A Comprehensive Empirical Study of Bias Mitigation Methods for Software Fairness

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Software bias is an increasingly important operational concern for software engineers. We present a large-scale, comprehensive empirical evaluation of 17 representative bias mitigation methods, evaluated with 12 Machine Learning (ML) performance metrics, 4 fairness metrics, and 24 types of fairness-performance trade-off assessment, applied to 8 widely-adopted benchmark software decision/prediction tasks. The empirical coverage is comprehensive, covering the largest numbers of bias mitigation methods, evaluation metrics, and fairness-performance trade-off measures compared to previous work on this important operational software characteristic. We find that (1) the bias mitigation methods significantly decrease the values reported by all ML performance metrics (including those not considered in previous work) in a large proportion of the scenarios studied (42%~75% according to different ML performance metrics); (2) the bias mitigation methods achieve fairness improvement in only approximately 50% over all scenarios and metrics (ranging between 29%~59% according to the metric used to assess bias/fairness); (3) the bias mitigation methods have a poor fairness-performance trade-off or even lead to decreases in both fairness and ML performance in 37% of the scenarios; (4) the effectiveness of the bias mitigation methods depends on tasks, models, and fairness and ML performance metrics, and there is no ‘silver bullet’ bias mitigation method demonstrated to be effective for all scenarios studied. The best bias mitigation method that we find outperforms other methods in only 29% of the scenarios. We have made publicly available the scripts and data used in this study in order to allow for future replication and extension of our work.

Additional Key Words and Phrases: Software fairness, machine learning performance, bias mitigation methods, fairness-performance trade-off

1 INTRODUCTION

Machine Learning (ML)-enabled software (in short as ML software) has made its way into a wide range of critical decision-making applications, such as hiring, criminal justice, credit risk prediction, and admissions [49]. There are several widely-known examples of software exhibiting unfair behaviours, relating to protected attributes such as gender [13, 15] and race [9, 14]. Unfair software behaviour may result in unacceptable and unethical consequences that adversely affect users in minority and/or historically disadvantaged groups. Moreover, when software falls within legal or regulatory frameworks, unfair behaviour also incurs legal risks to software engineers.

The issue of fairness has been studied for some time in Software Engineering (SE) research [37], pre-dating the recent upsurge in ML applications. However, the SE research community has increasingly focused on fairness since then. This increased focus is induced by increasing software systems’ reliance on ML as a powerful generic technique to tackle complex decision and prediction problems, bringing with it the potential for unfairness as a result of software bias.¹ As a result, the software engineering literature has witnessed a large number of recent results on software bias.

¹We use “bias” to refer to the opposite of “fairness” and treat “unfairness” and “bias” as synonyms.
and fairness [16, 19–21, 25–27, 38, 40, 41, 60, 66, 68]. Software engineers tend to regard fairness as a non-functional property (typically most pertinent to ML software [67], although also applicable more generally in SE [37]).

In SE nomenclature, unfairness can be thought of as ‘fairness bugs’, thereby motivating software engineers to tackle the problem using software testing [16, 38, 60, 68]. Alternatively, software engineers can regard fairness as a non-functional property [19, 25, 26, 40, 41] seeking techniques for bias mitigation, i.e., fixing fairness bugs to reduce software bias.

With the emergence of various bias mitigation methods, SE researchers have started to evaluate and compare these methods. Such empirical evaluations enable the development of scientific knowledge about how useful different bias mitigation methods are in different application scenarios. Since there is a widespread belief in the research community that bias mitigation methods often improve fairness at the cost of ML performance (i.e., fairness-performance trade-off) [18, 61], to evaluate the effectiveness of a bias mitigation method, researchers not only measure the improvement of fairness achieved by it, but also consider its effect on ML performance (e.g., accuracy).

However, existing evaluations of bias mitigation methods have yet to achieve full coverage and completeness to give a comprehensive picture. In particular, researchers often use only one or two metrics to measure the effects of existing bias mitigation methods on ML performance, overlooking other metrics that are widely used in industry and academia. For example, Zhang and Harman [66] and Hort et al. [41] measured ML performance in terms of only accuracy; Chakraborty et al. [26] used recall on favorable and unfavorable classes as only ML performance metrics; Biswas and Rajan [19, 20] measured only accuracy as well as F1-score on the favorable class.

Nevertheless, different situations require different metrics. For example, in an online advertising task targeting users with lower incomes, developers would more likely care about precision for this category of users, because it is common practice in online advertising to provide specific treatments to users for whom the algorithm is confident about the attributes [47]. However, existing work does not consider the corresponding metric (i.e., precision on the unfavorable class) when evaluating bias mitigation methods on benchmark tasks like the income prediction task [25, 26, 41, 66]. Therefore, based on the results of existing work, developers will have no findings on which to base their decisions for such scenarios.

This gap motivates us to evaluate existing bias mitigation methods in terms of comprehensive metrics. Since different metrics measure the functional or non-functional properties of ML software from different aspects, we believe that the results of this study can provide insightful implications for real-world applications as well as a foundational baseline for further research and follow-on studies.

We present a comprehensive study, evaluating 17 representative bias mitigation methods in 8 widely adopted benchmark tasks with 12 ML performance metrics, 4 fairness metrics, and 24 types of fairness-performance trade-offs (i.e., the fairness-performance trade-off in terms of different ML performance metrics and fairness metrics). Our study covers the largest number of bias mitigation methods, evaluation metrics, and fairness-performance trade-off measures in software fairness research literature. Specifically, our study yields the following implications for fairness research and practice:

(1) The values of all ML performance metrics that we use (including those not considered in previous work) decrease in a large proportion (42%~75%) of scenarios after applying bias mitigation methods. Therefore, it is important for researchers to use a comprehensive set of ML performance metrics in their evaluations, to be sure to capture any decreases in performance caused by bias mitigation methods.
(2) Existing bias mitigation methods improve fairness values in only approximately 50% of the scenarios we studied, and have a poor fairness-performance trade-off, or even lead to decreases in both fairness and ML performance in 37% of the scenarios. Therefore, a community effort is required to bring software fairness improvements to a level where it becomes more effective and usable in practice.

(3) The effectiveness of the bias mitigation methods depends on tasks, models, and fairness and ML performance metrics; there is no 'silver bullet' bias mitigation method demonstrated to be effective for all scenarios. Therefore, researchers and practitioners need to choose the bias mitigation method best suited to their intended application scenario(s). Our results provide empirical guidance for such choices.

(4) We have made available all scripts and data we used for this study [30] as an additional contribution to the research community for other researchers to replicate and extend this work.

The rest of this paper is organized as follows. Section 2 describes the background knowledge and related work about software fairness. Section 3 presents the research questions and methodology of this study. Section 4 reports and analyzes the results. Section 5 discusses threats to the validity, followed by concluding remarks in Section 6.

2 BACKGROUND

In this section, we briefly provide background knowledge on software fairness and introduce the literature on fairness research.

2.1 Definition of Fairness

As indicated in previous work [41, 59, 66], there are two primary types of fairness that researchers pursue, i.e., individual fairness and group fairness. Individual fairness requires an ML model to produce similar predictive outcomes for similar individuals, while group fairness requires an ML model to treat different groups equally. Since existing bias mitigation methods [20, 25, 26, 41, 61, 66] focus on group fairness, in this paper, we also focus on group fairness.

In the context of group fairness, a population is partitioned into the privileged and unprivileged groups based on the values of protected attributes, which refer to the sensitive characteristics (e.g., sex and race) that need to be protected against unfairness. Usually, an unfair ML model tends to favor the privileged group (i.e., inclined to produce the favorable class for its members), thereby putting the unprivileged group at disadvantage. For example, in the recidivism assessment task, race is a protected attribute yet existing recidivism assessment systems have been demonstrated to recommend favourable decisions for white defendants compared to otherwise equivalent black defendants [9].

2.2 Related Work

Fairness has attracted increasing interest from both the ML research community [49] and the SE research community [41] and also from practitioners as well as researchers. For example, Microsoft recently published the ethical principles of AI [11], stating that ML software must be fair in real-life applications, creating a research group named FATE [4] to promote software fairness. In addition, recently, researchers, Brun and Meliou [21] set out a vision for SE research approaches to tackle fairness problems, and a recent survey on ML testing [67] classified fairness as a non-functional software property, surveying SE approaches to tackling it.

The rising attention on fairness inspires the emergence of a series of fairness testing techniques. Themis [38] generated test suites to measure causal discrimination in software. Aeqitas [60]
exploited the inherent robustness property of ML models for directing fairness test generation. SG [16] combined symbolic execution and local explainability to generate test inputs for detecting individual discrimination. ADF [68] used gradient computation and clustering to generate individual discriminatory instances for DNNs.

In addition to testing software fairness, researchers also attempt to improve software fairness. Zhang and Harman [66] explored the factors that affect software fairness, and found that enlarging feature set is a possible way to improve fairness. Chakraborty et al. [26] removed ambiguous data points in training data and then applied multi-objective optimization to train fair ML models. To better improve software fairness, the follow-up work of Chakraborty et al. [25] not only removed ambiguous data points, but also balanced the internal distribution of training data. Moreover, IBM launched a software toolkit called AI Fairness 360 (abbreviated as IBM AIF360) [8], which integrated popular fairness improvement methods (i.e., bias mitigation methods) proposed in the ML community, including Adversarial Debiasing [65], Reweighting [42], Reject Option Classification [44], Learning Fair Representation [64], etc.

Furthermore, there is some work that empirically evaluates the effectiveness of different bias mitigation methods. For example, Biswas and Rajan [19, 20] evaluated seven bias mitigation methods on real-world ML models from a crowd-sourced platform and explored the impact of popular pre-processing procedures on ML performance and fairness. Chakraborty et al. [25, 26] compared the bias mitigation methods proposed by them with several methods proposed in the ML community. In these work, the changes in ML performance and fairness caused by bias mitigation methods are measured and visualised separately. Therefore, it is difficult to judge whether the improved fairness is simply the consequence of ML performance loss. To tackle this problem, Hort et al. [41] proposed a model behavior mutation method to quantitatively benchmark and evaluate the fairness-performance trade-off of different bias mitigation methods.

Nevertheless, existing evaluations of bias mitigation methods are conducted in terms of limited metrics and measures. In particular, researchers often use only one or two ML performance metrics in the evaluations. For example, most of fairness work [22–24, 35, 41–43, 45, 63, 66] measured ML performance in terms of only accuracy. Chakraborty et al. [26] used recall on the favorable class and false alarm (i.e., 1 minus recall on the unfavorable class) to compare different methods. Biswas and Rajan [19, 20] measured accuracy as well as F1-score on the favorable class. In contrast, Chakraborty et al. [25] employed the most ML performance metrics, including accuracy and precision/recall/F1-score on the favorable class, but they still ignored other metrics that measure ML performance on the unfavorable class and those that measure overall performance on favorable and unfavorable classes. Since different ML performance metrics indicate different functional properties of ML software, it is important to evaluate bias mitigation methods on various ML performance metrics to provide comprehensive and insightful implications for real-world applications. To fill the knowledge gap, in this paper, we aim to evaluate existing bias mitigation methods in terms of comprehensive metrics and fairness-performance trade-off measures.

In addition, existing work focuses on limited bias mitigation methods. For example, Bias and Rajan [19] evaluated seven of our used methods; Chakraborty et al. [26] evaluated five; Chakraborty et al. [25] evaluated three. In contrast, Hort et al. [41] evaluated the most bias mitigation methods, a total of twelve. However, they focused on only methods proposed in the ML community. In this paper, we aim to consider 17 representative bias mitigation methods from both the ML and SE communities. This large-scale study allows us to get a big picture of the literature as well as future research challenges and opportunities.

3 EXPERIMENTAL SETUP

In this section, we describe the research questions and experimental design of this study.
3.1 Overview of Experimental Design

Fig. 1 illustrates our experimental design in a nutshell. First, we use five widely-adopted benchmark datasets (covering eight different bias mitigation tasks) to train ML models with three traditional ML algorithms. Second, we apply 17 representative bias mitigation methods from the ML and SE communities to these ML models. Third, we adopt 12 ML performance metrics and 4 fairness metrics to evaluate different methods in terms of ML performance and fairness, separately. Finally, we consider performance and fairness together, and evaluate the fairness-performance trade-off of the 17 bias mitigation methods using 24 fairness-performance metric pairs. Specifically, we aim to answer the following research questions (RQs):

**RQ1 (Influence on ML performance):** How do existing bias mitigation methods affect ML software in terms of performance changes? ML performance (e.g., accuracy and precision) represents important functional requirements of ML software, but bias mitigation methods may improve fairness at the cost of ML performance. Therefore, we first investigate how existing methods change ML performance in terms of various metrics.

**RQ2 (Influence on fairness):** How do existing bias mitigation methods affect ML software in terms of fairness improvement? As the main goal of bias mitigation methods is to reduce bias in ML software, we explore how well existing bias mitigation methods achieve this goal in terms of various fairness metrics.

**RQ3 (Influence on fairness-performance trade-off):** How do existing bias mitigation methods affect ML software in terms of fairness-performance trade-off? We finally consider fairness and ML performance together, and evaluate existing bias mitigation methods in terms of different types of fairness-performance trade-offs, i.e., combinations of different fairness metrics and ML performance metrics.

In the following, we introduce the bias mitigation methods (Section 3.2), benchmark datasets (Section 3.3), metrics and measures (Section 3.4), and experimental settings (Section 3.5).

3.2 Bias Mitigation Methods

We focus our analysis on 17 representative bias mitigation methods proposed in the ML and SE communities. To the best of our knowledge, this work covers the most bias mitigation methods in software fairness research. As for the methods proposed in the ML community, we follow previous work [19, 26, 41, 66] to employ the state-of-the-art ones implemented in the IBM AIF360 framework [8]. Specifically, we employ all the ten methods listed on its homepage [8], covering three types, i.e., pre-processing, in-processing, and post-processing. Pre-processing methods aim to process the training data to mitigate data bias; in-precessing methods aim to improve group fairness during the
training process; post-processing methods aim to modify the prediction outcomes of ML models to improve fairness. Next, we briefly introduce each method by type.

**Pre-processing:** Optimized Pre-processing (OP) [34] learns a probabilistic transformation to modify data features and labels. Learning Fair Representation (LFR) [64] learns fair representations by obfuscating information about protected attributes. Reweighting (REW) [42] generates different weights for the training samples in each (group, label) combination. Disparate Impact Remover (DIR) [36] modifies feature values to improve group fairness while preserving rank-ordering within groups.

**In-processing:** Prejudice Remover (PR) [46] adds a discrimination-aware regularization term to the learning objective. Adversarial Debiasing (AD) [65] uses adversarial techniques to maximize accuracy and reduce evidence of protected attributes in the predictions simultaneously. Meta Fair Classifier (MFC) [24] takes the fairness metric as part of the input and returns a classifier optimized for that metric.

**Post-processing:** Reject Option Classification (ROC) [44] targets predictions with high uncertainty and tends to assign favorable outcomes to the unprivileged group and unfavorable outcomes to the privileged group. Calibrated Equalized Odds Post-processing (CEO) [54] optimizes over calibrated classifier score outputs to find probabilities with which to change output labels with an equalized odds objective. Equalized Odds Post-processing (EO) [39] solves a linear program to find probabilities with which to change output labels to optimize equalized odds.

As for the methods proposed in the SE community, we use two methods recently published on top SE venues, including Fairway [26] at ESEC/FSE 2020 and Fair-SMOTE [25] at ESEC/FSE 2021. Fairway [26] combines pre-processing and in-processing techniques to improve fairness. First, it evaluates the original labels of the training data and removes ambiguous data points that can eventually make the classifier biased. Then, it employs multi-objective optimization to maximize the model performance while making it fair.

Fair-SMOTE [25] is a pre-processing method that employs two strategies. First, it generates new data points to make the numbers of training data in different subgroups (i.e., combinations of different outcomes and protected attribute values) equal. Second, it uses the same method as Fairway to remove ambiguous data points from the training data.

In the IBM AIF360, MFC, ROC, and CEO are implemented with two, three, and three different metrics to guide the bias mitigation process, respectively. Specifically, MFC offers a choice between Disparate Impact (DI) and FDR (False Discovery Rate); ROC offers a choice among Statistical Parity Difference (SPD), Average Odds Difference (AOD), and Equal Opportunity Difference (EOD); CEO offers a choice among False Negative Rate (FNR), False Positive Rate (FPR), and a weighted metric to combine both. We implement and evaluate each of the settings. Therefore, we have a total of 17 bias mitigation methods for our study.

### 3.3 Benchmark Datasets

We follow previous work [66] to use five most widely studied benchmark datasets implemented in the IBM AIF360 (as listed in Table 1) for this study. The five datasets cover social, financial, and medical domains, and are the most widely adopted in fairness literature of the ML [49] and SE [20, 25, 26, 41, 66] communities. The number of datasets used in this study aligns with the fairness literature, as previous work [41] points out that 90% of fairness papers use no more than three datasets. Next, we briefly introduce each dataset that we use.

Adult Income dataset [1] (a.k.a., Adult dataset) contains demographic and financial information about individuals extracted from the 1994 U.S. census data, and is used to predict whether the income of a person exceeds $50K a year or not.
Table 1. Benchmark datasets used for bias mitigation.

| Name      | Size   | #Features | Protected attribute(s) | Favorable label              | Majority label   |
|-----------|--------|-----------|------------------------|------------------------------|------------------|
| Adult     | 45,222 | 14        | Sex, Race              | 1 (income > 50K)             | 0 (75.2%)        |
| Compas    | 6,167  | 10        | Sex, Race              | 0 (no recidivism)            | 0 (54.5%)        |
| German    | 1,000  | 20        | Sex, Age               | 1 (good credit)              | 1 (70.0%)        |
| Bank      | 30,488 | 20        | Age                    | 1 (subscriber)               | 0 (87.3%)        |
| Mep       | 15,830 | 41        | Race                   | 1 (utilizer)                 | 0 (82.8%)        |

ProPublica Recidivism dataset [3] (a.k.a., **Compas** dataset) contains demographic information and criminal histories of defendants from Broward County, and is used to predict whether a defendant will be re-offended within two years.

German Credit dataset [5] (a.k.a., **German** dataset) contains demographic and credit information of 1,000 individuals, and is used to predict people’s credit risk levels.

Bank Marketing dataset [2] (a.k.a., **Bank** dataset) contains demographic, social, and financial information of clients of a Portuguese banking institution, and is used to predict whether a client will subscribe a term deposit.

Medical Survey 2015 dataset [10] (a.k.a., **Mep** dataset) contains data measuring how Americans use and pay for medical care, health insurance, and out-of-pocket spending, and is used to predict health care utilization of individuals.

As shown in Table 1, each dataset has its protected attribute(s) determined by its provider based on its task. In line with previous work [20, 26, 41, 66], we consider one protected attribute each time and thus have eight dataset-attribute pairs (e.g., Adult-Sex and Adult-Race). We use the eight pairs as the eight bias mitigation tasks of this study and take each task as a binary classification problem.

### 3.4 Evaluation Metrics and Measures

We investigate 12 ML performance metrics, 4 fairness metrics, and 24 types of fairness-performance trade-offs for a comprehensive evaluation of existing bias mitigation methods. To the best of our knowledge, this work covers the most evaluation metrics and trade-off measures in software fairness research. In the following, we briefly introduce the metrics and measures that we use.

Given a bias mitigation task, let the protected attribute be $A$, with 0 as the unprivileged group and 1 the privileged group; let the real classification label be $Y$ and the predicted label $\hat{Y}$, with 0 as the unfavorable class and 1 the favorable class. In addition, we use $Pr$ to denote probability.

#### 3.4.1 ML Performance Metrics

For each bias mitigation method, we measure the ML performance changes caused by it on favorable and unfavorable classes in terms of precision, recall, and F1-score, which are widely employed in classification work in SE [28, 29, 52, 53].

**Precision** measures the exactness of a method. The precision for a given class $c$ (i.e., 0 or 1) is calculated as:

$$Precision@c = Pr[Y = c|\hat{Y} = c].$$

**Recall** measures the sensitivity of a method. The recall for a given class $c$ is calculated as:

$$Recall@c = Pr[\hat{Y} = c|Y = c].$$

**F1-score** measures a harmonic mean of precision and recall. The F1-score for a given class $c$ is calculated as:
\[ F1@c = \frac{2 \times \text{Precision}@c \times \text{Recall}@c}{\text{Precision}@c + \text{Recall}@c}. \]  

In addition, to measure the overall performance, we follow previous classification work in SE to use Area Under Curve (AUC) [17, 51, 55] and accuracy (Acc) [19, 20, 25, 41, 66]. AUC measures the area under the receiver operating characteristic curve, which is plotted using the true positive rate and the false positive rate by changing different prediction thresholds, while Acc measures how often a method makes the correct prediction and is calculated as:

\[ \text{Acc} = Pr[\hat{Y} = Y]. \]  

Acc is often criticized as not being suitable for the imbalanced class distribution, because it is easy for an ML model to obtain a high accuracy just by predicting all samples as the majority class in such a distribution. Considering that some datasets (e.g., the Bank dataset) that we use have an imbalanced class distribution, we follow previous SE work to use three additional macro-average metrics [29, 52, 53] and the Matthews Correlation Coefficient (MCC) metric [56, 62], which are all demonstrated to be suitable for dealing with imbalanced scenarios [31, 58]. As for the macro-average metrics, we use macro-precision (Mac-P), macro-recall (Mac-R), and macro-F1 (Mac-F1), which take the average of precision, recall, and F1-score on the favorable and unfavorable classes, respectively. As for MCC, it is calculated as:

\[ MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}, \]

where TP, TN, FP, and FN denote the numbers of favorable samples predicted as favorable, unfavorable samples predicted as unfavorable, unfavorable samples predicted as favorable, and favorable samples predicted as unfavorable, respectively.

To summarize, we use 12 ML performance metrics, including F-P (precision for the favorable), F-R (recall for the favorable), F-F1 (F1-score for the favorable), UnF-P (precision for the unfavorable), UnF-R (recall for the unfavorable), UnF-F1 (F1-score for the unfavorable), AUC, Acc, Mac-P, Mac-R, Mac-F1, and MCC. The values of F-P, F-R, F-F1, UnF-P, UnF-R, UnF-F1, AUC, Acc, Mac-P, Mac-R, and Mac-F1 are between 0 and 1. The value of MCC is between -1 and 1, where 1 represents a perfect prediction, 0 no better than random prediction, and -1 total disagreement between prediction and observation. For all the metrics, larger values indicate better ML performance.

### 3.4.2 Fairness Metrics

Based on different definitions of fairness, various fairness metrics have been proposed to measure the difference in classification between the privileged and unprivileged groups. In this work, we use the group fairness metrics that are most widely adopted in fairness research [19, 20, 25, 26, 41, 66].

Statistical Parity Difference (SPD) measures the difference in the acceptance rate of the favorable class between the privileged and unprivileged groups:

\[ SPD = Pr[\hat{Y} = 1|A = 0] - Pr[\hat{Y} = 1|A = 1]. \]  

Average Odds Difference (AOD) measures the average of differences in the true positive rate and the false positive rate between the privileged and unprivileged groups:

\[ AOD = \frac{1}{2}(|Pr[\hat{Y} = 1|A = 0, Y = 0] - Pr[\hat{Y} = 1|A = 1, Y = 0]| + |Pr[\hat{Y} = 1|A = 0, Y = 1] - Pr[\hat{Y} = 1|A = 1, Y = 1]|). \]
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Fig. 2. Illustration of Fairea [41]. (a) presents the fairness-performance trade-off baseline, where $P_{OM}$ represents the original model, BM the model after bias mitigation, and $P_{10}, ..., P_{100}$ the points obtained by model behavior mutation. (b) presents the effectiveness regions of bias mitigation methods based on the changes in ML performance and bias.

Equal Opportunity Difference (EOD) measures the difference in the true positive rate between the privileged and unprivileged groups:

$$EOD = Pr[\hat{Y} = 1|A = 0, Y = 1] - Pr[\hat{Y} = 1|A = 1, Y = 1]. \quad (8)$$

Error Rate Difference (ERD) measures the difference in the error rate between the privileged and unprivileged groups:

$$ERD = Pr[\hat{Y} \neq Y|A = 0] - Pr[\hat{Y} \neq Y|A = 1]. \quad (9)$$

There is another fairness metric called Disparate Impact (DI), which is also widely adopted in the fairness literature. DI and SPD both compare the probabilities of classifying samples as favorable in the privileged and unprivileged groups. Specifically, DI computes the ratio of the two probabilities, while SPD computes the difference of the two probabilities. When computing DI, we may encounter the divided-by-zero error. Therefore, between SPD and DI, we follow previous work [20, 41] to use only SPD in our evaluation.

For all the fairness metrics, we use their absolute values. In this way, values equal to 0 indicate the greatest fairness; larger values indicate more bias.

3.4.3 Fairness-performance Trade-off Measures. It is difficult to evaluate which bias mitigation method is better based on fairness alone, since it is unclear whether the improved fairness is simply the consequence of ML performance loss. Therefore, here, we consider fairness and ML performance together and measure the fairness-performance trade-off of different methods.

To this end, we employ Fairea [41], a model behavior mutation method proposed at ESEC/FSE 2021, to benchmark and quantify the fairness-performance trade-off achieved by existing bias mitigation methods. Next, we briefly introduce Fairea, which is illustrated in Fig. 2.² Specifically, Fairea includes three steps as follows:

1. **Create trade-off baseline.** Fairea presents the ML performance and fairness achieved by bias mitigation methods in a two-dimensional coordinate system as shown in Fig. 2(a). It constructs the fairness-performance trade-off baseline by connecting the original model without applying bias mitigation (i.e., $P_{OM}$) and a series of pseudo mitigation models generated by model behavior mutation (i.e., $P_{10}, ..., P_{100}$). The pseudo mitigation models are mutated based on the original model by sacrificing ML performance to reduce bias in a naive way. Specifically, Fairea randomly chooses

²The figure is taken from the original paper [41].
a subset of the predictions made by the original model and replaces them with the majority class of the data. It considers different mutation degrees (i.e., the fraction of chosen predictions) from 10% to 100%, with a step size of 10%, to obtain $P_{10}$, ..., $P_{100}$. The core insight of Fairea is that when the original model is mutated into a model that always predicts the same class, the fairness will be greatly improved as the predictive performance is equally worse in the privileged and unprivileged groups. The fairness-performance trade-offs of these naive mutated models are expected to be surpassed by any reasonable bias mitigation method, so we use these models as the baseline.

**Step 2: Divide effectiveness regions.** The obtained baseline categorizes bias mitigation methods into five regions that represent different effectiveness levels. As illustrated in Fig. 2(b), the **win-win region** contains bias mitigation methods that improve ML performance and decrease bias, while the **lose-lose region** contains methods that decrease ML performance and increase bias. Methods that improve both ML performance and bias fall in the **inverted trade-off region**. The remaining two regions contain methods that reduce bias but decrease ML performance. Specifically, if a method achieves a better trade-off than the baseline constructed by Fairea, it falls within the **good trade-off region**. Otherwise, it belongs to the **poor trade-off region**. The region division of Fairea provides an overview of the overall effectiveness of a bias mitigation method.

**Step 3: Quantify trade-off effectiveness.** Fairea also provides a solution to measure the effectiveness of a bias mitigation method in a quantitative way. Fig. 2(a) shows the area (indicated in grey) obtained by connecting the point of the model after applying a bias mitigation method (i.e., $BM$) and the Fairea baseline vertically and horizontally. Fairea calculates the size of the area as a quantitative measure of the fairness-performance trade-off achieved by a bias mitigation method. A larger area indicates a better trade-off. Using the area as a measure of the trade-off enables a convenient comparison among different bias mitigation methods.

In the original paper [41], Fairea evaluated only two types of fairness-performance trade-offs (i.e., SPD&Acc and AOD&Acc) on 12 bias mitigation methods proposed in the ML community. In this study, we aim to extend our evaluation to the trade-off between more fairness and performance metric pairs on 17 bias mitigation methods proposed in the ML and SE communities. Since we employ 12 ML performance metrics and 4 fairness metrics in this study, there are a total of 48 fairness-performance metric pairs. However, as Fairea replaces predictions with the majority class, in terms of ML performance metrics for a certain class (e.g., recall on the majority class), we may observe that ML performance and fairness are both improved with the increased mutation degrees. For such metrics, we cannot obtain the trade-off baselines as in Fig. 2(a). Therefore, here we choose only 6 ML performance metrics that measure performance on both the favorable and unfavorable classes, i.e., AUC, Acc, Mac-P, Mac-R, Mac-F1, and MCC, to reflect the overall performance of each bias mitigation method. As a result, we have 24 types of fairness-performance trade-offs, i.e., combinations of 6 ML performance metrics and 4 fairness metrics. To the best of our knowledge, this work covers the most types of fairness-performance trade-offs in software fairness research.

### 3.5 Experimental Settings

To ensure the verifiability and transparency of our study, in this section, we describe the experimental settings in details.

**Implementation of datasets:** We use the five benchmark datasets implemented in the IBM AIF360 via directly invoking off-the-shelf APIs [8]. Moreover, we follow previous work [25, 26, 41, 66] to normalize all feature values to be between 0 and 1.

**Implementation of bias mitigation methods:** For each bias mitigation task, we train original models for bias mitigation using three traditional classification algorithms that have been widely adopted in previous work: Logistic Regression (LR) [19, 26, 41, 66], Support Vector Machine (SVM) [19, 41], and Random Forest (RF) [19, 25, 66]. In line with previous work [25, 41, 66], we use the default
configuration provided by the scikit-learn library [12] to implement each classification algorithm. We apply 17 bias mitigation methods based on the original models, respectively. Specifically, pre- and post-processing methods are applied before and after model training, while in-processing methods are applied during the training process. We implement the 15 bias mitigation methods proposed in the ML community based on the IBM AIF360 framework [8], and implement the two methods proposed in the SE community based on the code released by their authors [6, 7]. Since the IBM AIF360 does not support the OP method for the Bank and Mep datasets, we apply OP only for six tasks. For the remaining 16 methods, we apply each of them for all the eight bias mitigation tasks. Each application is repeated 50 times. In each of the 50 runs, the dataset is shuffled and randomly split into 70% training data and 30% test data. We treat each single run as an individual mitigation case. As a result, for each task, each bias mitigation method has $3 \times 50 = 150$ mitigation cases.

**Implementation of Fairea:** For each (task, classification algorithm, fairness-performance metric pair) combination, to create the fairness-performance trade-off baseline, we train the original model 50 times. Each time, based on the original model, we repeat the mutation procedure 50 times for each mutation degree, i.e., 10%, 20%, ..., and 100%. Finally, as suggested by Fairea [41], we construct the baseline using the mean value of the multiple runs.

**Statistical analysis:** To test whether the difference between two bias mitigation methods is statistically significant on a metric, we employ the non-parametric Mann Whitney U-test [48]. This test suits our purpose well as it does not assume normality. The difference is considered significant, only if the $p$-value of the computed statistic is lower than a pre-specified level (usually 0.05). For example, when we compare two sets of accuracy values achieved by the 50 runs of methods $A$ and $B$ via the Mann Whitney U-test, the null hypothesis is that the accuracy of $A$ is similar to $B$. If we find that $p$-value < 0.05, we can conclude with 95% confidence that our alternative hypothesis is true, which indicates that $A$ achieves a significantly different accuracy than $B$. Furthermore, we compute the effect size with the Cohen’s $d$ [33], to check whether the difference has a meaningful effect. We consider the difference with $0 < d < 0.5$ a small effect, $0.5 \leq d < 0.8$ a medium effect, and $d \geq 0.8$ a large effect [57].

In addition, we employ the Spearman’s rank correlation coefficient $\rho$ [50] to investigate whether the value changes of different ML performance metrics or fairness metrics caused by bias mitigation methods are similar. Spearman’s rank correlation coefficient does not assume normality, and thus suits our purpose. The value of $\rho$ is between -1 to 1, where -1 indicates perfectly negative correlation, 0 no correlation, 1 perfectly positive correlation. Moreover, the $p$-value is reported together with the correlation coefficient. The correlation is considered statistically significant, only if the $p$-value is lower than a pre-specified level (usually 0.05).

**Experimental environment:** All experiments are implemented with Python 3.7.11 and TensorFlow 2.6.0, and executed on a Ubuntu 16.04 LTS with 128GB RAM, having 2.3 GHz Intel Xeon E5-2653 v3 Dual CPU and two NVidia Tesla M40 GPUs.

## 4 RESULTS

In this section, we first analyze the evaluation results for ML performance (Section 4.1) and fairness (Section 4.2), separately. Then, we present the measurement results for different types of fairness-performance trade-offs (Section 4.3).

### 4.1 RQ1: Influence on ML Performance

This section presents the results for 12 ML performance metrics. Based on the results, we dive into RQ1 by answering two specific questions:
RQ1.1 (Effects on ML performance metric values): How do the values of ML performance metrics change after applying bias mitigation methods? First, we investigate whether the values of ML performance metrics are significantly changed after applying existing bias mitigation methods. Additionally, we explore whether the value changes in different ML performance metrics are significantly correlated. If so, researchers and practitioners may employ the ML performance metrics used in previous work as the proxy of the unconsidered ones.

RQ1.2 (ML performance comparison among methods): How do different bias mitigation methods affect ML performance? Second, we compare existing bias mitigation methods in terms of different ML performance metrics. The results provide implications for the choice of bias mitigation methods in application scenarios where ML performance is critical.

4.1.1 RQ1.1: Effects on ML Performance Metric Values. To answer RQ1.1, we use the original models that do not apply any bias mitigation method as the baselines. Specifically, for each bias mitigation task, we use the LR, SVM, and RF algorithms to train the original models, with each algorithm repeated 50 times. Then, for each task-algorithm pair, we use the average level (i.e., mean values of ML performance metrics) of the corresponding 50 original models as the baseline. Since we apply each bias mitigation method in each task-algorithm pair, we have a total of $16 \times 8 \times 3 + 1 \times 6 \times 3 = 402$ applications. We repeat each application 50 times. For each application, we calculate the difference between the mean values achieved by the 50 models after applying the bias mitigation method and the corresponding 50 original models, for each ML performance metric. Then we analyze the significance and effect size of the difference using Mann Whitney U-test and Cohen’s $d$. In Fig. 3, for each ML performance metric, we present the proportions of applications that fall into different effects, i.e., decreasing ML performance significantly ($p$-value $< 0.05$) with a large effect ($d \geq 0.8$), decreasing ML performance significantly with a medium effect ($0.5 \leq d < 0.8$), decreasing ML
Table 2. **RQ1.1**: Correlation between ML performance metrics. In the table, * indicates a significant correlation (p-value < 0.05) overall, and numbers in parentheses indicate that in how many task-algorithm pairs the correlation shares the consistent pattern with the overall correlation. We observe that the effects of bias mitigation methods on the ML performance metrics that are not considered in previous work do not have a consistent correlation with any previously employed metric across all the task-algorithm pairs.

|                  | F-R         | F-F1        | UnF-P       | UnF-R       | UnF-F1       | AUC         | Acc         | Mac-P       | Mac-R       | Mac-F1       | MCC         |
|------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| F-P              | -0.614*(18/24) | -0.131*(8/24) | 0.776*(23/24) | 0.782*(22/24) | 0.058(2/24) | 0.379*(12/24) | 0.697*(13/24) | 0.085(2/24) | 0.414*(13/24) | 0.331*(6/24) |
| F-R              | -0.689*(22/24) | 0.763*(17/24) | -0.851*(23/24) | -0.501*(12/24) | 0.373*(14/24) | -0.103*(2/24) | -0.179*(5/24) | 0.373*(14/24) | 0.101*(7/24) | 0.217*(8/24) |
| F-F1             | -0.653*(23/24) | -0.401*(12/24) | 0.016*(13/24) | 0.587*(13/24) | 0.447*(13/24) | 0.294*(10/24) | 0.587*(15/24) | 0.610*(15/24) | 0.677*(10/24) |
| UnF-P            | -0.532*(12/24) | -0.173*(9/24) | 0.514*(14/24) | 0.201*(12/24) | 0.195*(12/24) | 0.514*(17/24) | 0.292*(7/24) | 0.424*(11/24) |
| UnF-R            | -0.818*(22/24) | 0.046(1/24) | 0.367*(6/24) | 0.368*(8/24) | 0.046(1/24) | 0.315*(10/24) | 0.202*(9/24) |
| UnF-F1           | -0.439*(12/24) | 0.682*(15/24) | 0.562*(14/24) | 0.439*(12/24) | 0.715*(19/24) | 0.620*(15/24) |
| AUC              | 0.287*(8/24) | 0.124*(7/24) | 0.287*(8/24) | 0.427*(11/24) | 0.445*(11/24) |
| Acc              | -0.841*(23/24) | 0.287*(8/24) | 0.652*(16/24) | 0.600*(14/24) |               |
| Mac-P            | -0.124*(7/24) | 0.447*(11/24) | 0.445*(11/24) |               |
| Mac-R            | -0.821*(21/24) | 0.868*(23/24) |               |
| Mac-F1           | -0.957*(24/24) |               |               |               |

performance significantly with a small effect (0 < d < 0.5), and increasing ML performance or decreasing ML performance insignificantly (p-value ≥ 0.05).

From Fig. 3, we observe that the values of the 12 ML performance metrics decrease significantly in an average of 58% of applications (ranging from 42% to 75% according to different metrics). In particular, the values of the 12 metrics significantly decrease with a large effect in an average of 46% of applications (ranging from 38% to 58%). However, as described in Section 1, existing studies often evaluate bias mitigation methods in terms of only one or two ML performance metrics, ignoring some important metrics such as UnF-P and UnF-F1. As a result, researchers and practitioners may be unaware of the significantly decreased performance caused by bias mitigation methods in these unconsidered metrics and thus choose inappropriate methods, making the functional properties of ML software not up to expectations.

Next, we calculate the Spearman’s rank correlation coefficient \( \rho \) between every pair of ML performance metrics. Specifically, we calculate the value differences of each ML performance metric before and after bias mitigation in the 402 applications. Then, for each two ML performance metrics, we calculate the overall correlation between the 402 value differences of the two metrics. In addition, we also calculate the correlation in the 8*3 = 24 task-algorithm pairs, separately. Table 2 shows the correlation results. For each metric pair, we present the overall \( \rho \), with * indicating a significant correlation (i.e., p-value < 0.05). Additionally, we list the number of task-algorithm pairs where the correlation shares the consistent pattern with the overall correlation in parentheses. For example, the correlation result of F-P and MCC is 0.331*(8/24), indicating that the value differences of F-P and MCC have a significantly positive correlation overall, but that the significantly positive correlation holds in only 8 out of 24 task-algorithm pairs. Overall, among the 66 metric pairs in Table 2, 51 show a significantly positive correlation, 10 a significantly negative correlation, 5 no significant correlation. Furthermore, we find that 64 metric pairs do not present a consistent correlation pattern across all the task-algorithm pairs. Specifically, only the (AUC, Mac-R) and (Mac-F1, MCC) pairs present a consistent correlation pattern. However, the four metrics are all not considered in previous software fairness work [19, 20, 25, 26, 41, 66]. Since all the metrics not considered in previous work do not have a consistent correlation with any previously employed metric, we may not use the latter as their proxy. This finding suggests that we take comprehensive ML performance metrics into account during the evaluation of bias mitigation methods, especially considering that different ML performance metrics measure the functional properties of ML software from different aspects and thus may provide different guidelines for real-world application scenarios.
RQ1.2: Effect distribution of different bias mitigation methods in ML performance. We find that only 7 out of 17 (41%) bias mitigation methods significantly decrease ML performance in less than 50% of scenarios.

Table 3. RQ1.2: Mean rank of each bias mitigation method in terms of different ML performance metrics. In terms of any ML performance metric, none of the 17 bias mitigation methods can consistently achieve better results than other methods in all the task-algorithm pairs.

| Metric | OP | LFR | RW | DIR | PR | AD | MFC-FDR | MFC-SR | ROC-SPD | ROC-AOD | ROC-EOD | CEO-FNR | CEO-FPR | CEO-W | EOP | Fair-way | Fair-SMOTE |
|--------|----|-----|----|-----|----|----|---------|---------|---------|---------|---------|---------|---------|-------|-----|---------|------------|
| F-P    | 12 | 15  | 5  | 7   | 5  | 6  | 12      | 11      | 7       | 7       | 8       | 9       | 8       | 7     | 9    | 7       | 6          |
| F-R    | 9  | 11  | 9  | 7   | 11 | 10 | 5       | 5       | 11      | 9       | 8       | 7       | 9       | 8     | 9    | 8       | 9          |
| F-F1   | 11 | 15  | 6  | 5   | 10 | 9  | 7       | 10      | 11      | 8       | 7       | 6       | 8       | 7     | 8    | 9       | 7          |
| Unf-P  | 12 | 16  | 8  | 7   | 11 | 9  | 4       | 4       | 10      | 8       | 7       | 10      | 8       | 9     | 8    | 8       | 8          |
| Unf-R  | 10 | 9   | 7  | 9   | 6  | 6  | 12      | 11      | 7       | 8       | 9       | 9       | 8       | 7     | 9    | 9       | 7          |
| Unf-F1 | 10 | 14  | 8  | 7   | 8  | 5  | 11      | 11      | 9       | 7       | 8       | 9       | 10      | 8     | 9    | 8       | 9          |
| AUC    | 11 | 16  | 7  | 8   | 11 | 8  | 5       | 6       | 7       | 4       | 3       | 11      | 12      | 10    | 10   | 9       | 6          |
| Acc    | 10 | 14  | 3  | 4   | 8  | 7  | 10      | 11      | 12      | 10      | 11      | 7       | 8       | 6     | 8    | 7       | 5          |
| Mac-P  | 11 | 16  | 4  | 5   | 6  | 7  | 10      | 11      | 11      | 9       | 10      | 7       | 8       | 6     | 10   | 6       | 7          |
| Mac-R  | 11 | 16  | 7  | 8   | 11 | 8  | 5       | 6       | 7       | 4       | 3       | 11      | 12      | 10    | 10   | 9       | 6          |
| Mac-F1 | 11 | 16  | 6  | 7   | 10 | 7  | 7       | 10      | 9       | 5       | 5       | 10      | 11      | 9     | 9    | 8       | 5          |
| MCC    | 12 | 16  | 6  | 6   | 10 | 8  | 7       | 9       | 9       | 4       | 4       | 10      | 11      | 9     | 10   | 8       | 5          |

Finding 1: The values of all the 12 ML performance metrics (including those not considered in previous work) decrease significantly in a notable proportion of applications (42% ~ 75% according to different metrics) after applying existing bias mitigation methods. Moreover, the effects of bias mitigation methods on the ML performance metrics unconsidered in previous work do not have a consistent correlation with previously employed metrics, and therefore the latter cannot be used as a proxy.

4.1.2 RQ1.2: ML Performance Comparison among Methods. To compare different bias mitigation methods in terms of ML performance degradation, we first calculate the proportions of scenarios, i.e., (task-algorithm pair, ML performance metric) combinations, that fall into different effects after applying each bias mitigation method. Fig. 4 show the results. We observe that only 7 (i.e., RW,
DIR, AD, MFC-FDR, ROC-AOD, ROC-EOD, and Fair-SMOTE) out of the 17 bias mitigation methods decrease ML performance significantly in less than 50% of scenarios. In particular, RW significantly decreases ML performance in only 33% of scenarios, with a large effect in only 13%. Meanwhile, we observe that some bias mitigation methods are at a considerable cost of ML performance. For instance, LFR decreases ML performance significantly with a large effect in 92% of scenarios.

Furthermore, for each ML performance metric, we follow previous work [19] to compute the average rank of each bias mitigation method in the 24 task-algorithm pairs. The smaller the rank value, the less the corresponding method reduces the ML performance metric value. Table 3 shows the results and highlights the top-ranked method for each metric. We observe that for any ML performance metric, none of the bias mitigation methods can consistently achieve better results than other methods in all the task-algorithm pairs. For example, although RW and PR are the top-ranked methods for F-P, the mean rank of them is only fifth. In addition, for different ML performance metrics, the rank results vary a lot. This indicates that a bias mitigation method may largely decrease ML performance in certain metrics. For example, although MFC-FDR is the top-ranked method for F-R, it ranks 12th among the 17 methods for F-P. This finding urges researchers and practitioners to determine which ML performance metrics they should focus on according to their intended goals. For instance, if one needs to perform bias mitigation in a scenario where precision for the favorable class is important, they may pay more attention to the F-P values achieved by different methods.

**Finding 2:** In terms of the 12 ML performance metrics, only 7 out of 17 (41%) bias mitigation methods significantly decrease ML performance in less than 50% of scenarios. Moreover, for any ML performance metric, none of the methods can consistently achieve better results than other methods in all the scenarios. Additionally, a bias mitigation method may largely decrease ML performance in certain metrics. For example, MFC-FDR ranks fifth for F-R among the 17 methods, but it ranks 12th for F-P.

### 4.2 RQ2: Influence on Fairness

Similar to Section 4.1, this section dives into the evaluation results for four fairness metrics (i.e., RQ2) by answering two specific questions:

**RQ2.1 (Effects on fairness metric values):** How do the values of fairness metrics change after applying bias mitigation methods? First, we investigate whether the values of fairness metrics are significantly changed after applying bias mitigation methods, and whether the changes in different fairness metrics are significantly correlated.

**RQ2.2 (Fairness comparison among methods):** How do different bias mitigation methods affect ML software fairness? Second, we compare existing bias mitigation methods in terms of different fairness metrics. The results provide implications for the choice of bias mitigation methods in application scenarios where fairness is critical.

#### 4.2.1 RQ2.1: Effects on Fairness Metric Values

We follow the procedures in Section 4.1.1 to analyze the value changes of the four fairness metrics caused by bias mitigation methods, and present the results in Fig. 5. We observe that after applying existing bias mitigation methods, the values of the four fairness metrics (i.e., SPD, AOD, EOD, and ERD) significantly decrease in only 59%, 55%, 57%, and 29% of applications, with an average of 50%. Considering that the main goal of bias mitigation methods is to improve software fairness (i.e., decrease the values of fairness metrics), our results warn the research community about the limitations of existing bias mitigation methods, especially in reducing ERD.
**RQ2.1:** Effects of bias mitigation methods on different fairness metrics. After applying existing bias mitigation methods, the values of the four fairness metrics significantly decrease in an average of only 50% of applications.

Furthermore, similar to Section 4.1.1, we calculate the correlation between each two fairness metrics in terms of their value differences before and after bias mitigation. Table 4 shows the results. We observe that the correlation coefficient between AOD and EOD is 0.888 at a significant level, and the significantly positive correlation holds in all the 24 task-algorithm pairs. This suggests that bias mitigation methods that perform well in AOD may also perform well in EOD, and that the evaluation results of bias mitigation methods using AOD may also provide guidance for method selection in application scenarios that pursue a low EOD. Therefore, it is not surprising to find that some previous work [41] employ only one of them for evaluation.

In other fairness metric pairs, we find that the correlations vary in different task-algorithm pairs, which is consistent with the finding in previous work [19] that analyzes the metric correlation in only two bias mitigation tasks. For instance, we find that SPD and EOD have a significantly positive correlation in only 15 out of the 24 task-algorithm pairs.

Additionally, we observe that ERD has a negative correlation with other fairness metrics overall. This indicates that bias mitigation methods that decrease the ERD value often increase bias in terms of other three fairness metrics. Moreover, ERD changes do not have a consistent correlation with changes of any other metric across the task-algorithm pairs. This indicates that other metrics may not act as a proxy of ERD. However, some existing work [25, 26, 41, 67] does not take ERD into account. To perform a comprehensive evaluation, we suggest that researchers follow Biswas and Rajan [19, 20] to consider this metric in future work.

**Finding 3:** Existing bias mitigation methods improve fairness significantly (in terms of SPD, AOD, EOD, and ERD) in an average of only 50% of applications, according to the evaluation results of 17 methods and 8 bias mitigation tasks. Additionally, fairness improvement measured by different metrics are not necessarily correlated. In particular, ERD changes do not have a consistent correlation with the changes of any other fairness metric.

**4.2.2 RQ2.2: Fairness Comparison among Methods.** Similar to Section 4.1.2, we calculate the proportions of scenarios, i.e., (task-algorithm pair, fairness metric) combinations, that fall into different
Table 4. **RQ2.1:** Correlation between fairness metrics. In the table, * indicates a significant correlation (p-value < 0.05) overall, and numbers in parentheses indicate the number of task-algorithm pairs the correlation shares the same pattern with the overall correlation. We find that AOD and EOD have a consistently positive correlation across all the task-algorithm pairs, and that ERD does not have a consistent correlation with any other metric.

| Metric | AOD | EOD | ERD |
|--------|-----|-----|-----|
| SPD    | 0.861*(23/24) | 0.651*(15/24) | -0.037*(18/24) |
| AOD    | -    | 0.888*(24/24) | -0.101*(0/24) |
| EOD    | -    | -    | -0.139*(4/24) |

Fig. 6. **RQ2.2:** Effect distribution of different bias mitigation methods in fairness. We observe that 10 out of 17 (59%) bias mitigation methods significantly reduce bias in more than 50% of scenarios.

Table 5. **RQ2.2:** Mean rank of each bias mitigation method in terms of different fairness metrics. It is difficult for bias mitigation methods to achieve fairness with respect to all the metrics.

| Metric | OP | LFR | RW | DIR | PR | AD | MFC -FDR | MFC -SR | ROC -SPD | ROC -AOD | ROC -EOD | CEO -FNR | CEO -FPR | CEO -W | EOP | Fair -way | Fair -SMOTE |
|--------|----|-----|----|-----|----|----|---------|---------|----------|----------|----------|----------|----------|--------|-----|--------|------------|
| SPD    | 7  | 2   | 3  | 8   | 5  | 9  | 13      | 11      | 4        | 8        | 11       | 10       | 11       | 14     | 4    | 10     | 12         |
| AOD    | 6  | 3   | 4  | 6   | 8  | 12 | 11      | 11      | 6        | 7        | 8        | 10       | 13       | 15     | 1    | 11     | 11         |
| EOD    | 6  | 4   | 6  | 7   | 8  | 13 | 10      | 8       | 9        | 5        | 6        | 11       | 11       | 15     | 3    | 11     | 10         |
| ERD    | 10 | 15  | 6  | 7   | 12 | 8  | 10      | 9       | 5        | 5        | 7        | 9        | 9        | 5      | 8    | 12     | 6          |

We find that only 10 out of the 17 bias mitigation methods can significantly improve fairness in more than 50% of scenarios. In particular, RW significantly improves fairness in the most scenarios (72%). The superiority of RW in reducing bias is also observed in previous work [19]. As we find that LFR significantly decreases ML performance with a large effect in the most scenarios in Section 4.1.2, it is not surprising to observe that it also significantly improves fairness with a large effect in the most scenarios (59%).

Next, we calculate the mean rank of each bias mitigation method in the 24 task-algorithm pairs for each fairness metric. Table 5 shows the results. For SPD, the top-ranked method is LFR. However, we find that LFR achieves poor fairness for ERD, ranking 15th among the 17 methods. Similarly, we
observe the different top-ranked bias mitigation methods for ERD and AOD/EOD. This observation is consistent with the finding in previous work [18, 19, 32] that it is difficult for bias mitigation methods to achieve fairness with respect to all the metrics, and for some pairs of fairness metrics, mathematically impossible.

**Finding 4:** 10 out of 17 (59%) bias mitigation methods significantly improve fairness in more than 50% of scenarios. Moreover, it is difficult for bias mitigation methods to achieve fairness with respect to all metrics that we consider. For example, LFR is the top-ranked method for SPD, but it ranks 15th among the 17 methods for ERD.

### 4.3 RQ3: Influence on Fairness-performance Trade-off

In this section, we present the measurement results of 24 types of fairness-performance trade-offs, i.e., combinations of four fairness metrics (SPD, AOD, EOD, and ERD) and six ML performance metrics (AUC, Acc, Mac-P, Macro-R, Mac-F1, and MCC), achieved by different bias mitigation methods using Fairea [41].
As described in Section 3.4.3, the first step of Fairea is to construct the trade-off baseline using a series of pseudo models generated via model behavior mutation. For each \((\text{task-algorithm pair, fairness-performance metric pair})\) combination, we construct the baseline separately. As a result, we construct a total of \(8 \times 3 \times 4 \times 6 = 576\) baselines. Based on the 576 baselines, we observe that the pseudo models show a fairness-performance trade-off for SPD, AOD, and EOD, i.e., the higher the value of SPD, AOD, or EOD, the higher the value of each ML performance metric. However, we fail to construct such trade-off baselines for ERD. We take the baselines constructed for the LR model in the Adult-Sex task (shown in Fig. 7) as an example. Based on the generated pseudo models, ERD shows a different trade-off pattern from SPD, AOD, and EOD. The different trade-off patterns shown by ERD and other fairness metrics can be explained by their different definitions (i.e., calculation methods). Based on their calculation methods presented in Section 3.4.2, we can find that when all samples are predicted as the same label (i.e., the model achieves the worst ML performance), SPD, AOD, and EOD all equal to 0 (their minimum), but ERD equals to the difference of favorable rates between the privileged and unprivileged groups (not its minimum). This means that ERD does not meet the hypothesis behind Fairea, i.e., the bias measured by fairness metrics monotonically decrease with the increased mutation degrees. Therefore, it is reasonable that we fail to observe the trade-off between ERD and ML performance based on the baselines constructed by Fairea.

Since Fairea fails to construct the trade-off baseline between ERD and ML performance, the effectiveness region division method and the trade-off quantification method provided by Fairea are also not applicable to ERD. Therefore, we consider 18 types of fairness-performance trade-offs, i.e., combinations of three fairness metrics (SPD, AOD, and EOD) and six ML performance metrics (AUC, Acc, Mac-P, Macro-R, Mac-F1, and MCC), and the corresponding \(8 \times 3 \times 3 \times 6 = 432\) baselines, in the rest of the paper.

Based on the measurement results of the 18 types of trade-offs, we take a deep dive into RQ3 by answering two specific questions:

**RQ3.1 (Effectiveness region distribution):** What effectiveness regions do existing bias mitigation methods fall into according to Fairea? This research question evaluates the overall effectiveness of existing bias mitigation methods by analyzing how the mitigation cases achieved by them are matched into the five effectiveness regions in Fig. 2(b).

**RQ3.2 (Quantitative assessment of trade-off):** What fairness-performance trade-off do existing bias mitigation methods achieved based on Fairea? This research question evaluates existing bias mitigation methods in terms of quantitative assessment of fairness-performance trade-off. Specifically, we calculate the area shown in Fig. 2(a) for each bias mitigation method and then compare these methods quantitatively.

### 4.3.1 RQ3.1: Effectiveness Region Distribution

We use the 432 baselines to evaluate the effectiveness of 17 bias mitigation methods in 24 task-algorithm pairs. As described in Section 3.5, we apply each bias mitigation method to each task-algorithm pair 50 times and treat each individual run as a mitigation case. Therefore, we have \(8 \times 3 \times 50 = 1,200\) mitigation cases for each bias mitigation method.\(^4\) In Fig. 8(a), we present the overall results of different bias mitigation methods for all the task-algorithm pairs and fairness-performance metric pairs.

In Fig. 8(a), we observe that only 9 of the 17 bias mitigation methods achieve a win-win or good trade-off in more than 50% of mitigation cases, including OP (51%), RW (80%), DIR (74%), PR (62%), ROC-SPD (58%), ROC-AOD (63%), ROC-EOD (57%), EOP (75%), and Fairway (62%). From this perspective, RW makes the best trade-off in general, achieving a good trade-off in 54% of cases (ranging from 41% to 65% according to different fairness-performance metric pairs) and a

\(^4\)For the OP method, we have \(6 \times 3 \times 50 = 900\) mitigation cases, as we apply it in only six tasks.
RQ3.1: Proportion of mitigation cases that fall into each mitigation region organized by (a) bias mitigation methods, (b) classification algorithms, (c) bias mitigation tasks, and (d) fairness-performance metric pairs. We observe that a notable proportion (37%) of mitigation cases fall into a lose-lose or poor trade-off region, and that the effectiveness of bias mitigation methods depends on models, tasks, and fairness and ML performance metrics.
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win-win trade-off in 26% (ranging from 21% to 38%). One possible reason behind the superiority of RW is that it modifies the weights of different training samples so that it tackles the training data imbalance problem, which has been recognized as a root cause of bias in ML software [25, 49]. Similarly, previous work [41] covering 12 bias mitigation methods and two types of trade-offs (i.e., SPD&Acc and AOD&Acc) reports that only 6 out of the 12 methods can achieve a win-win or good trade-off in more than 50% of cases, and that RW achieves such trade-offs in 77% of cases.

Nevertheless, we still observe that 15% of mitigation cases fall into a lose-lose or poor trade-off after applying RW, and the situation is even worse for other bias mitigation methods. For example, CEO-W achieves a lose-lose trade-off in 72% of cases; LFR achieves a poor trade-off in 40% of cases. Overall, the average proportion of cases that fall into the lose-lose or poor trade-off region obtained by each method is 26% and 11%, respectively. The notable proportion of the lose-lose and poor trade-offs is also observed in previous work [41], and our results increase the confidence of this finding with more bias mitigation methods and fairness-performance metric pairs. One possible reason behind the high percentage of the lose-lose and poor trade-offs is that bias mitigation methods are often designed to optimize one fairness metric, which may affect other fairness metrics. For instance, ROC-SPD achieves a lose-lose or poor trade-off between AOD and Acc in 53% of mitigation cases. However, we find that the percentage of lose-lose and poor trade-offs can still be high even for the optimized metric. For example, after applying ROC-AOD, 49% of mitigation cases fall into a lose-lose or poor trade-off between AOD and Acc.

Furthermore, we organize the results by different classification algorithms, bias mitigation tasks, and fairness-performance metric pairs, to analyze whether the region distribution is influenced by these factors. The results are presented in Figs. 8(b), (c), and (d), respectively, and the analysis is as follows.

Comparison among classification algorithms: From Fig. 8(b), we observe that the region distribution is model-dependent. Although LR, SVM, and RF share similar proportions of mitigation cases that fall into the lose-lose, poor, and win-win trade-off regions, they have obvious differences in the proportions of the inverted and good trade-offs. Specifically, LR and SVM achieve a relatively higher percentage of the good trade-off (a lower percentage of the inverted trade-off) than RF. For example, the difference between LR and RF in the proportion of the good trade-off is 12% (i.e., 39% v.s. 27%). Therefore, we suggest that researchers consider different classification algorithms when evaluating the effectiveness of bias mitigation methods.

Comparison among tasks: From Fig. 8(c), we find that the region distribution is task-dependent. For example, in the Compas-Sex task, the proportion of the lose-lose trade-off is 12%, but in the Adult-Sex task, the corresponding proportion is more than three times the value (i.e., 37%). Furthermore, we observe that even for the same dataset, the selection of different protected attributes also affects the region distribution. For example, the proportions of the lose-lose trade-off in the Compas-Sex and Compas-Race tasks are 12% and 26%, with a difference of 14%. This finding suggests that (1) researchers evaluate bias mitigation methods in diverse tasks to improve the generalizability of the results, and (2) practitioners need to be careful when choosing bias mitigation methods for their own tasks based on existing evaluation results on other tasks.

Comparison among fairness-performance metric pairs: From Fig. 8(d), we find that different fairness-performance metric pairs result in different region distributions. In particular, the mitigation cases that obtain a win-win or good trade-off between AOD and Mac-P account for 39%, the lowest among all the fairness-performance metric pairs. In contrast, the corresponding proportion between EOD and AUC is 17% higher (i.e., 56%). This finding further demonstrates the necessity of this study that measures the trade-off in terms of various fairness-performance metric pairs to obtain more general and comprehensive results.
Finding 5: Based on the results in terms of 18 types of fairness-performance trade-offs, 9 out of 17 (53%) bias mitigation methods achieve a win-win or good trade-off in more than 50% of mitigation cases according to Fairea. Furthermore, a notable proportion of cases fall into a lose-lose trade-off (26%) or a poor trade-off (11%) on average for each bias mitigation method. The effectiveness of bias mitigation methods depends on models, tasks, and the metrics of fairness and ML performance.

4.3.2 RQ3.2: Quantitative Assessment of Trade-off. We finally use Fairea to quantify the fairness-performance trade-off of different bias mitigation methods. Fairea quantifies only the cases that fall into the good trade-off region, as the other regions are either dominating the original model (the win-win region), dominated by the Fairea baseline (the poor trade-off region), or do not improve fairness (the inverted and lose-lose trade-off regions) [41].

For each mitigation scenario, i.e., (task-algorithm pair, fairness-performance metric pair) combination, we calculate the mean ML performance and fairness results of the 50 runs of each bias mitigation method to indicate its average effectiveness. Then we quantify the trade-off effectiveness of each method with the help of the trade-off baselines. The trade-off quantification enables a direct and convenient comparison among different bias mitigation methods. For example, in terms of the SPD&Acc trade-off for the RF model in the Compas-Race task, the quantitative results of DIR, PR, ROC-SPD, and Fairway are 0.065, the win-win trade-off, 0.176, and the inverted trade-off, respectively. In this scenario, the four methods in descending order of the quantitative results are PR, ROC-SPD, DIR, and Fairway. According to this rule, for each bias mitigation task, we calculate the proportion of scenarios where each bias mitigation method achieves the best quantitative result. Table 6 shows the result for each task and the overall result in all the tasks. We highlight the highest proportion for each row (i.e., each bias mitigation task). Note that the sum of the numbers in a row is larger than 100%, since there may be multiple methods to achieve the best quantitative result in a scenario.

At a glance of Table 6, we find that the distributions of the best results vary in different bias mitigation tasks, further demonstrating the aforementioned finding in Section 4.3.1 that the effectiveness of bias mitigation methods is task-dependent. For instance, RW achieves the best quantitative result in 74% of scenarios in the Bank-Age task, but the corresponding proportion is 0% in the Adult-Sex and Adult-Race tasks.

Furthermore, we compare the overall quantitative results achieved by different bias mitigation methods. From this perspective, the top five methods are ROC-AOD (achieving the best quantitative result in 29% of all the scenarios), Fair-SMOTE and ROC-EOD (both 23%), ROC-SPD (21%), Fairway

Table 6. RQ3.2: Numbers of scenarios where each method achieves the best quantitative result, organized by different bias mitigation tasks. Overall, none of existing bias mitigation methods can achieve a better trade-off than other methods in all the scenarios, as even the best method that we find outperforms other methods in only 29% of scenarios.

| Dataset-Attr | OP | LFR | RW | DIR | PR | AD | MFC-FDR | MFC-SR | ROC-SPD | ROC-AOD | ROC-EOD | CEO-FNR | CEO-FFR | CEO-W | EOP | Fairway | Fair-SMOTE |
|--------------|----|-----|----|-----|----|----|---------|---------|---------|---------|---------|---------|---------|-------|-----|--------|------------|
| Adult-Sex    | 0% | 0%  | 0% | 11% | 16%| 16%| 0%      | 0%      | 11%     | 18%     | 11%     | 0%      | 0%      | 0%    | 3%  | 16%    | 48%        |
| Adult-Race   | 0% | 0%  | 0% | 5%  | 0% | 14%| 7%      | 7%      | 23%     | 31%     | 18%     | 0%      | 0%      | 0%    | 3%  | 37%    | 44%        |
| Compas-Sex   | 50%| 0%  | 9% | 27% | 33%| 0% | 11%     | 0%      | 9%      | 3%      | 0%      | 0%      | 0%      | 0%    | 0%  | 33%    | 33%        |
| Compas-Race  | 33%| 0%  | 29%| 5%  | 33%| 22%| 0%      | 0%      | 11%     | 28%     | 0%      | 0%      | 0%      | 0%    | 0%  | 0%     | 0%         |
| German-Sex   | 0% | 0%  | 3% | 12% | 0% | 0% | 7%      | 33%     | 37%     | 61%     | 61%     | 0%      | 9%      | 0%    | 3%  | 12%    | 16%        |
| German-Age   | 0% | 0%  | 11%| 28% | 0% | 0% | 0%      | 38%     | 33%     | 50%     | 44%     | 0%      | 5%      | 0%    | 0%  | 0%     | 18%        |
| Bank-Age     | -  | 0%  | 7% | 4%  | 0% | 3% | 0%      | 7%      | 14%     | 14%     | 0%      | 12%     | 61%     | 0%    | 29% | 27%    | 0%         |
| Mep-Race     | -  | 0%  | 24%| 16% | 33%| 16%| 14%     | 0%      | 25%     | 48%     | 40%     | 16%     | 0%      | 0%    | 16% | 16%    | 27%        |
| Overall      | 13%| 0%  | 18%| 12% | 13%| 8% | 6%      | 11%     | 21%     | 29%     | 23%     | 9%      | 1%      | 0%    | 7%  | 18%    | 23%        |
and RW (both 18%). Given that the highest proportion is only 29%, we conclude that there is no ‘silver bullet’ method that can achieve superior results than other methods in most of scenarios.

**Finding 6:** According to the quantitative assessment results using Fairea for 18 types of fairness-performance trade-offs, there is no ‘silver bullet’ bias mitigation method that can achieve the best trade-off in all the scenarios we studied, as even the best method that we observe outperforms other methods in only 29% of the scenarios.

5 THREATS TO VALIDITY

The primary threat to internal validity lies in the implementation of the code used in this study. To mitigate this threat, we conduct the experiments based on the widely-adopted IBM AIF360 framework and the released code of Fairway, Fair-SMOTE, and Fairea. We also make all scripts and data publicly available to allow for reproductions and replications.

The threat to external validity concerns the generalizability of our experimental results. To alleviate this threat, we adopt eight bias mitigation tasks, which cover social, financial, and medical domains, and are well adopted in the fairness literature of ML and SE. Moreover, we employ 17 representative bias mitigation methods proposed in the ML and SE communities. For each method, we use three traditional ML algorithms for implementation, reducing the influence of algorithm selection on the generalization of results. In terms of evaluation measures, we use 12 ML performance metrics, 4 fairness metrics, and 24 types of fairness-performance trade-offs to obtain comprehensive measurement results. The 12 ML performance metrics measure not only the performance on individual class, but also the overall performance; the 4 fairness metrics are the most widely adopted in previous fairness work; the 24 types of fairness-performance trade-offs are considerable given that previous work uses only two types. Nevertheless, with increasing attention on software fairness, researchers are proposing more and more bias mitigation methods, fairness metrics, and datasets. In the future, one could replicate this study with more methods, metrics, measures, and datasets. In addition, we follow previous work [19, 20, 41] to treat each protected attribute individually for each bias mitigation task, since most of existing bias mitigation methods do not support dealing with multiple protected attributes at the same time. In the future, when more methods that support this functionality are proposed, one could evaluate them with multiple protected attributes considered at the same time.

6 CONCLUSION

This paper presents a large-scale empirical study evaluating 17 representative bias mitigation methods with 12 ML performance metrics, 4 fairness metrics, and 24 types of fairness-performance trade-offs for 8 widely adopted benchmark tasks. The results of our comprehensive study reveal a series of findings. In particular, we find that (1) the bias mitigation methods significantly decrease the values of all ML performance metrics (including those not considered in previous work) in a notable proportion of scenarios (42%~75% according to different metrics); (2) the bias mitigation methods achieve fairness improvement in only 50% of scenarios (29%~59% according to different fairness metrics); (3) the bias mitigation methods have a poor fairness-performance trade-off, or even lead to decreases in both fairness and ML performance in 37% of scenarios; (4) the effectiveness of the bias mitigation methods depends on tasks, models, and fairness and ML performance metrics, and there is no ‘silver bullet’ bias mitigation method that works for all scenarios. The best bias mitigation method that we find outperforms other methods in only 29% of scenarios. We have
made publicly available the scripts and data used in this study for other researchers to replicate and extend this work.

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