportunity as defined here generalizes the definition in [Hardt et al., 2016]. It recovers equalized odds if $\mathcal{A} = \mathcal{Y}$, and it recovers equal opportunity of [Hardt et al., 2016] for $\mathcal{A} = \{1\}$ in binary classification.

B ERMI: General Definition, Properties, and Special Cases Unraveled

We begin by stating a notion of fairness that generalizes demographic parity, equalized odds, and equal opportunity fairness definitions (the three notions considered in this paper). This will be convenient for defining ERMI in its general form and presenting the results in Appendix C. Consider a learner who trains a model to make a prediction, $\widehat{Y}$, e.g., whether or not to extend a loan, supported on a set $\mathcal{Y}$. Here we allow $\widehat{Y}$ to be either discrete or continuous. The prediction is made using a set of features, $\mathbf{X}$, e.g., financial history features. We assume that there is a set of discrete sensitive attributes, S, e.g., race and sex, supported on $\mathcal{S}$, associated with each sample. Further, let $\mathcal{A} \subseteq \mathcal{Y}$ denote an advantaged outcome class, e.g., the outcome where a loan is extended.

Definition 5 ($(Z, \mathcal{Z})$-fairness)**.** *Given a random variable Z, let $\mathcal{Z}$ be a subset of values that Z can take. We say that a learning machine satisfies $(Z, \mathcal{Z})$-fairness if for every $z \in \mathcal{Z}$, $\widehat{Y}$ is conditionally independent of S given $Z = z$, i.e. $\forall \hat{y} \in \mathcal{Y}, s \in \mathcal{S}, z \in \mathcal{Z}$, $p_{\widehat{Y},S|Z}(\hat{y}, s|z) = p_{\widehat{Y}|Z}(\hat{y}|z)p_{S|Z}(s|z)$.*

$(Z, \mathcal{Z})$-fairness includes the popular demographic parity, equalized odds, and equal opportunity notions of fairness as special cases:

1. $(Z, \mathcal{Z})$-fairness recovers demographic parity [Dwork et al., 2012] if $Z = 0$ and $\mathcal{Z} = \{0\}$. In this case, conditioning on Z has no effect, and hence $(0, \{0\})$ fairness is equivalent to the independence between $\widehat{Y}$ and S (see Definition 2, Appendix A).
2. $(Z, \mathcal{Z})$-fairness recovers equalized odds [Hardt et al., 2016] if $Z = Y$ and $\mathcal{Z} = \mathcal{Y}$. In this case, $Z \in \mathcal{Z}$ is trivially satisfied. Hence, conditioning on Z is equivalent to conditioning on Y, which recovers the equalized odds notion of fairness, i.e., conditional independence of $\widehat{Y}$ and S given Y (see Definition 3, Appendix A).
3. $(Z, \mathcal{Z})$-fairness recovers equal opportunity [Hardt et al., 2016] if $Z = Y$ and $\mathcal{Z} = \mathcal{A}$. This is also similar to the previous case with $\mathcal{Y}$ replaced with $\mathcal{A}$ (see Definition 4, Appendix A).

Note that verifying $(Z, \mathcal{Z})$-fairness requires having access to the joint distribution of random variables $(Z, \widehat{Y}, S)$. This joint distribution is unavailable to the learner in the context of machine learning, and hence the learner would resort to empirical estimation of the amount of violation of independence, measured through some divergence. See [Williamson and Menon, 2019] for a related discussion.

In this general context, here is the general definition of ERMI:

Definition 6 (ERMI – exponential Rényi mutual information)**.** *We define the exponential Rényi mutual information between $\widehat{Y}$ and S given $Z \in \mathcal{Z}$ as*

$$D_R(\widehat{Y}; S|Z \in \mathcal{Z}) := \mathbb{E}_{Z,\widehat{Y},S}\left\{ \frac{p_{\widehat{Y},S|Z}(\widehat{Y}, S|Z)}{p_{\widehat{Y}|Z}(\widehat{Y}|Z)p_{S|Z}(S|Z)} \middle| Z \in \mathcal{Z} \right\} - 1. \tag{ERMI}$$

Notice that ERMI is in fact the χ^2-divergence between the conditional joint distribution, $p_{\widehat{Y},S}$, and the Kronecker product of conditional marginals, $p_{\widehat{Y}} \otimes p_S$, where the conditioning is on $Z \in \mathcal{Z}$.

Further, χ^2-divergence is an f-divergence with $f(t) = (t-1)^2$. See [Csiszár and Shields, 2004, Section 4] for a discussion. As an immediate result of this observation and well-known properties of f-divergences, we can state the following property of ERMI:

Remark 1. *$D_R(\widehat{Y}; S|Z \in \mathcal{Z}) \geq 0$ with equality if and only if for all $z \in \mathcal{Z}$, $\widehat{Y}$ and S are conditionally independent given $Z = z$.*

To further clarify the definition of ERMI, especially as it relates to demographic parity, equalized odds, and equal opportunity, we will unravel the definition explicitly in a few special cases.

First, let $Z = 0$ and $\mathcal{Z} = \{0\}$. In this case, $Z \in \mathcal{Z}$ trivially holds, and conditioning on Z has no effect, resulting in:

$$\begin{aligned} D_R(\widehat{Y}; S) &:= D_R(\widehat{Y}; S|Z \in \mathcal{Z})\Big|_{Z=0, \mathcal{Z}=\{0\}} \\ &= \mathbb{E}_{\widehat{Y},S}\left\{\frac{p_{\widehat{Y},S}(\widehat{Y}, S)}{p_{\widehat{Y}}(\widehat{Y})p_S(S)}\right\} - 1 \\ &= \sum_{s\in\mathcal{S}} \int_{\hat{y}\in\mathcal{Y}} \frac{p_{\widehat{Y},S}(\hat{y}, s) - p_{\widehat{Y}}(\hat{y})p_S(s)}{p_{\widehat{Y}}(\hat{y})p_S(s)} p_{\widehat{Y},S}(\hat{y}, s) d\hat{y}. \end{aligned} \tag{2}$$

$D_R(\widehat{Y}; S)$ is the notion of ERMI that should be used when the desired notion of fairness is demographic parity. In particular, $D_R(\widehat{Y}; S) = 0$ implies that χ^2 divergence between $p_{\widehat{Y},S}$, and the Kronecker product of marginals, $p_{\widehat{Y}} \otimes p_S$ is zero. This in turn implies that $\widehat{Y}$ and S are independent, which is the definition of demographic parity. We note that when $\widehat{Y}$ and S are discrete, this special case ($Z = 0$ and $\mathcal{Z} = \{0\}$) of ERMI is referred to as χ^2-information by Calmon et al. [2017b].

Next, we consider $Z = Y$ and $\mathcal{Z} = \mathcal{Y}$. In this case, $Z \in \mathcal{Z}$ is trivially satisfied, and hence,

$$\begin{aligned} D_R(\widehat{Y}; S|Y) &:= D_R(\widehat{Y}; S|Z \in \mathcal{Z})\Big|_{Z=Y, \mathcal{Z}=\mathcal{Y}} \\ &= \mathbb{E}_{Y,\widehat{Y},S}\left\{\frac{p_{\widehat{Y},S|Y}(\widehat{Y}, S|Y)}{p_{\widehat{Y}|Y}(\widehat{Y}|Y)p_{S|Y}(S|Y)}\right\} - 1 \\ &= \sum_{s\in\mathcal{S}} \int_{y\in\mathcal{Y}} \int_{\hat{y}\in\mathcal{Y}} \frac{p_{\widehat{Y},S|Y}(\hat{y}, s|y) - p_{\widehat{Y}|Y}(\hat{y}|y)p_{S|Y}(s|y)}{p_{\widehat{Y}|Y}(\hat{y}|y)p_{S|Y}(s|y)} p_{Y,\widehat{Y},S}(y, \hat{y}, s) d\hat{y}dy \\ &= \sum_{s\in\mathcal{S}} \int_{y\in\mathcal{Y}} \int_{\hat{y}\in\mathcal{Y}} \frac{p_{\widehat{Y},S|Y}(\hat{y}, s|y)^2}{p_{\widehat{Y}|Y}(\hat{y}|y)p_{S|Y}(s|y)} p_Y(y) d\hat{y}dy - 1. \end{aligned} \tag{3}$$

$D_R(\widehat{Y}; S|Y)$ should be used when the desired notion of fairness is equalized odds. In particular, $D_R(\widehat{Y}; S|Y) = 0$ directly implies the conditional independence of $\widehat{Y}$ and S given Y.

Finally, we consider $Z = Y$ and $\mathcal{Z} = \mathcal{A}$. In this case, we have

$$\begin{aligned} D_R^{\mathcal{A}}(\widehat{Y}; S|Y) &:= D_R(\widehat{Y}; S|Z \in \mathcal{Z})\Big|_{Z=Y, \mathcal{Z}=\mathcal{A}} \\ &= \mathbb{E}_{Y,\widehat{Y},S}\left\{\frac{p_{\widehat{Y},S|Y}(\widehat{Y}, S|Y)}{p_{\widehat{Y}|Y}(\widehat{Y}|Y)p_{S|Y}(S|Y)}\middle| Y \in \mathcal{A}\right\} - 1 \\ &= \sum_{s\in\mathcal{S}} \int_{y\in\mathcal{A}} \int_{\hat{y}\in\mathcal{Y}} \frac{p_{\widehat{Y},S|Y}(\hat{y}, s|y) - p_{\widehat{Y}|Y}(\hat{y}|y)p_{S|Y}(s|y)}{p_{\widehat{Y}|Y}(\hat{y}|y)p_{S|Y}(s|y)} p_Y^{\mathcal{A}}(y) d\hat{y}dy \\ &= \sum_{s\in\mathcal{S}} \int_{y\in\mathcal{A}} \int_{\hat{y}\in\mathcal{Y}} \frac{p_{\widehat{Y},S|Y}(\hat{y}, s|y)^2}{p_{\widehat{Y}|Y}(\hat{y}|y)p_{S|Y}(s|y)} p_{\widehat{Y},S|Y}(\hat{y}, s|y) p_Y^{\mathcal{A}}(y) d\hat{y}dy - 1, \end{aligned} \tag{4}$$

where

$$p_Y^{\mathcal{A}}(y) := \frac{p_Y(y)}{\int_{y'\in\mathcal{A}} p_Y(y')dy'}. \tag{5}$$

This notion is what should be used when the desired notion of fairness is equal opportunity. This can be further simplified when the advantaged class is a singleton (which is the case in binary classification). If $Z = Y$ and $\mathcal{Z} = \{y\}$, then

$$\begin{aligned} D_R(\widehat{Y}; S|Y = y) &:= D_R^{\{y\}}(\widehat{Y}; S|Y) \\ &= \sum_{s \in \mathcal{S}} \int_{\hat{y} \in \mathcal{Y}} \frac{p_{\widehat{Y},S|Y}(\hat{y}, s|y) - p_{\widehat{Y}|Y}(\hat{y}|y) p_{S|Y}(s|y)}{p_{\widehat{Y}|Y}(\hat{y}|y) p_{S|Y}(s|y)} p_{\widehat{Y},S|Y}(\hat{y}, s|y) d\hat{y} \\ &= \sum_{s \in \mathcal{S}} \int_{\hat{y} \in \mathcal{Y}} \frac{p_{\widehat{Y},S|Y}(\hat{y}, s|y)^2}{p_{\widehat{Y}|Y}(\hat{y}|y) p_{S|Y}(s|y)} d\hat{y} - 1. \end{aligned} \tag{6}$$

Finally, we note that we use the notation $D_R(\widehat{Y}; S|Y)$ and $D_R(\widehat{Y}; S|Y = y)$ to be consistent with the definition of conditional mutual information in [Cover and Thomas, 1991].

C Relations Between ERMI and Other Fairness Violation Notions

Recall that most existing in-processing methods use some notion of fairness violation as a regularizer to enforce fairness in the trained model. These notions of fairness violation typically take the form of some information divergence between the sensitive attributes and the predicted targets (e.g. Mary et al. [2019], Baharlouei et al. [2020], Cho et al. [2020b]). In this section, we show that ERMI provides an upper bound on all of the existing measures of fairness violations for demographic parity, equal opportunity, and equalized odds. As mentioned in the main body, this insight might help explain the favorable empirical performance of our algorithm compared to baselines–even when full batch is used. In particular, the results in this section imply that FERMI algorithm leads to small fairness violation with respect to ERMI and all of these other measures.

We should mention that many of these properties of f divergences are well-known or easily derived from existing results, so we do not intend to claim great originality with any of these results. That said, we include proofs of all results for which we are not aware of any references with proofs. The results in this section also hold for continuous (or discrete) $\widehat{Y}$. We will now state and discuss these results before proving them.

Definition 7 (Rényi mutual information [Rényi, 1961])**.** *Let the Rényi mutual information of order $\alpha > 1$ between random variables $\widehat{Y}$ and S given $Z \in \mathcal{Z}$ be defined as:*

$$I_\alpha(\widehat{Y}; S|Z \in \mathcal{Z}) := \frac{1}{\alpha - 1} \log \left(\mathbb{E}_{Z,\widehat{Y},S} \left\{ \left(\frac{p_{\widehat{Y},S|Z}(\widehat{Y}, S|Z)}{p_{\widehat{Y}|Z}(\widehat{Y}|Z) p_{S|Z}(S|Z)} \right)^{\alpha-1} \middle| Z \in \mathcal{Z} \right\} \right), \tag{RMI}$$

which generalizes Shannon mutual information

$$I_1(\widehat{Y}; S|Z \in \mathcal{Z}) := \mathbb{E}_{Z,\widehat{Y},S} \left\{ \log \left(\frac{p_{\widehat{Y},S|Z}(\widehat{Y}, S|Z)}{p_{\widehat{Y}|Z}(\widehat{Y}|Z) p_{S|Z}(S|Z)} \right) \middle| Z \in \mathcal{Z} \right\}, \tag{MI}$$

and recovers it as $\lim_{\alpha \to 1^+} I_\alpha(\widehat{Y}; S|Z \in \mathcal{Z}) = I_1(\widehat{Y}; S|Z \in \mathcal{Z})$.

Note that $I_\alpha(\widehat{Y}; S|Z \in \mathcal{Z}) \geq 0$ with equality if and only if $(Z, \mathcal{Z})$-fairness is satisfied.

The following is a minor change from results in Sason and Verdú [2016]:

Lemma 1 (ERMI provides an upper bound for Shannon mutual information)**.** *We have*

$$0 \leq I_1(\widehat{Y}; S|Z \in \mathcal{Z}) \leq I_2(\widehat{Y}; S|Z \in \mathcal{Z}) \leq e^{I_2(\widehat{Y}; S|Z \in \mathcal{Z})} - 1 = D_R(\widehat{Y}; S|Z \in \mathcal{Z}). \tag{7}$$

Lemma 1 also shows that ERMI is exponentially related to the Rényi mutual information of order 2. We include a proof below for completeness.

Definition 8 (Rényi correlation [Hirschfeld, 1935, Gebelein, 1941, Rényi, 1959])**.** *Let $\mathcal{F}$ and $\mathcal{G}$ be the set of measurable functions such that for random variables $\widehat{Y}$ and S, $\mathbb{E}_{\widehat{Y}}\{f(\widehat{Y}; z)\} = \mathbb{E}_S\{g(S; z)\} = 0$, $\mathbb{E}_{\widehat{Y}}\{f(\widehat{Y}; z)^2\} = \mathbb{E}_S\left\{g(S; z)^2\right\} = 1$, for all $z \in \mathcal{Z}$. Rényi correlation is:*

$$\rho_R(\widehat{Y}, S|Z \in \mathcal{Z}) := \sup_{f,g \in \mathcal{F} \times \mathcal{G}} \mathbb{E}_{Z,\widehat{Y},S} \left\{ f(\widehat{Y}; Z) g(S; Z) \middle| Z \in \mathcal{Z} \right\}. \tag{RC}$$

Rényi correlation generalizes Pearson correlation,

$$\rho(\widehat{Y}, S|Z \in \mathcal{Z}) := \mathbb{E}_Z \left\{ \frac{\mathbb{E}_{\widehat{Y},S}\{\widehat{Y} S|Z\}}{\sqrt{\mathbb{E}_{\widehat{Y}}\{\widehat{Y}^2|Z\} \mathbb{E}_S\{S^2|Z\}}} \middle| Z \in \mathcal{Z} \right\}, \tag{PC}$$

to capture nonlinear dependencies between the random variables by finding functions of random variables that maximize the Pearson correlation coefficient between the random variables. In fact, it is true that $\rho_R(\widehat{Y}, S|Z \in \mathcal{Z}) \geq 0$ with equality if and only if $(Z, \mathcal{Z})$-fairness is satisfied. Rényi correlation has gained popularity as a measure of fairness violation [Mary et al., 2019, Baharlouei et al., 2020, Grari et al., 2020]. Rényi correlation is also upper bounded by ERMI. The following result has already been shown by Mary et al. [2019] and we present it for completeness.

Lemma 2 (ERMI provides an upper bound for Rényi correlation)**.** *We have*

$$0 \leq |\rho(\widehat{Y}, S|Z \in \mathcal{Z})| \leq \rho_R(\widehat{Y}, S|Z \in \mathcal{Z}) \leq D_R(\widehat{Y}; S|Z \in \mathcal{Z}), \tag{8}$$

and if $|\mathcal{S}| = 2$, $D_R(\widehat{Y}; S|Z \in \mathcal{Z}) = \rho_R(\widehat{Y}, S|Z \in \mathcal{Z})$.

Definition 9 (L_q fairness violation)**.** *We define the* L_q *fairness violation for* $q \geq 1$ *by:*

$$L_q(\widehat{Y}, S|Z \in \mathcal{Z}) := \mathbb{E}_Z\left\{\left(\int_{\hat{y}\in\mathcal{Y}_0}\sum_{s\in\mathcal{S}_0}\left|p_{\widehat{Y},S|Z}(\widehat{y}, s|Z) - p_{\widehat{Y}|Z}(\widehat{y}|Z)p_{S|Z}(s|Z)\right|^q dy\right)^{\frac{1}{q}}\middle| Z \in \mathcal{Z}\right\}. \tag{Lq}$$

Note that $L_q(\widehat{Y}, S|Z \in \mathcal{Z}) = 0$ if and only if $(Z, \mathcal{Z})$-fairness is satisfied. In particular, L_∞ fairness violation recovers demographic parity violation [Kearns et al., 2018, Definition 2.1] if we let $\mathcal{Z} = \{0\}$ and $Z = 0$. It also recovers equal opportunity violation [Hardt et al., 2016] if $\mathcal{Z} = \mathcal{A}$ and $Z = Y$.

Lemma 3 (ERMI provides an upper bound for L_∞ fairness violation)**.** *Let* $\widehat{Y}$ *be a discrete or continuous random variable, and* S *be a discrete random variable supported on a finite set. Then for any* $q \geq 1$*,*

$$0 \leq L_q(\widehat{Y}, S|Z \in \mathcal{Z}) \leq \sqrt{D_R(\widehat{Y}, S|Z \in \mathcal{Z})}. \tag{9}$$

The above lemma says that if a method controls ERMI value for imposing fairness, then L_∞ violation is controlled. In particular, the variant of ERMI that is specialized to demographic parity also controls L_∞ demographic parity violation [Kearns et al., 2018]. The variant of ERMI that is specialized to equal opportunity also controls the L_∞ equal opportunity violation [Hardt et al., 2016]. While our algorithm uses ERMI as a regularizer, in our experiments, we measure fairness violation through the more commonly used L_∞ violation. Despite this, we show that our approach leads to better tradeoff curves between fairness violation and performance.

Remark. The bounds in Lemmas 1-3 are not tight in general, but this is not of practical concern. They show that bounding ERMI is sufficient because any model that achieves small ERMI is guaranteed to satisfy any other fairness violation. This makes ERMI an effective regularizer for promoting fairness. In fact, in Sec. 3, we saw that our algorithm, FERMI, achieves the best tradeoffs between fairness violation and performance across state-of-the-art baselines.

Proof of Lemma 1. We proceed to prove all the (in)equalities one by one:

- $0 \leq I_S(\widehat{Y}; S|Z \in \mathcal{Z})$. This is well known and the proof can be found in any information theory textbook [Cover and Thomas, 1991].
- $I_1(\widehat{Y}; S|Z \in \mathcal{Z}) \leq I_2(\widehat{Y}; S|Z \in \mathcal{Z})$. This is a known property of Rényi mutual information, but we provide a proof for completeness in Lemma 4 below.
- $I_2(\widehat{Y}; S|Z \in \mathcal{Z}) \leq e^{I_2(\widehat{Y};S|Z\in\mathcal{Z})} - 1$. This follows from the fact that $x \leq e^x - 1$.
- $e^{I_2(\widehat{Y};S)|Z\in\mathcal{Z}} - 1 = D_R(\widehat{Y}; S|Z \in \mathcal{Z})$. This follows from simple algebraic manipulation.

□

Lemma 4. *Let* $\widehat{Y}, S, Z$ *be discrete or continuous random variables. Then:*

(a) For any $\alpha, \beta \in [1, \infty]$*,* $I_\beta(\widehat{Y}; S|Z \in \mathcal{Z}) \geq I_\alpha(\widehat{Y}; S|Z \in \mathcal{Z})$ *if* $\beta > \alpha$*.*

(b) $\lim_{\alpha\to 1^+} I_\alpha(\widehat{Y}; S|Z \in \mathcal{Z}) = I_1(\widehat{Y}; S) := \mathbb{E}_Z\left\{D_{KL}(p_{\widehat{Y},S|Z}||p_{\widehat{Y}|Z} \otimes p_{S|Z})\middle| Z \in \mathcal{Z}\right\}$*, where* $I_1(\cdot;\cdot)$ *denotes the Shannon mutual information and* D_{KL} *is Kullback-Leibler divergence (relative entropy).*

(c) For all $\alpha \in [1, \infty]$*,* $I_\alpha(\widehat{Y}; S|Z \in \mathcal{Z}) \geq 0$ *with equality if and only if for all* $z \in \mathcal{Z}$*,* $\widehat{Y}$ *and* S *are conditionally independent given* z*.*

Proof. *(a)* First assume $0 < \alpha < \beta < \infty$ and that $\alpha, \beta \neq 1$. Define $a = \alpha - 1$, and $b = \beta - 1$. Then the function $\phi(t) = t^{b/a}$ is convex for all $t \geq 0$, so by Jensen's inequality we have:

$$\frac{1}{b}\log\left(\mathbb{E}\left\{\left(\frac{p(\widehat{Y},S|Z)}{p(\widehat{Y}|Z)p(S|Z)}\right)^b \middle| Z \in \mathcal{Z}\right\}\right) \geq \frac{1}{b}\log\left(\mathbb{E}\left\{\left(\frac{p(\widehat{Y},S|Z)}{p(\widehat{Y}|Z)p(S|Z)}\right)^a \middle| Z \in \mathcal{Z}\right\}^{b/a}\right)$$
$$= \frac{1}{a}\log\left(\mathbb{E}\left\{\left(\frac{p(\widehat{Y},S|Z)}{p(\widehat{Y}|Z)p(S|Z)}\right)^a \middle| Z \in \mathcal{Z}\right\}\right). \tag{10}$$

Now suppose $\alpha = 1$. Then by the monotonicity for $\alpha \neq 1$ proved above, we have $I_1(\widehat{Y};S) = \lim_{\alpha\to 1^-} I_\alpha(\widehat{Y};S) = \sup_{\alpha\in(0,1)} I_\alpha(\widehat{Y};S) \leq \inf_{\alpha>1} I_\alpha(\widehat{Y};S)$. Also, $I_\infty(\widehat{Y};S) = \lim_{\alpha\to\infty} I_\alpha(\widehat{Y};S) = \sup_{\alpha>0} I_\alpha(\widehat{Y};S)$.

(b) This is a standard property of the cumulant generating function (see [Dembo and Zeitouni, 2009]).

(c) It is straightforward to observe that independence implies that Rényi mutual information vanishes. On the other hand, if Rényi mutual information vanishes, then part (a) implies that Shannon mutual information also vanishes, which implies the desired conditional independence. □

Proof of Lemma 2. The proof is completed using the following pieces.

- $0 \leq |\rho(\widehat{Y},S|Z \in \mathcal{Z})| \leq \rho_R(\widehat{Y},S|Z \in \mathcal{Z})$. This is obvious from the definition of $\rho_R(\widehat{Y},S|Z \in \mathcal{Z})$.
- $\rho_R(\widehat{Y},S|Z \in \mathcal{Z}) \leq D_R(\widehat{Y};S|Z \in \mathcal{Z})$. This follows from Lemma 5 below.
- Notice that if $|\mathcal{S}| = 2$, Lemma 5 implies that $D_R(\widehat{Y};S|Z \in \mathcal{Z}) = \rho_R(\widehat{Y},S|Z \in \mathcal{Z})$.

□

Next, we recall the following lemma, which is stated in Mary et al. [2019] and derives from Witsenhausen's characterization of Renyi correlation:

Lemma 5. *Suppose that $\mathcal{S} = [k]$. Let the $k \times k$ matrix P be defined as $P = \{P_{ij}\}_{i,j\in[k]\times[k]}$, where*

$$P_{ij} := \frac{1}{\sqrt{p_S(i)p_S(j)}}\int_{y\in\mathcal{Y}}\left(\frac{p_{\widehat{Y},S}(y,i)p_{\widehat{Y},S}(y,j)}{p_{\widehat{Y}}(y)}\right)dy. \tag{11}$$

Let $1 = \sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_k \geq 0$ be the eigenvalues of P. Then,

$$\rho_R(\widehat{Y},S) = \sigma_2, \tag{12}$$

$$D_R(\widehat{Y};S) = \mathrm{Tr}(P) - 1 = \sum_{i=2}^{k}\sigma_i. \tag{13}$$

Proof. Eq. (12) is proved in [Witsenhausen, 1975, Section 3]. To prove Eq. (13), notice that

$$\begin{aligned}\mathrm{Tr}(P) &= \sum_{i\in[k]} P_{ii}\\ &= \sum_{i\in[k]}\frac{1}{p_S(i)}\int_{y\in\mathcal{Y}}\left(\frac{p_{\widehat{Y},S}(y,i)^2}{p_{\widehat{Y}}(y)}\right)dy\\ &= E_{\widehat{Y},S}\left\{\left(\frac{p_{\widehat{Y},S}(\widehat{Y},S)}{p_{\widehat{Y}}(\widehat{Y})p_S(S)}\right)\right\}\\ &= 1 + D_R(\widehat{Y};S),\end{aligned}$$

which completes the proof. □

Proof of Lemma 3. It suffices to prove the inequality for L_1, as L_q is bounded above by L_1 for all $q \geq 1$. The proof for the case where $Z = 0$ and $\mathcal{Z} = \{0\}$ follows from the following set of inequalities:

$$L_1(\widehat{Y}, S|Z \in \mathcal{Z}) = \sum_{s\in\mathcal{S}} \int_{y\in\mathcal{Y}} \left| p_{\widehat{Y},S}(y,s) - p_{\widehat{Y}}(y)p_S(s) \right| dy \tag{14}$$

$$= \sum_{s\in\mathcal{S}} \int_{y\in\mathcal{Y}} \sqrt{p_{\widehat{Y}}(y)p_S(s)} \frac{\left| p_{\widehat{Y},S}(y,s) - p_{\widehat{Y}}(y)p_S(s) \right|}{\sqrt{p_{\widehat{Y}}(y)p_S(s)}} dy \tag{15}$$

$$\leq \sqrt{\left(\sum_{s\in\mathcal{S}} \int_{y\in\mathcal{Y}} p_{\widehat{Y}}(y)p_S(s)dy \right) \left(\sum_{s\in\mathcal{S}} \int_{y\in\mathcal{Y}} \left(\frac{(p_{\widehat{Y},S}(y,s) - p_{\widehat{Y}}(y)p_S(s))^2}{p_{\widehat{Y}}(y)p_S(s)} \right) \right)} \tag{16}$$

$$\leq \sqrt{\sum_{s\in\mathcal{S}} \int_{y\in\mathcal{Y}} \left(\frac{(p_{\widehat{Y},S}(y,s) - p_{\widehat{Y}}(y)p_S(s))^2}{p_{\widehat{Y}}(y)p_S(s)} \right) dy} \tag{17}$$

$$= \sqrt{D_R(\widehat{Y}; S)}, \tag{18}$$

where Eq. (16) follows from Cauchy-Schwarz inequality, and Eq. (18) follows from Lemma 6. The extension to general Z and $\mathcal{Z}$ is immediate by observing that $\rho(\widehat{Y}, S|Z \in \mathcal{Z}) = \mathbb{E}_Z \left[\rho(\widehat{Y}, S|Z) \middle| Z \in \mathcal{Z} \right]$, $\rho_R(\widehat{Y}, S|Z \in \mathcal{Z}) = \mathbb{E}_Z \left[\rho_R(\widehat{Y}, S|Z) \middle| Z \in \mathcal{Z} \right]$, and $D_R(\widehat{Y}, S|Z \in \mathcal{Z}) = \mathbb{E}_Z \left[D_R(\widehat{Y}, S|Z) \middle| Z \in \mathcal{Z} \right]$.

□

Lemma 6. *We have*

$$D_R(\widehat{Y}; S) = \sum_{s\in\mathcal{S}} \int_{y\in\mathcal{Y}} \left(\frac{(p_{\widehat{Y},S}(y,s) - p_{\widehat{Y}}(y)p_S(s))^2}{p_{\widehat{Y}}(y)p_S(s)} \right) dy. \tag{19}$$

Proof. The proof follows from the following set of identities:

$$\begin{aligned} \sum_{s\in\mathcal{S}} \int_{y\in\mathcal{Y}} \left(\frac{(p_{\widehat{Y},S}(y,s) - p_{\widehat{Y}}(y)p_S(s))^2}{p_{\widehat{Y}}(y)p_S(s)} \right) dy &= \sum_{s\in\mathcal{S}} \int_{y\in\mathcal{Y}} \frac{(p_{\widehat{Y},S}(y,s))^2}{p_{\widehat{Y}}(y)p_S(s)} dy \\ &\quad - 2\sum_{s\in\mathcal{S}} \int_{y\in\mathcal{Y}} p_{\widehat{Y},S}(y,s)dy \\ &\quad + \sum_{s\in\mathcal{S}} \int_{y\in\mathcal{Y}} p_{\widehat{Y}}(y)p_S(s)dy \qquad (20) \\ &= E\left\{ \frac{p_{\widehat{Y},S}(\widehat{Y}, S)}{p_{\widehat{Y}}(\widehat{Y})p_S(S)} \right\} - 1 \qquad (21) \\ &= D_R(\widehat{Y}; S). \qquad (22) \end{aligned}$$

□

Next, we present some alternative fairness definitions and show that they are also upper bounded by ERMI.

Definition 10 (conditional demographic parity L_∞ violation)**.** *Given a predictor $\widehat{Y}$ supported on $\mathcal{Y}$ and a discrete sensitive attribute S supported on a finite set $\mathcal{S}$, we define the conditional demographic parity violation by:*

$$\widetilde{dp}(\widehat{Y}|S) := \sup_{\widehat{y}\in\mathcal{Y}} \max_{s\in\mathcal{S}} \left| p_{\widehat{Y}|S}(\widehat{y}|s) - p_{\widehat{Y}}(\widehat{y}) \right|. \tag{23}$$

First, we show that $\widetilde{\mathrm{dp}}(\widehat{Y}|S)$ is a reasonable notion of fairness violation.

Lemma 7. *$\widetilde{dp}(\widehat{Y}|S) = 0$ iff (if and only if) $\widehat{Y}$ and S are independent.*

Proof. By definition, $\widetilde{\mathrm{dp}}(\widehat{Y}|S) = 0$ iff for all $\widehat{y} \in \mathcal{Y}, s \in \mathcal{S}$, $p_{\widehat{Y},S}(\hat{y}|s) = p_{\widehat{Y}}(\hat{y})$ iff $\widehat{Y}$ and S are independent (since we always assume $p(s) > 0$ for all $s \in \mathcal{S}$). □

Lemma 8 (ERMI provides an upper bound for conditional demographic parity L_∞ violation)**.** *Let $\widehat{Y}$ be a discrete or continuous random variable supported on $\mathcal{Y}$, and S be a discrete random variable supported on a finite set $\mathcal{S}$. Denote $p_S^{\min} := \min_{s\in\mathcal{S}} p_S(s) > 0$. Then,*

$$0 \leq \widetilde{dp}(\widehat{Y}|S) \leq \frac{1}{p_S^{\min}}\sqrt{D_R(\widehat{Y};S)}. \tag{24}$$

Proof. The proof follows from the following set of (in)equalities:

$$\begin{aligned}
\left(\widetilde{\mathrm{dp}}(\widehat{Y}|S)\right)^2 &= \sup_{\widehat{y}\in\mathcal{Y}} \max_{s\in\mathcal{S}} \left(p_{\widehat{Y}|S}(\widehat{y}|s) - p_{\widehat{Y}}(\widehat{y})\right)^2 && (25)\\
&\leq \frac{1}{(p_S^{\min})^2} \sup_{\widehat{y}\in\mathcal{Y}} \max_{s\in\mathcal{S}} \left(p_{\widehat{Y},S}(\widehat{y},s) - p_{\widehat{Y}}(\widehat{y})p_S(s))\right)^2 && (26)\\
&\leq \frac{1}{(p_S^{\min})^2} \int_{\hat{y}\in\mathcal{Y}} \sum_{s\in\mathcal{S}} \left(p_{\widehat{Y},S}(\widehat{y},s) - p_{\widehat{Y}}(\widehat{y})p_S(s))\right)^2 && (27)\\
&= \frac{1}{(p_S^{\min})^2} D_R(\widehat{Y};S), && (28)
\end{aligned}$$

where Eq. (28) follows from Lemma 3. □

Definition 11 (conditional equal opportunity L_∞ violation [Hardt et al., 2016])**.** *Let $Y, \widehat{Y}$ take values in $\mathcal{Y}$ and let $\mathcal{A} \subseteq \mathcal{Y}$ be a compact subset denoting the advantaged outcomes (For example, the decision "to interview" an individual or classify an individual as a "low risk" for financial purposes). We define the conditional equal opportunity L_∞ violation of $\widehat{Y}$ with respect to the sensitive attribute S and the advantaged outcome $\mathcal{A}$ by*

$$\widetilde{eo}(\widehat{Y}|S, Y\in\mathcal{A}) := \mathbb{E}_Y\left\{\sup_{\widehat{y}\in\mathcal{Y}} \max_{s\in\mathcal{S}} \left|p_{\widehat{Y},S|Y}(\widehat{y}|s,Y) - p_{\widehat{Y}|Y}(\widehat{y}|Y)\right| Y\in\mathcal{A}\right\}. \tag{29}$$

Lemma 9 (ERMI provides an upper bound for conditional equal opportunity L_∞ violation)**.** *Let $\widehat{Y}$, Y, be discrete or continuous random variables supported on $\mathcal{Y}$, and let S be a discrete random variable supported on a finite set $\mathcal{S}$. Let $\mathcal{A} \subseteq \mathcal{Y}$ be a compact subset of $\mathcal{Y}$.*

Denote $p_{S|\mathcal{A}}^{\min} = \min_{s\in\mathcal{S}, y\in\mathcal{A}} p_{S|Y}(s|y)$. Then,

$$0 \leq \widetilde{eo}(\widehat{Y}|S, Y\in\mathcal{A}) \leq \frac{1}{p_{S|\mathcal{A}}^{\min}}\sqrt{D_R(\widehat{Y};S|Y\in\mathcal{A})}. \tag{30}$$

Proof. Notice that the same proof for Lemma 8 would give that for all $y \in \mathcal{A}$:

$$\begin{aligned}
0 \leq \sup_{\widehat{y}\in\mathcal{Y}} \max_{s\in\mathcal{S}} \left|p_{\widehat{Y},S|Y}(\widehat{y}|s,y) - p_{\widehat{Y}|Y}(\widehat{y}|y)\right| &:= \widetilde{\mathrm{eo}}(\widehat{Y}|S, Y=y)\\
&\leq \frac{1}{p_{S|y}^{\min}(y)}\sqrt{D_R(\widehat{Y};S|Y=y)}\\
&\leq \frac{1}{p_{S|\mathcal{C}}^{\min}}\sqrt{D_R(\widehat{Y};S|Y=y)}.
\end{aligned}$$

Hence,

$$\begin{aligned}
\widetilde{\mathrm{eo}}(\widehat{Y}|S, Y \in \mathcal{A}) &= \mathbb{E}_Y \left\{ \widetilde{\mathrm{eo}}(\widehat{Y}|S, Y) \middle| Y \in \mathcal{A} \right\} \\
&\leq \frac{1}{p_{S|\mathcal{A}}^{\min}} \mathbb{E}_Y \left\{ \sqrt{D_R(\widehat{Y}; S|Y)} \middle| Y \in \mathcal{A} \right\} \\
&\leq \frac{1}{p_{S|\mathcal{A}}^{\min}} \sqrt{\mathbb{E}_Y \left\{ D_R(\widehat{Y}; S|Y) \middle| Y \in \mathcal{A} \right\}} \\
&= \frac{1}{p_{S|\mathcal{A}}^{\min}} \sqrt{D_R(\widehat{Y}; S|Y \in \mathcal{A})},
\end{aligned}$$

where the last inequality follows from Jensen's inequality. This completes the proof. □

D Precise Statement and Proofs of Theorem 1

Corollary 1 (Re-statement of Proposition 1)**.** *Let* $(\mathbf{x}_i, s_i, y_i)$ *be a random draw from* $\mathbf{D}$*. Then, Eq.* (FERMI obj.) *is equivalent to*

$$\min_{\boldsymbol{\theta}} \max_{W \in \mathbb{R}^{k \times m}} \left\{ \widehat{F}(\boldsymbol{\theta}, W) := \widehat{\mathcal{L}}(\boldsymbol{\theta}) + \lambda \widehat{\Psi}(\boldsymbol{\theta}, W) \right\}, \tag{31}$$

where $\widehat{\Psi}(\boldsymbol{\theta}, W) = -\operatorname{Tr}(W \widehat{P}_{\hat{y}} W^T) + 2\operatorname{Tr}(W \widehat{P}_{\hat{y},s} \widehat{P}_s^{-1/2}) - 1 = \frac{1}{N}\sum_{i=1}^N \widehat{\psi}_i(\boldsymbol{\theta}, W)$ *and*

$$\begin{aligned}\widehat{\psi}_i(\boldsymbol{\theta}, W) &:= -\operatorname{Tr}(W \mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i, \boldsymbol{\theta}) \widehat{\mathbf{y}}(\mathbf{x}_i, \boldsymbol{\theta})^T | \mathbf{x}_i] W^T) + 2\operatorname{Tr}(W \mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i; \boldsymbol{\theta}) \mathbf{s}_i^T | \mathbf{x}_i, s_i] \widehat{P}_s^{-1/2}) - 1 \\ &= -\operatorname{Tr}(W \operatorname{diag}(\mathcal{F}_1(\boldsymbol{\theta}, \mathbf{x}_i), \ldots, \mathcal{F}_m(\boldsymbol{\theta}, \mathbf{x}_i)) W^T) + 2\operatorname{Tr}(W \mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i; \boldsymbol{\theta}) \mathbf{s}_i^T | \mathbf{x}_i, s_i] \widehat{P}_s^{-1/2}) - 1.\end{aligned}$$

Proof. The proof simply follows the fact that

$$\max_{W \in \mathbb{R}^{k \times m}} \mathbb{E}\left[\widehat{\psi}_i(\boldsymbol{\theta}, W)\right] = \max_{W \in \mathbb{R}^{k \times m}} \left(-\operatorname{Tr}(W \widehat{P}_{\hat{y}} W^T) + 2\operatorname{Tr}(W \widehat{P}_{\hat{y},s} \widehat{P}_s^{-1/2}) - 1 \right) = \widehat{D}_R(\widehat{Y}; S),$$

where the expectation is taken w.r.t. to the empirical distribution. □

Next, we will state and prove the precise form of Theorem 1. We first recall some basic definitions:

Definition 12. *A function* f *is* L*-Lipschitz if for all* $\mathbf{u}, \mathbf{u}' \in$ *domain*(f) *we have* $\|f(\mathbf{u}) - f(\mathbf{u})\| \leq L\|\mathbf{u} - \mathbf{u}'\|$.

Definition 13. *A differentiable function* f *is* β*-smooth if for all* $\mathbf{u}, \mathbf{u}' \in$ *domain*(∇f) *we have* $\|\nabla f(\mathbf{u}) - \nabla f(\mathbf{u})\| \leq \beta\|\mathbf{u} - \mathbf{u}'\|$.

Definition 14. *A differentiable function* f *is* μ*-strongly concave if for all* $\mathbf{x}, \mathbf{y} \in$ *domain*(f)*, we have* $f(\mathbf{x}) + f(\mathbf{x})^T(\mathbf{y} - \mathbf{x}) - \frac{\mu}{2}\|\mathbf{y} - \mathbf{x}\|^2 \geq f(\mathbf{y})$

Definition 15. *A point* $\boldsymbol{\theta}^* = \mathcal{A}(\mathbf{D})$ *output by a randomized algorithm* $\mathcal{A}$ *is an* ϵ*-stationary point of a differentiable function* Φ *if* $\mathbb{E}\|\nabla \Phi(\boldsymbol{\theta}^*)\| \leq \epsilon$*, where the expectation is taken over the randomness of* $\mathcal{A}$*. We say* $\boldsymbol{\theta}^*$ *is an* ϵ*-stationary point of the nonconvex-strongly concave min-max problem* $\min_{\boldsymbol{\theta}} \max_W F(\boldsymbol{\theta}, W)$ *if it is an* ϵ*-stationary point of the differentiable function* $\Phi(\boldsymbol{\theta}) := \max_W F(\boldsymbol{\theta}, W)$.

Recall that Eq. (FERMI obj.) is equivalent to

$$\min_{\boldsymbol{\theta}} \max_{W \in \mathbb{R}^{k \times m}} \left\{ \widehat{F}(\boldsymbol{\theta}, W) := \widehat{\mathcal{L}}(\boldsymbol{\theta}) + \lambda \widehat{\Psi}(\boldsymbol{\theta}, W) = \frac{1}{N}\sum_{i=1}^N \left[\ell(\mathbf{x}_i, y_i, \boldsymbol{\theta}) + \lambda \widehat{\psi}_i(\boldsymbol{\theta}, W) \right] \right\}, \tag{32}$$

where $\widehat{\Psi}(\boldsymbol{\theta}, W) = -\operatorname{Tr}(W \widehat{P}_{\hat{y}} W^T) + 2\operatorname{Tr}(W \widehat{P}_{\hat{y},s} \widehat{P}_s^{-1/2}) - 1 = \frac{1}{N}\sum_{i=1}^N \widehat{\psi}_i(\boldsymbol{\theta}, W)$ and

$$\begin{aligned}\widehat{\psi}_i(\boldsymbol{\theta}, W) &:= -\operatorname{Tr}(W \mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i, \boldsymbol{\theta}) \widehat{\mathbf{y}}(\mathbf{x}_i, \boldsymbol{\theta})^T | \mathbf{x}_i] W^T) + 2\operatorname{Tr}(W \mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i; \boldsymbol{\theta}) \mathbf{s}_i^T | \mathbf{x}_i, s_i] \widehat{P}_s^{-1/2}) - 1 \\ &= -\operatorname{Tr}(W \operatorname{diag}(\mathcal{F}_1(\boldsymbol{\theta}, \mathbf{x}_i), \ldots, \mathcal{F}_m(\boldsymbol{\theta}, \mathbf{x}_i)) W^T) + 2\operatorname{Tr}(W \mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i; \boldsymbol{\theta}) \mathbf{s}_i^T | \mathbf{x}_i, s_i] \widehat{P}_s^{-1/2}) - 1,\end{aligned}$$

where $\widehat{\mathbf{y}}(\mathbf{x}_i; \boldsymbol{\theta})$ and $\mathbf{s}_i$ are the one-hot encodings of $\widehat{y}(\mathbf{x}_i; \boldsymbol{\theta})$ and s_i, respectively.

Assumption 1.

- $\ell(\cdot, \mathbf{x}, y)$ *is* G*-Lipscthiz, and* β_ℓ*-smooth for all* $\mathbf{x}, y$*.*
- $\mathcal{F}(\cdot, \mathbf{x})$ *is* L*-Lipschitz and* b*-smooth for all* $\mathbf{x}$*.*
- *There is a neighborhood* $\mathcal{N}(\boldsymbol{\theta}^*)$ *of* $\boldsymbol{\theta}^*$ *such that* $\widehat{p}_{\hat{y}}^{\min} := \inf_{\boldsymbol{\theta} \in \mathcal{N}(\boldsymbol{\theta}^*)} \min_{j \in [m]} \frac{1}{N}\sum_{i=1}^N \mathcal{F}_j(\boldsymbol{\theta}, x_i) \geq \frac{\mu}{2} > 0$.
- $\hat{p}_S^{\min} := \frac{1}{N}\sum_{i=1}^N \mathbb{1}_{\{s_i = j\}} > 0$.

Theorem 2 (Precise statement of Theorem 1)**.** *Let* $\{\mathbf{x}_i, \mathbf{y}_i, \mathbf{s}_i\}_{i \in [N]}$ *be any given data set of features, labels, and sensitive attributes and grant Assumption 1. Let* $\mathcal{W} := B_F(0, D) \subset \mathbb{R}^{k \times m}$ *(Frobenius norm ball of radius* D*), where* $D := \frac{2}{\hat{p}_{\hat{Y}}^{\min}\sqrt{\hat{p}_S^{\min}}}$ *in Algorithm 1. Denote* $\Delta_{\widehat{\Phi}} := \widehat{\Phi}(\boldsymbol{\theta}_0) - \inf_{\boldsymbol{\theta}} \widehat{\Phi}(\theta)$*, where* $\widehat{\Phi}(\boldsymbol{\theta}) := \max_W \widehat{F}(\boldsymbol{\theta}, W)$*. In Algorithm 1, choose the step-sizes as* $\eta_\theta = \Theta(1/\kappa^2\beta)$ *and*

$\eta_W = \Theta(1/\beta)$ *and mini-batch size as* $|B_t| = \Theta\left(\max\left\{1, \kappa\sigma^2\epsilon^{-2}\right\}\right)$. *Then under Assumption 1, the iteration complexity of Algorithm 1 to return an* ϵ*-stationary point of* $\widehat{\Phi}$ *is bounded by*

$$\mathcal{O}\left(\frac{\kappa^2\beta\Delta_{\widehat{\Phi}} + \kappa\beta^2 D^2}{\epsilon^2}\right),$$

which gives the total stochastic gradient complexity of

$$\mathcal{O}\left(\left(\frac{\kappa^2\beta\Delta_{\widehat{\Phi}} + \kappa\beta^2 D^2}{\epsilon^2}\right)\max\left\{1, \kappa\sigma^2\epsilon^{-2}\right\}\right),$$

where

$$\begin{aligned}
\beta &= 2\left(\beta_\ell + 2\lambda Dmb\left(D + \frac{1}{\sqrt{\hat{p}_S^{\min}}}\right) + 2 + 8L\left(D + \frac{1}{\sqrt{\hat{p}_S^{\min}}}\right)\right),\\
\mu &= 2\lambda\hat{p}_{\widehat{Y}}^{\min},\\
\kappa &= \beta/\mu,\\
\sigma^2 &= 16\lambda^2(D^2+1) + 4G^2 + 32\lambda^2 D^2 L^2\left(1 + \frac{mk}{\hat{p}_S^{\min}}\right).
\end{aligned}$$

Remark 2. *The larger minibatch size is necessary to obtain the faster* $\mathcal{O}(\epsilon^{-4})$ *convergence rate via two-timescale SGDA. However, as noted in [Lin et al., 2020, p.8], their proof readily extends to any batch size* $|B_t| \geq 1$*, showing that two-timescale SGDA still converges. But with* $|B_t| = 1$*, the iteration complexity becomes slower:* $\mathcal{O}(\kappa^3\epsilon^{-5})$*. This is the informal Theorem 1 that was stated in the main body.*

Theorem 2 follows from [Lin et al., 2020, Theorem 4.5]–noting that the proof still goes through with projection of θ^t iterates due to non-expansiveness of projection–combined with the following technical lemmas. We assume Assumption 1 holds for the remainder of the proof of Theorem 2:

Lemma 10. *If* $\mathbf{x}_i, y_i, s_i$ *are drawn uniformly at random from data set* $\mathbf{D}$*, then the gradients of* $\ell(\mathbf{x}_i, y_i, \boldsymbol{\theta}) + \lambda\nabla\widehat{\psi}_i(\boldsymbol{\theta}, W)$ *are unbiased estimators of the gradients of* $\widehat{F}(\boldsymbol{\theta}, W)$ *for all* $\boldsymbol{\theta}, W, \lambda$*:*

$$\begin{aligned}
&\mathbb{E}[\nabla_{\boldsymbol{\theta}}\ell(\mathbf{x}_i, y_i, \boldsymbol{\theta}) + \lambda\nabla_{\boldsymbol{\theta}}\widehat{\psi}_i(\boldsymbol{\theta}, W)] = \nabla_{\boldsymbol{\theta}}\widehat{F}(\boldsymbol{\theta}, W), \text{ and}\\
&\mathbb{E}[\lambda\nabla_W\widehat{\psi}_i(\boldsymbol{\theta}, W)] = \nabla_W\widehat{F}(\boldsymbol{\theta}, W).
\end{aligned}$$

Furthermore, if $\|W\|_F \leq D$*, then the variance of the stochastic gradients is bounded as follows:*

$$\sup_{\boldsymbol{\theta}, W}\mathbb{E}\|\nabla\ell(\mathbf{x}_i, y_i, \boldsymbol{\theta}) + \lambda\nabla\widehat{\psi}_i(\boldsymbol{\theta}, W) - \nabla\widehat{F}(\boldsymbol{\theta}, W)\|^2 \leq \sigma^2, \tag{33}$$

where $\sigma^2 = 16\lambda^2(D^2+1) + 4G^2 + 32\lambda^2 D^2 L^2\left(1 + \frac{mk}{\hat{p}_S^{\min}}\right)$.

Proof. Unbiasedness is obvious. For the variance bound, we will show that

$$\sup_{\boldsymbol{\theta}, W}\mathbb{E}\|\lambda\nabla_W\widehat{\psi}_i(\boldsymbol{\theta}, W) - \nabla_W\widehat{F}(\boldsymbol{\theta}, W)\|^2 \leq \sigma_w^2, \tag{34}$$

and

$$\sup_{\boldsymbol{\theta}, W}\mathbb{E}\|\nabla_{\boldsymbol{\theta}}\ell(\mathbf{x}_i, y_i, \boldsymbol{\theta}) + \lambda\nabla_{\boldsymbol{\theta}}\widehat{\psi}_i(\boldsymbol{\theta}, W) - \nabla_{\boldsymbol{\theta}}\widehat{F}(\boldsymbol{\theta}, W)\|^2 \leq \sigma_{\boldsymbol{\theta}}^2, \tag{35}$$

where $\sigma^2 = \sigma_{\boldsymbol{\theta}}^2 + \sigma_w^2$. First,

$$\nabla_W\widehat{\psi}_i(\boldsymbol{\theta}, W) = -2W\mathbb{E}[\hat{\mathbf{y}}(\mathbf{x}_i, \boldsymbol{\theta})\hat{\mathbf{y}}(\mathbf{x}_i, \boldsymbol{\theta})^T|\mathbf{x}_i] + 2\widehat{p}_s(r)^{-1/2}\mathbb{E}[\mathbf{s}_i\hat{\mathbf{y}}(\mathbf{x}_i, \boldsymbol{\theta})|\mathbf{x}_i, s_i]. \tag{36}$$

Thus, for any $\boldsymbol{\theta}, W, \lambda$, we have

$$\begin{aligned}
\mathbb{E}\|\lambda\nabla_W\widehat{\psi}_i(\boldsymbol{\theta},W)-\nabla_W\widehat{F}(\boldsymbol{\theta},W)\|_F^2 &= \frac{4\lambda^2}{N}\sum_{i=1}^N\Bigg\|W\mathbb{E}[\hat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})\hat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i]-\widehat{p}_s(r)^{-1/2}\mathbb{E}[\mathbf{s}_i\hat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i,s_i] \\
&\quad -\frac{1}{N}\sum_{i=1}^N\Big(W\mathbb{E}[\hat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})\hat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i]-\widehat{p}_s(r)^{-1/2}\mathbb{E}[\mathbf{s}_i\hat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i,s_i]\Big)\Bigg\|_F^2 \\
&\le \frac{4\lambda^2}{N}\sum_{i=1}^N 2\Bigg[\|W\|_F^2\left\|\mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i]-\widehat{P}_{\hat{y}}\right\|_F^2 \\
&\quad +\left\|\widehat{P}_s^{-1/2}\left(\mathbb{E}[\mathbf{s}_i\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i,s_i]-\widehat{P}_{\hat{y},s}^T\right)\right\|_F^2\Bigg] \\
&\le \frac{4\lambda^2}{N}\sum_{i=1}^N 2\left[2D^2+\left\|\widehat{P}_s^{-1/2}\left(\mathbb{E}[\mathbf{s}_i\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i,s_i]-\widehat{P}_{\hat{y},s}^T\right)\right\|_F^2\right] \\
&\le \frac{4\lambda^2}{N}\sum_{i=1}^N 2\left[2D^2+2\right] \\
&\le 16\lambda^2(D^2+1),
\end{aligned}$$

where we used Young's inequality, the Frobenius norm inequality $\|AB\|_F \le \|A\|_F\|B\|_F$, the facts that $\|\mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i]\|_F^2 = \sum_{j=1}^m \mathcal{F}_j(\boldsymbol{\theta},\mathbf{x}_i)^2 \le 1$ and $\|\widehat{P}_s^{-1/2}\mathbb{E}[\mathbf{s}_i\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i,s_i]\|_F^2 = \sum_{j=1}^k \mathbf{s}_{i,j}^2\sum_{l=1}^m \mathcal{F}_l(\mathbf{x}_i,\boldsymbol{\theta})^2 \le 1$ for all $i\in[N]$ (since for every $i\in[N]$, only one of the $\mathbf{s}_{i,j}$ is non-zero and equal to 1, and $\sum_{l=1}^m \mathcal{F}_l(\boldsymbol{\theta},\mathbf{x}_i)=1$).
Next,

$$\begin{aligned}
\lambda\nabla_{\boldsymbol{\theta}}\widehat{\psi}_i(\boldsymbol{\theta},W) = \lambda\Big[&-\nabla_{\boldsymbol{\theta}}\operatorname{vec}(\mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i])^T\operatorname{vec}(W^TW) \\
&+2\nabla_{\boldsymbol{\theta}}\operatorname{vec}(\mathbb{E}[\mathbf{s}_i\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i,s_i])\operatorname{vec}(W^T\widehat{P}_s^{-1/2})\Big].
\end{aligned} \tag{37}$$

Hence, for any $\boldsymbol{\theta}, W$, we have

$$\begin{aligned}
&\mathbb{E}\|\nabla_{\boldsymbol{\theta}}\ell(\mathbf{x}_i,y_i,\boldsymbol{\theta})+\lambda\nabla_{\boldsymbol{\theta}}\widehat{\psi}_i(\boldsymbol{\theta},W)-\nabla_{\boldsymbol{\theta}}\widehat{F}(\boldsymbol{\theta},W)\|^2 \le \\
&2\Bigg[2\sup_{\mathbf{x}_i,y_i}\|\nabla_{\boldsymbol{\theta}}\ell(\mathbf{x}_i,y_i,\boldsymbol{\theta})\|^2+\lambda^2\sup_{\mathbf{x}_i,y_i,s_i}\Big\|-\nabla_{\boldsymbol{\theta}}\operatorname{vec}(\mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i])^T\operatorname{vec}(W^TW) \\
&\quad+2\nabla_{\boldsymbol{\theta}}\operatorname{vec}(\mathbb{E}[\mathbf{s}_i\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i,s_i])\operatorname{vec}(W^T\widehat{P}_s^{-1/2})\Big\|^2\Bigg] \\
&\le 4\Bigg[G^2+2\lambda^2\Bigg(\sup_{\mathbf{x}_i}\left\|\nabla_{\boldsymbol{\theta}}\operatorname{vec}(\mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i])^T\operatorname{vec}(W^TW)\right\|^2 \\
&\quad+4\sup_{\mathbf{x}_i,s_i}\left\|\nabla_{\boldsymbol{\theta}}\operatorname{vec}(\mathbb{E}[\mathbf{s}_i\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i,s_i])\operatorname{vec}(W^T\widehat{P}_s^{-1/2})\right\|^2\Bigg)\Bigg],
\end{aligned}$$

by Young's and Jensen's inequalities and the assumption that $\ell(\mathbf{x}_i,y_i,\cdot)$ is G-Lipschitz. Now,

$$\nabla_{\boldsymbol{\theta}}\operatorname{vec}(\mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i])^T\operatorname{vec}(W^TW) = \sum_{l=1}^m\nabla\mathcal{F}_l(\mathbf{x}_i,\boldsymbol{\theta})\sum_{j=1}^k W_{j,1}W_{j,l},$$

which implies

$$\|\nabla_{\boldsymbol{\theta}}\operatorname{vec}(\mathbb{E}[\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})\widehat{\mathbf{y}}(\mathbf{x}_i,\boldsymbol{\theta})^T|\mathbf{x}_i])^T\operatorname{vec}(W^TW)\|^2 \le \sum_{j,l}W_{j,l}^2\sup_{l\in[m],\mathbf{x},\boldsymbol{\theta}}\|\nabla\mathcal{F}_l(\mathbf{x},\boldsymbol{\theta})\|^2 \le D^2L^2, \tag{38}$$

by L-Lipschitzness of $\mathcal{F}(\cdot, \mathbf{x})$. Also,

$$\nabla_{\boldsymbol{\theta}} \operatorname{vec}(\mathbb{E}[\mathbf{s}_i \widehat{\mathbf{y}}(\mathbf{x}_i, \boldsymbol{\theta})^T | \mathbf{x}_i, s_i]) \operatorname{vec}(W^T \widehat{P}_s^{-1/2}) = \sum_{r=1}^{k} \sum_{j=1}^{m} \nabla \mathcal{F}_j(\boldsymbol{\theta}, \mathbf{x}_i) \frac{\mathbf{s}_{i,r} W_{r,j}}{\sqrt{\hat{p}_S(r)}},$$

which implies

$$\begin{aligned} \left\| \nabla_{\boldsymbol{\theta}} \operatorname{vec}(\mathbb{E}[\mathbf{s}_i \widehat{\mathbf{y}}(\mathbf{x}_i, \boldsymbol{\theta})^T | \mathbf{x}_i, s_i]) \operatorname{vec}(W^T \widehat{P}_s^{-1/2}) \right\|^2 &\leq mk \sum_{r=1}^{k} \sum_{j=1}^{m} \sup_{\mathbf{x}_i, \boldsymbol{\theta}} \|\nabla \mathcal{F}_j(\boldsymbol{\theta}, \mathbf{x}_i)\|^2 \left(\frac{\mathbf{s}_{i,r} W_{r,j}}{\sqrt{\hat{p}_S(r)}} \right)^2 \\ &\leq \frac{mk}{\hat{p}_S^{\min}} L^2 D^2. \end{aligned}$$

Thus,

$$\sigma_{\boldsymbol{\theta}}^2 \leq 4G^2 + 32\lambda^2 D^2 L^2 \left(1 + \frac{mk}{\hat{p}_S^{\min}} \right).$$

Combining the $\boldsymbol{\theta}$- and W-variance bounds yields the lemma. □

E Fair Binary Classification using Neural Models

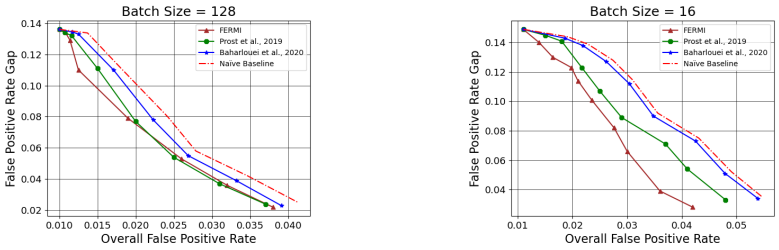

Figure 4: Fair toxic comment detection with different batch sizes. For $|B| = 128$, the performance of [Prost et al., 2019] and FERMI are close to each other, however, when the batch size is reduced to 16, FERMI demonstrates a better fairness/ performance trade-off. The performance and fairness are measured by the overall false positive rate and the false positive gap between different religious sub-groups (Christians vs Muslum-Jews), respectively.

In this experiment, our goal is to showcase the efficacy of FERMI in stochastic optimization with neural network function approximation. To this end, we apply FERMI, [Prost et al., 2019], [Baharlouei et al., 2020], and [Mary et al., 2019] (which coincides with [Baharlouei et al., 2020]) to the Toxic Comment Classification dataset where the underlying task is to predict whether a given published comment in social media is toxic. The sensitive attribute is religion that is binarized into two groups: Christians in one group; Muslims and Jews in the other group. Training a neural network without considering fairness leads to higher false positive rate for the Jew-Muslim group. Figure 4 demonstrates the performance of FERMI, MinDiff [Prost et al., 2019], Baharlouei et al. [2020], and naïve baseline on two different batch-sizes: 128 and 16. Performance is measured by the overall false positive rate of the trained network and fairness violation is measured by the false positive gap between two sensitive groups (Christians and Jews-Muslims). The network structure is exactly same as the one used by MinDiff [Prost et al., 2019]. We can observe that by decreasing the batch size, FERMI maintains the best fairness-accuracy tradeoff compared to other baselines.

F Beyond Fairness: Domain Parity Regularization for Domain Generalization

In this section, we demonstrate that our approach may extend beyond fair empirical risk minimization to other problems such as domain generalization. In fact, Li and Vasconcelos [2019], Lahoti et al. [2020], Creager et al. [2021] have already established connections between fair ERM and domain generalization. We consider the Color MNIST dataset [Li and Vasconcelos, 2019], where all 60,000 training digits are colored with different colors drawn from a class conditional Gaussian distribution with variance σ^2 around a certain average color for each digit, while the test set remains black and white. Li and Vasconcelos [2019] show that as $\sigma^2 \to 0$, a convolutional network model overfits

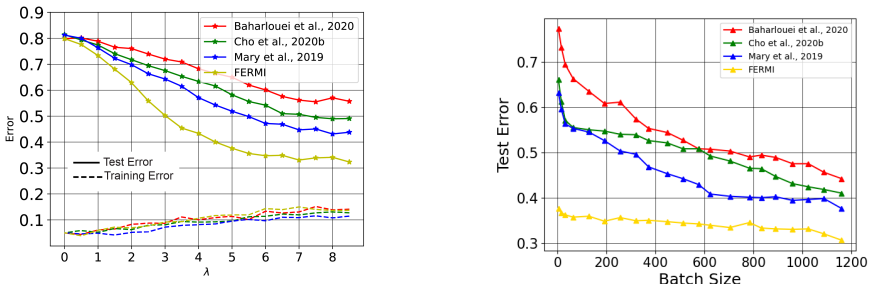

Figure 5: Domain generalization on Color MNIST [Li and Vasconcelos, 2019] using in-process fair algorithms for demographic parity. **Left panel:** The dashed line is the training error and the solid line is test error. As λ increases, fairness regularization results in a learned representation that is less dependent on color; hence training error increases while test error decreases (all algorithms reach a plateau around $\lambda = 8$). We use $|B| = 512$ for all baselines. **Right panel:** We plot test error vs. batch size using an optimized value of λ for each algorithm selected via a validation set. The performance of baselines drops 10-20% as batch size becomes small, whereas FERMI is less sensitive to batch size.

significantly to each digit's color on the training set, and achieves vanishing training error. However, the learned representation does not generalize to the black and white test set, due to the spurious correlation between digits and color.

Conceptually, the goal of the classifier in this problem is to achieve *high classification accuracy with predictions that are independent of the color of the digit*. We view color as the sensitive attribute in this experiment, and apply fairness baselines for the demographic parity notion of fairness. One would expect that by promoting such independence through a fairness regularizer, generalization would improve (i.e. lower test error on the black and white test set), at the cost of increased training error (on the colored training set). We compare against Mary et al. [2019], Baharlouei et al. [2020], and Cho et al. [2020a] as baselines in this experiment.

The results of this experiment are illustrated in Fig. 5. In the left panel, we see that with no regularization ($\lambda = 0$), the test error is around 80%. As λ increases, all methods achieve smaller test error while training error increases. We also observe that *FERMI offers the best test error* in this setup. In the right panel, we observe that decreasing the batch size results in significantly worse generalization for the three baselines considered (due to their biased estimators for the regularizer). However, the negative impact of small batch size is much less severe for FERMI, since FERMI uses unbiased stochastic gradients. In particular, *the performance gap between FERMI and other baselines is more than 20% for* $|B| = 64$. Moreover, *FERMI with minibatch size* $|B| = 64$ *still outperforms all other baselines with* $|B| > 1,000$. Finally, notice that the test error achieved by FERMI when $\sigma = 0$ is $\sim 30\%$, as compared to more than 50% obtained using REPAIR [Li and Vasconcelos, 2019] for $\sigma \leq 0.05$.

G Experiment Details and Additional Results

G.1 Model description

For all the experiments, the model's output is of the form $O = \mathrm{softmax}(Wx + b)$. The model outputs are treated as conditional probabilities $\mathbf{p}(\hat{y} = i|x) = O_i$ which are then used to estimate the ERMI regularizer. We encode the true class label Y and sensitive attribute S using one-hot encoding. We define $\ell(\cdot)$ as the cross-entropy measure between the one-hot encoded class label Y and the predicted output vector O.

We use logistic regression as the base classification model for all experiments in Fig. 1. The choice of logistic regression is due to the fact that all of the existing approaches demonstrated in Fig. 1, use the same classification model. The model parameters are estimated using the algorithm described in Algorithm 1. The trade-off curves for FERMI are generated by sweeping across different values for $\lambda \in [0, 10000]$. The learning rates η_θ, η_w is constant during the optimization process and is chosen from the interval $[0.0005, 0.01]$ for all datasets. Moreover, the number of iterations T for experiments in Fig. 1 is fixed to 2000. Since the training and test data for the Adult dataset are separated and fixed, we do not consider confidence intervals for the test accuracy. We generate ten distinct train/test sets for each one of the German and COMPAS datasets by randomly sampling 80% of data points as

the training data and the rest 20% as the test data. For a given method in Fig. 1, the corresponding curve is generated by taking the average test accuracy on 10 training/test datasets. Furthermore, the confidence intervals are estimated based on the test accuracy's standard deviation on these 10 datasets.

To perform the experiments in Sec. 3.2 we use a a linear model with softmax activation. The model parameters are estimated using the algorithm described in Sec. 3. The data set is cleaned and processed as described in [Kearns et al., 2018]. The trade-off curves for FERMI are generated by sweeping across different values for λ in $[0, 100]$ interval, learning rate η in $[0.0005, 0.01]$, and number of iterations T in $[50, 200]$. The data set is cleaned and processed as described in [Kearns et al., 2018].

For the experiments in Appendix F, we create the synthetic color MNIST as described by Li and Vasconcelos [2019]. We set the value $\sigma = 0$. In Fig. 5, we compare the performance of stochastic solver (Algorithm 1) against the baselines. We use a mini-batch of size 512 when using the stochastic solver. The color MNIST data has 60000 training samples, so using the stochastic solver gives a speedup of around 100x for each iteration, and an overall speedup of around 40x. We present our results on two neural network architectures; namely, LeNet-5 [Lecun et al., 1998] and a Multi-layer perceptron (MLP). We set the MLP with two hidden layers (with 300 and 100 nodes) and an output layer with ten nodes. A ReLU activation follows each hidden layer, and a softmax activation follows the output layer.

Some general advice for tuning λ: Larger value for λ generally translates to better fairness, but one must be careful to not use a very large value for λ as it could lead to poor generalization performance of the model. The optimal values for λ, η, and T largely depend on the data and intended application. We recommend starting with $\lambda \approx 10$. In Appendix G.5, we can observe the effect of changing λ on the model accuracy and fairness for the COMPAS dataset.

G.2 The effect of missing sensitive attributes on fairness/accuracy tradeoffs

Sensitive attributes might be partially unavailable in many real-world applications due to legal issues, privacy concerns, and data gathering limitations [Zhao et al., 2022, Coston et al., 2019]. Missing sensitive attributes make fair learning tasks more challenging in practice. The unbiased nature of the estimator used in FERMI algorithm motivates that it may be able to handle cases where sensitive attributes are *partially* available and are dropped uniformly at random. As a case study on the Adult dataset, we randomly masked 90% of the sensitive attribute (i.e., gender entries). To estimate the fairness regularization term, we rely on the remaining 10% of the training samples ($\approx 3k$) with sensitive attribute information. Figure 6 depicts the tradeoff between accuracy and fairness (demographic parity) violation for FERMI and other baselines. We suspect that the superior accuracy-fairness tradeoff of FERMI compared to other approaches is due to the fact that the estimator of the gradient remains unbiased since the missing entries are missing completely at random (MCAR). Note that the *Naïve Baseline* is similar to the one implemented in the previous section, and *Full-sensitive FERMI* is an oracle method that applies FERMI to the data with no missing attributes (for comparison purposes only). We observe that FERMI achieves a slightly worse fairness-accuracy tradeoff compared to Full-sensitive FERMI oracle, whereas the other baselines are hurt significantly and are only narrowly outperforming the Naïve Baseline.

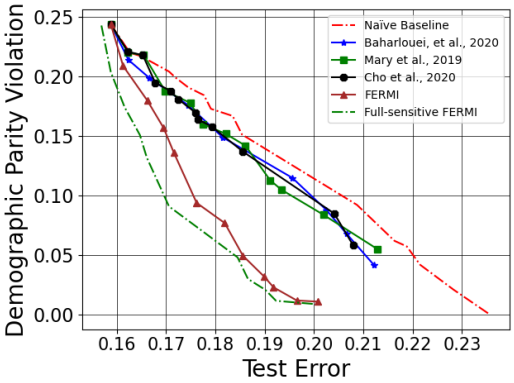

Figure 6: Performance of FERMI and other state-of-the-art approaches on the Adult dataset where 90% of gender entries are missing. Full-sensitive FERMI is obtained by applying FERMI on the data without any missing entries.

G.3 More comparison to [Mary et al., 2019]

The algorithm proposed by Mary et al. [2019] backpropagates the batch estimate of ERMI, which is biased especially for small minibatches. Our work uses a correct and unbiased implementation of a stochastic ERMI estimator. Furthermore, *Mary et al. [2019] does not establish any convergence guarantees, and in fact their algorithm does not converge*. See Fig. 7 for the evolution of *training loss* (i.e. value of the objective function) and *test accuracy*. For this experiment, we follow the same setup used in [Mary et al., 2019, Table 1]; the minibatch size for this experiment is 128.

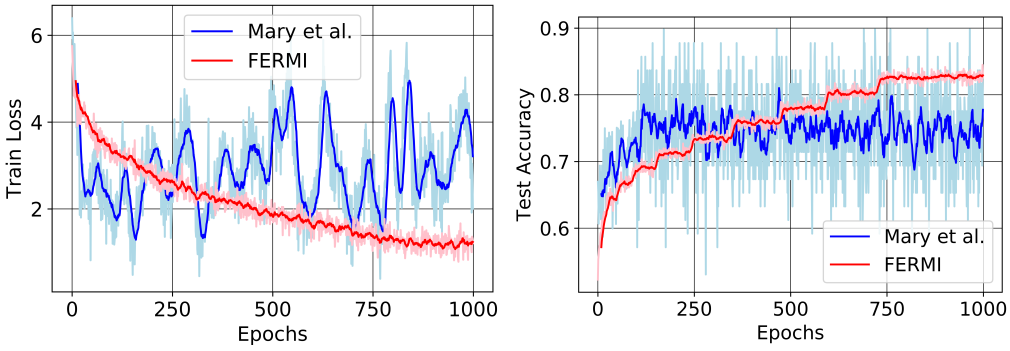

Figure 7: [Mary et al., 2019] fails to converge to a stationary point whereas our stochastic algorithm easily converges.

G.4 Performance in the presence of outliers & class-imbalance

We also performed an additional experiment on Adult (setup of Fig 1) with a random 10% of sensitive attributes in *training* forced to 0. FERMI offers the most favorable tradeoffs on *clean test* data, however, all methods reach a higher plateau (see Fig 8). The interplay between fairness, robustness, and generalization is an important future direction. With respect to imbalanced sensitive groups, the experiments in Fig 3 are on a naturally imbalanced dataset, where $\max_{s\in\mathcal{S}} p(s)/\min_{s\in\mathcal{S}} p(s) > 100$ for 3-18 sensitive attrib, and FERMI offers the favorable tradeoffs.

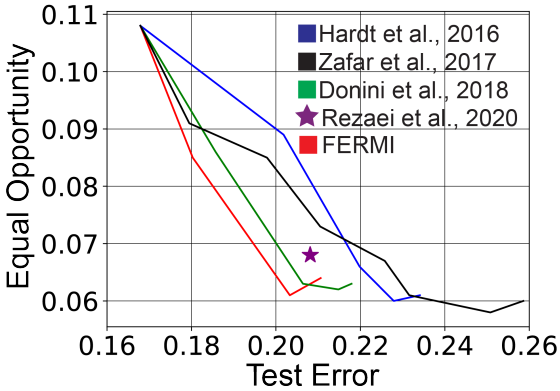

Figure 8: Comparing FERMI with other methods in the presence of outliers (random 10% of sensitive attributes in *training* forced to 0. FERMI still achieves a better trade-off compared to all other baselines.

G.5 Effect of hyperparameter λ on the accuracy-fairness tradeoffs

We run ERMI algorithm for the binary case to COMPAS dataset to investigate the effect of hyper-parameter tuning on the accuracy-fairness trade-off of the algorithm. As it can be observed in Fig. 9, by increasing λ from 0 to 1000, test error (left axis, red curves) is slightly increased. On the other

hand, the fairness violation (right axis, green curves) is decreased as we increase λ to 1000. Moreover, for both notions of fairness (demographic parity with the solid curves and equality of opportunity with the dashed curves) the trade-off between test error and fairness follows the similar pattern. To measure the fairness violation, we use demographic parity violation and equality of opportunity violation defined in Section equation 3 for the solid and dashed curves respectively.

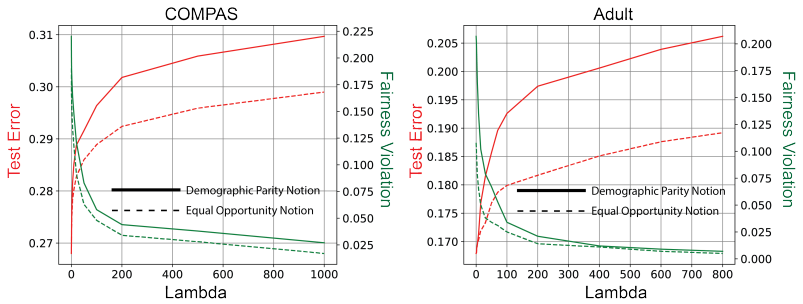

Figure 9: Tradeoff of fairness violation vs test error for FERMI algorithm on COMPAS and Adult datasets. The solid and dashed curves correspond to FERMI algorithm under the demographic parity and equality of opportunity notions accordingly. The left axis demonstrates the effect of changing λ on the test error (red curves), while the right axis shows how the fairness of the model (measured by equality of opportunity or demographic parity violations) depends on changing λ.

G.6 Complete version of Figure 1 (with pre-processing and post-processing baselines)

In Figure 1 we compared FERMI with several state-of-the-art in-processing approaches. In the next three following figures we compare the in-processing approaches depicted in Figure 1 with pre-processing and post-processing methods including [Hardt et al., 2016, Kamiran et al., 2010, Feldman et al., 2015].

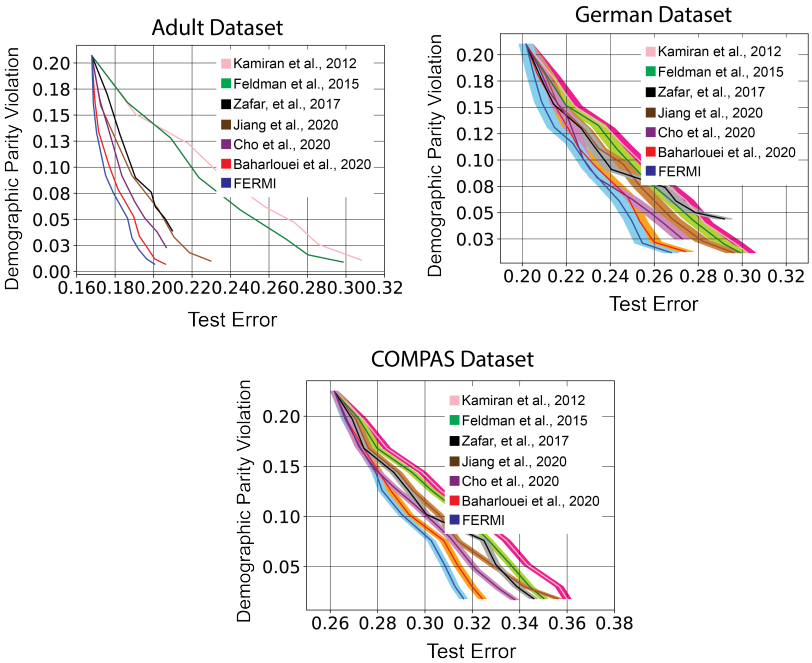

Figure 10: Tradeoff of demographic parity violation vs test error for FERMI algorithm on COMPAS, German, and Adult datasets.

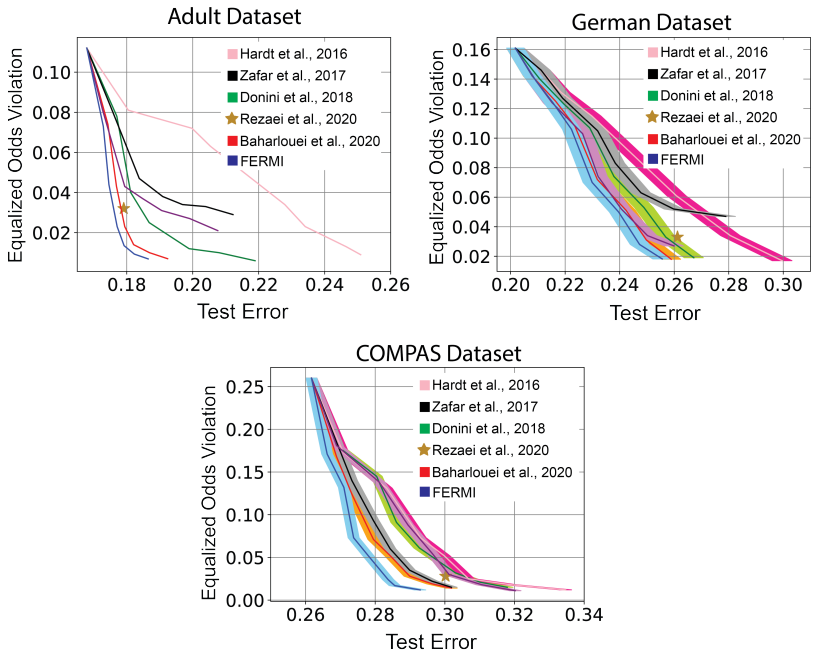

Figure 11: Tradeoff of equalized odds violation vs test error for FERMI algorithm on COMPAS, German, and Adult datasets.

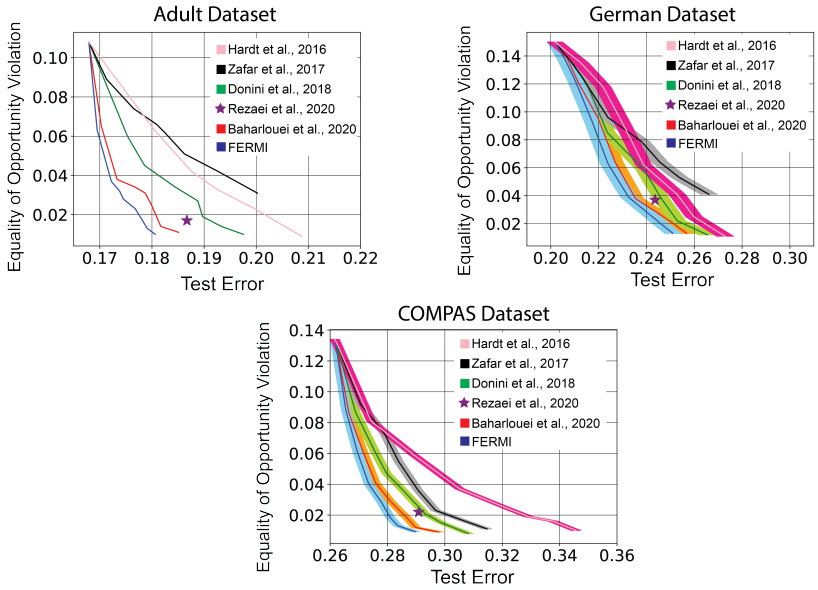

Figure 12: Tradeoff of equality of opportunity violation vs test error for FERMI algorithm on COMPAS, German, and Adult datasets.

G.7 Description of datasets

All of the following datasets are publicly available at UCI repository.

German Credit Dataset.[4] German Credit dataset consists of 20 features (13 categorical and 7 numerical) regarding to social, and economic status of 1000 customers. The assigned task is to classify customers as good or bad credit risks. Without imposing fairness, the DP violation of the

[4] `https://archive.ics.uci.edu/ml/datasets/statlog+(german+credit+data)`

trained model is larger than 20%. We choose 80% of customers as the train data and the remaining 20% customers as the test data. The sensitive attributes are gender, and marital-status.

Adult Dataset.[5] Adult dataset contains the census information of individuals including education, gender, and capital gain. The assigned classification task is to predict whether a person earns over 50k annually. The train and test sets are two separated files consisting of $32,000$ and $16,000$ samples respectively. We consider gender and race as the sensitive attributes (For the experiments involving one sensitive attribute, we have chosen gender). Learning a logistic regression model on the training dataset (without imposing fairness) shows that only 3 features out of 14 have larger weights than the gender attribute. Note that removing the sensitive attribute (gender), and retraining the model does not eliminate the bias of the classifier. the optimal logistic regression classifier in this case is still highly biased. For the clustering task, we have chosen 5 continuous features (Capital-gain, age, fnlwgt, capital-loss, hours-per-week), and $10,000$ samples to cluster. The sensitive attribute of each individual is gender.

Communities and Crime Dataset.[6] The dataset is cleaned and processed as described in [Kearns et al., 2018]. Briefly, each record in this dataset summarizes aggregate socioeconomic information about both the citizens and police force in a particular U.S. community, and the problem is to predict whether the community has a high rate of violent crime.

COMPAS Dataset.[7] Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) is a famous algorithm which is widely used by judges for the estimation of likelihood of reoffending crimes. It is observed that the algorithm is highly biased against the black defendants. The dataset contains features used by COMPAS algorithm alongside with the assigned score by the algorithm within two years of the decision.

Colored MNIST Dataset.[8] We use the code by Li and Vasconcelos [2019] to create a Colored MNIST dataset with $\sigma = 0$. We use the provided LeNet-5 model trained on the colored dataset for all baseline models of Baharlouei et al. [2020], Mary et al. [2019], Cho et al. [2020a] and FERMI, where we further apply the corresponding regularizer in the training process.

H Anonymized Code for Experiments

The anonymized code for all of the experiments in this paper is available on Dropbox:
https://www.dropbox.com/sh/516cm8olq0idpsd/AADD0LOcPWpx4AAhzsEkFTOca?dl=0

[5] https://archive.ics.uci.edu/ml/datasets/adult.
[6] http://archive.ics.uci.edu/ml/datasets/communities+and+crime
[7] https://www.kaggle.com/danofer/compass
[8] https://github.com/JerryYLi/Dataset-REPAIR/