Bias Mitigation for Machine Learning Classifiers: A Comprehensive Survey

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This article provides a comprehensive survey of bias mitigation methods for achieving fairness in Machine Learning (ML) models. We collect a total of 341 publications concerning bias mitigation for ML classifiers. These methods can be distinguished based on their intervention procedure (i.e., pre-processing, in-processing, post-processing) and the technique they apply. We investigate how existing bias mitigation methods are evaluated in the literature. In particular, we consider datasets, metrics, and benchmarking. Based on the gathered insights (e.g., What is the most popular fairness metric? How many datasets are used for evaluating bias mitigation methods?), we hope to support practitioners in making informed choices when developing and evaluating new bias mitigation methods.

CCS Concepts: Computing methodologies → Supervised learning by classification; Artificial intelligence;

Additional Key Words and Phrases: Fairness, bias mitigation, debiasing, fairness-aware machine learning, classification

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1 INTRODUCTION

Machine Learning (ML) has been increasingly popular in recent years, both in the diversity and importance of applications [76]. ML is used in a variety of critical applications such as justice risk assessments [24, 38], job recommendations [413], and autonomous driving [227].

While ML systems have the advantage to relieve humans from tedious tasks and are able to perform complex calculations at a higher speed [287], they are only as good as the data on which
they are trained [34]. ML algorithms, which are never designed to intentionally incorporate bias, run the risk of replicating or even amplifying bias present in real-world data [34, 283, 348]. This may cause unfair treatment in which some individuals or groups of people are privileged (i.e., receive a favorable treatment) and others are unprivileged (i.e., receive an unfavorable treatment). In this context, a fair treatment of individuals constitutes that decisions are made independent of sensitive attributes such as gender or race, such that individuals are treated based on merit [187, 188, 256]. For example, one can aim for an equal probability of population groups to receive a positive treatment, or an equal treatment of individuals that only differ in sensitive attributes.

Human bias has been transferred to various real-world systems relying on ML and there are many examples of this in the literature. For instance, bias has been found in advertisement and recruitment processes [93, 413], affecting university admissions [41] and human rights [256]. Not only is such a biased behavior undesired, but it can fall under regulatory control and risk the violation of anti-discrimination laws [67, 283, 311], as sensitive attributes such as age, disability, gender identity, race are protected by US law in the Fair Housing Act and Equal Credit Opportunity Act [212].

Another example for a biased treatment of population groups can be found in the COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) software, used by courts in US to determine the risks of an individual to reoffend. These scores are used to motivate decisions on whether and when defendants are to be set free, in different stages of the justice system. Problematically, this software falsely labeled non-white defendants with higher risk scores than white defendants [24].

To reduce the degree of bias that such systems exhibit, practitioners use three types of bias mitigation methods [123]:

- **Pre-processing**: bias mitigation in the training data, to prevent it from reaching ML models;
- **In-processing**: bias mitigation while training ML models;
- **Post-processing**: bias mitigation on trained ML models.

In this survey, we use the terms "bias mitigation" and "fairness improvement" interchangeably and treat fairness as the absence of bias.

There has been a growing interest in fairness research, including definitions, measurements, and improvements of ML models [70, 71, 76, 108, 287]. In particular, a variety of recent work addresses the mitigation of bias in binary classification models: given a collection of observations (training data) are labeled with a binary label (testing data) [350].

Despite the large amount of existing bias mitigation methods and surveys on fairness research, as Pessach and Shmueli [287] pointed out, there remain open challenges that practitioners face when designing new bias mitigation methods: “It is not clear how newly proposed mechanisms should be evaluated, and in particular which measures should be considered? which datasets should be used? and which mechanisms should be used for comparison?” [287]

To combat this challenge, we set out to perform a comprehensive survey of existing research on bias mitigation for ML models. We analyze 341 publications to identify practices applied in fairness research when creating bias mitigation methods. In particular, we consider the datasets to which bias mitigation methods are applied, the metrics used to determine the degree of bias, and the approaches used for benchmarking the effectiveness of bias mitigation methods. By doing so, we allow practitioners to focus their effort on creating bias mitigation methods rather than requiring a lot of time to determine their experimental setup (e.g., which datasets to test on, which benchmark to consider).

To the best of our knowledge, this is the most comprehensive survey to systematically search and cover bias mitigation methods and their empirical evaluation. To summarize, the contributions of this survey are:
(1) we provide a comprehensive overview of the research on bias mitigation methods for ML classifiers;
(2) we introduce the experimental design details for evaluating existing bias mitigation methods;
(3) we identify challenges and opportunities for future research on bias mitigation methods.
(4) we make the collected paper repository public to allow for future replication and manual investigation of our results: https://solar.cs.ucl.ac.uk/os/softwarefairness.html

The rest of this article is structured as follows: Section 2 presents an overview of related surveys. The search methodology is described in Section 3. Sections 4–7 describe research on bias mitigation methods. Opportunities and challenges that the field of fairness research and bias mitigation methods face are discussed in Section 8. Section 9 provides recommendations to practitioners, distilled from the collected publications. Section 10 concludes this survey.

2 RELATED SURVEYS
In this section, we provide an overview of existing surveys in the fairness literature and their contents. This allows us to identify the knowledge gap filled by our survey.

Mehrabi et al. [256] and Pessach and Shmueli [287] provided an overview of bias and discrimination types, fairness definitions and metrics, bias mitigation methods, and existing datasets. For example, Pessach and Shmueli [288] listed the datasets and metrics used by 27 bias mitigation methods. A similar focus has been pursued by Dunkelau and Leuschel [108], who provided an extensive overview on fairness notions, available frameworks, and bias mitigation methods for classification problems. They moreover provided a classification of approaches for each type (i.e., pre-, in-, and post-processing). The most exhaustive categorization of bias mitigation methods, to date, has been conducted by Caton and Haas [52], who also presented fairness metrics and fairness platforms.

A detailed collection of prominent fairness definitions for classification problems is provided by Verma and Rubin [350]. Similarly, Žliobaite [417] surveyed measures for indirect discrimination for ML. While these collections describe current metrics used to determine the fairness of ML models, Hutchinson and Mitchell [156] drew parallels from fairness research in the 1960s and 1970s concerning test fairness, for education and hiring, to current advances. Similar to modern metrics and evaluation approaches, past work considered fairness with regards to individuals and groups, or the use of confusion matrix measures (Section 6).

In addition to the surveys on fairness metrics, Le Quy et al. [219] provided a survey with 15 frequently used datasets in fairness research. For each dataset, they described the available features and their relationships with sensitive attributes.

Other surveys are concerned with fairness and consider the following perspectives: learning-based sequential decision algorithms [407], criminal justice [38], graph representations [406], ML testing [398], Software Engineering [68, 336], or Natural Language Processing [44, 338].

While previous surveys focused on ML classification, and some mentioned bias mitigation methods, none has yet systematically covered the evaluation bias mitigation methods (e.g., how are methods benchmarked, what datasets are used). The surveys related closest to ours are provided by Dunkelau and Leuschel [108] and Pessach and Shmueli [288].

Dunkelau and Leuschel [108] provided an overview of bias mitigation methods with a focus on their implementation and underlying algorithms. However, further evaluation details of these methods, such as dataset and metric usage, were not addressed. While Pessach and Shmueli [288] listed the datasets and metrics used by 27 bias mitigation methods, they did not provide actionable insights to support developers. In addition to combining aspects of both surveys (i.e., extensive collection of bias mitigation methods like Dunkelau and Leuschel [108], and providing information
on datasets and metrics similar to Pessach and Shmueli [287]), we aim to analyze the findings of a comprehensive literature search to devise recommendations.

3 SURVEY METHODOLOGY

The purpose of this survey is to gather and categorize research work that mitigates bias in ML models. Given that the existing literature focuses on classification for tabular data, this survey also focuses on bias mitigation methods for such classification tasks.

3.1 Search Methodology

This section outlines our search procedure. We start with a preliminary search, followed by a repository search and snowballing.

Preliminary Search. Prior to systematically searching online repositories, we conduct a preliminary search. The goal of the preliminary search is to gain a deeper understanding of the field and assess whether there is a sufficient number of publications to allow for subsequent analysis. In particular, we collect bias mitigation publications from four existing surveys (see Section 2):

— Mehrabi et al. [256]: 24 bias mitigation methods;
— Pessach and Shmueli [288]: 30 bias mitigation methods;
— Dunkelau and Leuschel [108]: 40 bias mitigation methods;
— Caton and Haas [52]: 70 bias mitigation methods.

In total, we collect 100 unique publications with bias mitigation methods from these four surveys.

Repository Search. After the preliminary search, we conduct a search of six established online repositories (IEEE, ACM, ScienceDirect, Scopus, arXiv, and Google Scholar).

The search procedure is guided by two groups of keywords:

— Domain: machine learning, deep learning, artificial intelligence;
— Bias Mitigation: fairness-aware, discrimination-aware, bias mitigation, debias*, unbias*;

In this context, Domain keywords ensure that the bias discussed in the publication affects machine learning systems. Bias Mitigation keywords ensure that the publication addresses bias reduction via the use of bias mitigation methods. For the six repositories, we collected publications that contain at least one Domain and one Bias mitigation keyword (i.e., we check each possible combination of keywords for the two categories).

Selection. To ensure that the publications included in this survey are relevant to the context of bias mitigation for ML models, we consider the following inclusion criteria: (1) describe human biases; (2) address classification problems; (3) use tabular data (e.g., do not make decisions based on images or text alone).

To ensure that irrelevant publications are excluded from the search results, we manually check publications in three stages [251]:

(1) Title: Publications with irrelevant titles to the survey are excluded;
(2) Abstract: The abstract of every publication is checked. Publications that show to be irrelevant to the survey at this step are excluded (e.g., not about ML, do not apply debiasing);
(3) Body: For publications that passed the previous two steps, we check the entire publication to determine whether they satisfy the inclusion criteria. If not, then they are excluded.

Snowballing. After conducting the repository search, we apply backward snowballing (i.e., finding new publications that are cited by publications we already selected) for each publication retained after the “Body” stage [365]. This snowballing step is repeated for every new publication
3.2 Selected Publications

In total, we gathered 341 publications over the different stages of our search procedure. Table 2 summarizes the results of the two repository searches. The first search was conducted from the 7th of October to 10th of October 2021, and the second search was conducted on the 21st of July 2022. The purpose of the second search is to collect publications from the year 2022 (i.e., we filtered search results for the publication year 2022). In October 2021, Google Scholar provided 8,738 publications that were in line with the search keywords. We restricted our search to the first 1,000 entries as prioritized by Google Scholar based on relevance. Similarly, the second search yielded 1,995 results and we focused on the first 1,000 entries.

To ensure that our survey is comprehensive and accurate, we contacted the corresponding authors of the 309 publications collected via the preliminary search, the two repository searches, and snowballing. We asked them to check whether our description about their work is correct. Based on their feedback, we included an additional 32 publications. In Table 1, we summarize the number of publications we found at each step of the search.

In Figure 2, we show the distribution of the publications per year and venue type. We categorized the 341 publications in five venue types, in line with the categories by Soremekun et al. [336]: Artificial Intelligence (AI), Data, Fairness, Software Engineering (SE), other. Note that the category “other” consists of 100 publications, 68 of which are published on arXiv. The category SE combines publications form Software Engineering, Programming Language, and Security venues. From this figure, we can see that there is an increasing interest in bias mitigation methods and a
steady increase of publications over the years. In particular, we observe a huge jump in the number of publications in 2018, more than doubling the number of publications from 2017 (i.e., from 20 to 46 publications). Prior years, from 2009–2016, have seen less than 10 publications each. The venues with the highest number of publications are: NeurIPS (38 publications), ICML (27 publications), AAAI (18 publications), FAccT (13 publications), AIES (12 publications).

### 3.3 Visibility

In this section, we address the visibility of bias mitigation methods by using the amount of publications and number of citations as a proxy for bias mitigation method visibility across different venues.\(^1\)

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\(^1\)We obtained the number of citations for each publication from Google Scholar on February 24, 2023, and included them in our online repository [25].
As shown in Figure 2, there is an increasing trend in the number of publications on bias mitigation methods per year, which supports the claim that the visibility and relevance of bias mitigation is growing. Among the five venue types (AI, Data, Fairness, SE, other), bias mitigation methods exhibit the highest visibility in terms of number of publications for AI (139 publications), data (59 publications), and other venues (most notably, arXiv, with 68 publications). The past five years, from 2018 onwards, saw an uptick of bias mitigation methods in a wider range of venues, with the inclusion of bias mitigation methods in Software Engineering venues and the creation of the ACM Conference on Fairness, Accountability, and Transparency (ACM FAccT), as well as specialized venues co-located with well-renowned international conference such as the IEEE/ACM International Workshop on Equitable Data & Technology (FairWare) at the International Conference of Software Engineering.

Figure 3 provides a closer look at the average number of citations of publications per venue type. We can observe that publications from early years of bias mitigation methods have a high average visibility (i.e., number of citations). A reason for this can be found in the low number of publications, with only 3–7 publications yearly from 2009–2016, and the relevance of such publications to be the foundation of proceeding work. Data venues published bias mitigation methods consistently, every year, from 2009 to 2022. While Fairness and SE venues have fewer publications per year, the respective papers achieve a high visibility, frequently with a higher average number of citations than Data and AI venues for the same years. The highest average number of citations was achieved by publications in fairness venues in 2018, 2019, and 2021.

Among the most cited publications (19 of which publications have been cited more than 500 times) only two have not been published in AI or data venues. This includes the work by Dwork et al. [109] (published in the Proceedings of the 3rd Innovations in Theoretical Computer Science Conference) and Zhang et al. [393] (published at the AAAI/ACM Conference on AI, Ethics, and Society). We note that 10 out of the 15 most cited works have publicly available implementations in fairness frameworks [31, 36, 42].

3.4 Limitations
This survey focuses on investigating the fairness of ML models from an algorithmic point of view. While fairness is a multi-disciplinary field of research and has been addressed by various communities, including law [45], health studies [272], and criminal justice [32], we focus on the algorithmic fairness and bias as exhibited by ML models.

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2https://facctconference.org/index.html
3https://dblp.org/db/conf/fairware-ws/index.html
Moreover, our search procedure is designed to find publications that mitigate bias for tabular data. This does not mean that we exclude a priori relevant publications if they have been published at Computer Vision or Natural Language Processing venues. In fact, such publications are considered in our survey if bias mitigation for tabular data is addressed, whereas bias mitigation methods that are solely applied for visual or textual tasks are not included.

Furthermore, we note that the overview presented herein is based on bias mitigation methods as proposed by the research community, often applied to publicly available data. While these data can be based on real-world scenarios, results might not transfer to real-world applications [32, 99].

4 ALGORITHMS

In this section, we discuss the bias mitigation methods found in our literature search. We distinguished bias mitigation methods based on their type (i.e., in which stage of the ML process are they applied): pre-processing (Section 4.1), in-processing (Section 4.2), and post-processing (Section 4.3) methods [123]. Moreover, we organize methods in categories (i.e., the bias mitigation approach). For this, we follow taxonomies devised by Dunkelau and Leuschel [108], as well as Caton and Haas [52]. Figure 1 illustrates the 13 categories we use.

Among the 341 publications, 123 used pre-processing (Section 4.1), 212 used in-processing (Section 4.2), and 56 used post-processing methods (Section 4.3). We observe that a single publication may investigate up to three different types of bias mitigation methods, and as such it can be counted multiple times (for example, an approach can apply pre-processing before adapting the training procedure during an in-processing stage). This is the case for 70 publications analyzed in this survey, for which we provide more information in Section 4.4.

4.1 Pre-processing Bias Mitigation Methods

In this section, we present bias mitigation methods that combat bias by applying changes to the training data. Table 3 lists the 123 publications we found, according to the type of pre-processing method used.

4.1.1 Relabeling and Perturbation. This section presents bias mitigation methods that apply changes to the values of the training data. Changes have been applied to the ground truth labels (relabeling) or the remaining features (perturbation).

A popular approach for relabeling datasets is “massaging,” proposed by Kamiran and Calders [183]. In the first stage, “massaging” uses a ranker to determine the best candidates for relabeling. In particular, instances close to the decision boundary are selected to minimize the negative impact of relabeling on accuracy. Typically, an equal amount of instances with positive and negative labels are selected, according to their rank and their labels are switched.

Massaging has later been extended by Kamiran and Calders [185] and Calders et al. [47]. Moreover, Žliobaite et al. [418] created a related method called “local massaging.” “Massaging” has also been applied by other work [164, 400].

Another relabeling approach was proposed by Luong et al. [242], who relabeled instances based on their k-nearest neighbors, such that similar individuals receive similar labels.

Feldman et al. [118] used perturbation to modify non-protected attributes, such that their values for privileged and unprivileged groups are comparable. In particular, the values are adjusted to bring their distributions closer together while preserving the respective ranks within a group (e.g., the highest values of attribute a for the privileged group remains highest after perturbation). Johndrow and Lum [173], Lum and Johndrow [240] used conditional models for perturbation, which allowed for modification of multiple variables (continuous or discrete). Li et al. [226] proposed an iterative approach for perturbation. At each step, the most bias-prone attribute is
### Table 3. Publications on Pre-processing Bias Mitigation Methods

| Type         | Authors [Ref] | Year | Venue           |
|--------------|---------------|------|-----------------|
| Relabel      | Zhang et al.  | 2018 | TKDE            |
|              | Kamiran and   | 2012 | KDD             |
|              | Calders and   | 2019 | ICM             |
|              | Sun et al.    | 2022 | EuroS&G         |
|              | Alabdulmohain et al. | 2016 | arXiv          |
| Perturbation  | Hajian and    | 2013 | TKDE            |
|              | Domingo-Ferrer | 2012 | KDD             |
|              | Wang et al.   | 2019 | ICM             |
|              | Li et al.     | 2022 | SSRN            |
|              | Li et al.     | 2022 | ICSE            |
| Sampling     | Calder et al. | 2009 | KDDM            |
|              | Kamiran and   | 2010 | IC3M            |
|              | Zliobaite et  | 2011 | ICDD           |
|              | Luong et al.  | 2011 | KDD             |
|              | Hajian and    | 2012 | KDD             |
|              | Zhang et al.  | 2012 | IC3M            |
|              | Sun et al.    | 2017 | TKDE            |
|              | Li et al.     | 2022 | ICSE            |
|              | Calder et al. | 2009 | KDDM            |
|              | Kamiran and   | 2010 | IC3M            |
|              | Zliobaite et  | 2011 | ICDD           |
|              | Kamiran and   | 2012 | IC3M            |
|              | Zhang et al.  | 2012 | IC3M            |
|              | Chen et al.   | 2012 | IC3M            |
|              | Iosifidis et  | 2018 | Big Data        |
|              | Xu et al.     | 2018 | ThWebConf       |
|              | Krasanakis et | 2018 | report           |
|              | Abusitta et al. | 2019 | arXiv          |
|              | Xu et al.     | 2019 | Big Data        |
|              | Hu et al.     | 2020 | DS              |
|              | Chakraborty et al. | 2020 | PSE            |
|              | Jiang and    | 2020 | AISTATS         |
|              | Sharma et al. | 2020 | AIES            |
|              | Celis et al.  | 2020 | ICML            |
|              | Morano [263]  | 2020 | Thesis           |
|              | Yan et al.    | 2020 | CIKM            |
|              | Chuang and    | 2021 | IEEE Access     |
|              | Salazar et al. | 2021 | PAKDD          |
|              | Zhang et al.  | 2021 | PAKDD          |
|              | Yu [381]      | 2021 | arXiv          |
|              | Ioinovs et al. | 2021 | arXiv          |
|              | Rob et al.    | 2021 | arXiv          |
|              | Hu and Wu     | 2021 | CIKM            |
|              | Singh et al.  | 2021 | MAKE            |
|              | Amend and     | 2021 | JSCC            |
|              | Jang et al.   | 2021 | AAAI            |
|              | Verma et al.  | 2021 | arXiv          |
|              | Chakraborty et al. | 2019 | FSE            |
|              | Cruz et al.   | 2021 | ICDD            |
|              | Wang et al.   | 2022 | ICML            |
|              | Pentylala et al. | 2019 | arXiv          |
|              | Rajabi and    | 2022 | PAKDD          |
|              | Sun et al.    | 2022 | EuroS&G        |
|              | Chen et al.   | 2022 | PMLR           |
|              | Li et al.     | 2022 | arXiv          |
|              | Chakraborty et al. | 2020 | FairWARE       |
|              | Almuzaini et al. | 2020 | arXiv          |
|              | Chai and Wang | 2022 | ICML            |

### Table 4. Publications on Post-processing Bias Mitigation Methods

| Authors [Ref] | Year | Venue |
|---------------|------|-------|
| Calder et al. | 2000 | ICML  |
| Kamiran et al.| 2003 | ICML  |
| Zhi et al.    | 2012 | ICM   |
| Luong et al.  | 2013 | ICML  |
| Kamiran and   | 2014 | ICML  |
| Chen et al.   | 2014 | ICML  |
| Zhang et al.  | 2014 | ICML  |
| Iosifidis et  | 2015 | ICML  |
| Seker et al.  | 2016 | ICML  |
| Sun et al.    | 2016 | arXiv |

### Table 5. Publications on Representation Bias Mitigation Methods

| Authors [Ref] | Year | Venue |
|---------------|------|-------|
| Calder et al. | 2009 | ICML  |
| Kamiran et al.| 2009 | ICML  |
| Zhi et al.    | 2012 | ICML  |
| Luong et al.  | 2013 | ICML  |
| Kamiran and   | 2014 | ICML  |
| Chen et al.   | 2014 | ICML  |
| Zhang et al.  | 2014 | ICML  |
| Iosifidis et  | 2015 | ICML  |
| Seker et al.  | 2015 | ICML  |
| Sun et al.    | 2016 | arXiv |
| Alabdulmohain et al. | 2016 | arXiv |

### Table 6. Publications on Latent Bias Mitigation Methods

| Authors [Ref] | Year | Venue |
|---------------|------|-------|
| Calder et al. | 2009 | ICML  |
| Kamiran et al.| 2009 | ICML  |
| Zhi et al.    | 2012 | ICML  |
| Luong et al.  | 2013 | ICML  |
| Kamiran and   | 2014 | ICML  |
| Chen et al.   | 2014 | ICML  |
| Zhang et al.  | 2014 | ICML  |
| Iosifidis et  | 2015 | ICML  |
| Seker et al.  | 2015 | ICML  |
| Sun et al.    | 2016 | arXiv |
| Alabdulmohain et al. | 2016 | arXiv |

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selected and transformed until the degree of bias exhibited by a classification model is below a specified threshold.

Other than perturbing the underlying data for all groups to move them closer [118, 173, 240], Wang et al. [354, 355] considered only the unprivileged group for perturbation, seeking to resolve disparity by improving the performance of the unprivileged group. Hajian and Domingo-Ferrer [143] applied both relabeling and perturbation (i.e., changes to the sensitive attribute).

4.1.2 Sampling. Sampling methods change the training data by changing the distribution of samples (e.g., adding, removing samples) or adapting their impact on training. Similarly, the impact of training data instances can be adjusted by reweighing their importance [7, 20, 47, 56, 59, 105, 164, 185, 225, 284, 381].

Reweighing was first introduced by Calders et al. [47]. Each instance receives a weight according to its label and protected attribute (e.g., instances in the unprivileged group and positive label receive a higher weight, as this is less likely). In the training process of classification models, a higher instance weight causes higher losses when misclassified. Weighted instances are sampled with replacement according to their weights. If the classification model is able to process weighted instances, then the dataset can be used for training without resampling [185].

Jiang and Nachum [169] and Krasanakis et al. [211] used reweighing to combat biased labels in the original training data.

Instead of assigning equal weights to data instances of the same population subgroup, Li and Liu [225] assigned individual weights to instances of the training data.

Other sampling strategies include the removal of data points (downsampling) [62, 69, 89, 158, 309, 319, 349, 358, 401] or the addition of new data points (upsampling). Popular methods for upsampling are oversampling for duplicating instances of the minority group [21, 160, 263, 389] and the use of SMOTE [64]. SMOTE does not duplicate instances but generates synthetic ones in the neighborhood of the minority group [60, 61, 91, 160, 263, 318, 332, 376, 389].

To sample datapoints, uniform [185] and preferential [153, 184, 185, 389, 418] strategies have been followed, where preferential sampling changes the distribution of instances close to the decision boundary.

Xu et al. [372, 374, 375] used a generative approach to generate discrimination-free data for training [8, 168, 299]. Zhang et al. [399] used causal networks to create a new dataset. The initial dataset is used to create a causal network, which is then modified to reduce discrimination. The debiased causal network is used to generate a new dataset. Sharma et al. [328] created additional data for augmentation by duplicating existing datasets and swapping the protected attribute of each instance. The newly created data is successively added to the existing dataset.

4.1.3 Latent Variables. Latent variables describe the augmentation of training data with additional features that are preferably unbiased. In previous work, latent variables have been used to represent labels [198, 362] and group memberships (i.e., protected or unprotected group) [61, 65, 97, 137, 140, 179, 230, 276, 340] and are frequently considered when dealing with causal graphs [137, 202, 245].

For instance, Calders and Verwer [49] clustered the instances to detect those that should receive a positive latent label and those that should receive a negative one. For this purpose, they used an expectation maximization algorithm.

Gupta et al. [140] tackled the problem of bias mitigation for situations where group labels are missing in the datasets. To combat this issue, they created a latent “proxy” variable for the group membership and incorporated constraints for achieving fairness for such proxy groups in the training procedure.
4.1.4 Representation. Representation learning aims at learning a transformation of the training data such that bias is reduced while maintaining as much information as possible.

The first representation learning approach for bias mitigation was Learning Fair Representations (LFR), proposed by Zemel et al. [390]. LFR translates representation learning into an optimization problem with two objectives: (1) removing information about the protected attribute; (2) minimizing the information loss of non-sensitive attributes.

A popular used approach for generating fair representations is optimization [50, 106, 133, 142, 215, 216, 254, 266, 330, 335, 388]. Other used techniques are:

- adversarial learning [111, 119, 135, 166, 180, 204, 244, 292, 314, 371, 411, 416];
- variational autoencoders [88, 232, 238, 273, 301];
- adversarial variational autoencoder [367];
- normalizing flows [30, 58];
- dimensionality reduction [182, 285, 320, 342];
- residuals [209];
- contrastive learning [141];
- neural style transfer [295, 296].

Another method for improving the fairness of data representations is the removal [139, 243, 360] or addition of features [122, 126, 317]. Grgić-Hlača et al. [139] investigated fairness while using different sets of features, thereby making training feature choices. Madhavan and Wadhwa [243] removed discriminating features from the training data. Salazar et al. [317] applied feature creation techniques that apply nonlinear transformation and drop biased features.

4.2 In-processing Bias Mitigation Methods

This section presents in-processing methods; methods that mitigate bias during the training procedure of the algorithm. Overall, we found a total of 212 publications (see Table 4, Table 5 for more details) that apply in-processing methods. For more details on in-processing methods, we refer to the survey by Wan et al. [352], which provides information on 38 in-processing approaches developed for various ML tasks.

4.2.1 Regularization and Constraints. Regularization and constraints are both approaches that apply changes to the learning algorithm’s loss function. Regularization adds a term to the loss function. While the original loss function is based on accuracy metrics, the purpose of a regularization term is to penalize discrimination (i.e., discrimination leads to a higher loss of the ML algorithm). Constraints, however, determine specific bias levels (according to loss functions) that cannot be breached during training.

To widen the range of fairness definitions that can be considered when applying constraints, Celis et al. [53] proposed a Meta-algorithm. This Meta-algorithm takes a fairness constraint as input.

When applied to Decision Trees, regularization can be used to modify the splitting criteria [186, 300, 356, 402–405]. Traditionally, leaves are iteratively split to achieve an improvement in accuracy. To improve fairness while training, Kamiran et al. [186] considered fairness in addition to accuracy when leaf splitting. They applied three splitting strategies:

1. only allow non-discriminatory splits;
2. choose best split according to \( \delta_{\text{accuracy}}/\delta_{\text{discrimination}} \);
3. choose best split according to \( \delta_{\text{accuracy}} + \delta_{\text{discrimination}} \).

While constraints and regularization usually utilize group fairness definitions, they have also been applied for achieving individual fairness [109, 130, 178, 206]. Moreover, they can be applied...
### Table 4. Publications on In-processing Bias Mitigation Methods

| Type | Authors [Ref] | Year | Venue |
|------|---------------|------|-------|
|       | Kamiran et al. [186] | 2010 | ICDM |
|       | Kamishima et al. [192] | 2011 | ICDM |
|       | Kamishima et al. [189] | 2012 | ECML PKDD |
|       | Rastanowski et al. [306] | 2013 | CIKM |
|       | Fish et al. [120] | 2015 | FATML |
|       | Pérez-Suay et al. [285] | 2017 | ECML PKDD |
|       | Bechavod and Ligett [55] | 2017 | arXiv |
|       | Berk et al. [37] | 2017 | arXiv |
|       | Quadranto and Sharmanska [294] | 2017 | NeurIPS |
|       | Raff et al. [298] | 2017 | AIES |
|       | Enni and Assent [113] | 2018 | ICDM |
|       | Goel et al. [311] | 2018 | AAAI |
|       | Zhang et al. [405] | 2019 | ICDM |
|       | Mary et al. [253] | 2019 | ICML |
|       | Beutel et al. [39] | 2019 | AIES |
|       | Huang and Vihanoo [154] | 2019 | ICML |
|       | Aghaee et al. [14] | 2019 | AAAI |
|       | Zhang and Ntoutsi [402] | 2019 | JICAI |
|       | Keya et al. [199] | 2020 | arXiv |
|       | Kim et al. [203] | 2020 | ICML |
|       | Jiang et al. [170] | 2020 | UAI |
|       | Di Stefano et al. [96] | 2020 | arXiv |
|       | Abay et al. [7] | 2020 | arXiv |
|       | Baharlouei et al. [28] | 2020 | ICLR |
|       | Liu et al. [234] | 2020 | Preprint |
|       | Kamari et al. [181] | 2020 | Thesis |
|       | Ravichandran et al. [302] | 2020 | arXiv |
|       | Tavakol [134] | 2020 | SIGIR |
|       | Romano et al. [310] | 2020 | NeurIPS |
|       | Hickey et al. [148] | 2020 | ECML PKDD |
|       | Wang et al. [361] | 2021 | SIGKDD |
|       | Chuang and Mroueh [77] | 2021 | ICLR |
|       | Lowy et al. [239] | 2021 | arXiv |
|       | Zhang and Weiss [404] | 2021 | ICDM |
|       | Grari et al. [136] | 2021 | JICAI |
|       | Yurochkin and Sun [383] | 2021 | ICLR |
|       | Zhao et al. [412] | 2021 | arXiv |
|       | Ramanzo et al. [380] | 2021 | CIKM |
|       | Mishler and Kennedy [258] | 2021 | arXiv |
|       | Kang et al. [195] | 2021 | arXiv |
|       | Sun et al. [337] | 2022 | EuroS&P |
|       | Zhao et al. [411] | 2022 | WSDM |
|       | Wang et al. [356] | 2022 | CAV |
|       | Deng et al. [95] | 2022 | Entropy |
|       | Lee et al. [221] | 2022 | AAAH |
|       | Zhang and Weiss [405] | 2022 | ICLR |
|       | Jiang et al. [171] | 2022 | ICASSP |
|       | Lee et al. [220] | 2022 | ICML |
|       | Do et al. [302] | 2022 | ICML |
|       | Patil and Purcell [281] | 2022 | Future Internet |
|       | Kim and Cho [205] | 2022 | Neurocomputing |

### Constraints

- Dwork et al. [189] | 2012 | ITCS |
- Calders et al. [48] | 2013 | ICDM |
- Fukushima and Sakuma [125] | 2015 | arXiv |
- Fukushima et al. [124] | 2015 | IEEE Trans. Inf. & Syst. |
- Goh et al. [132] | 2016 | NeurIPS |
- Woodworth et al. [366] | 2017 | COLT |
- Zafar et al. [346] | 2017 | ThWebConf |
- Corbett-Davies et al. [82] | 2017 | KDD |
- Zafar et al. [387] | 2017 | AISTATS |
- Komiyama and Shimao [209] | 2017 | arXiv |
- Zafar et al. [386] | 2017 | NeurIPS |
- Quadranto and Sharmanska [294] | 2017 | NeurIPS |
- Russell et al. [313] | 2017 | NeurIPS |
- Kilbertus et al. [302] | 2017 | NeurIPS |
- Agarwal et al. [11] | 2018 | ICML |
- Kim et al. [206] | 2018 | NeurIPS |
- Narasimhan et al. [209] | 2018 | AISTATS |
- Gullen et al. [130] | 2018 | NeurIPS |
- Grefa-Hlaca et al. [139] | 2018 | AAAI |
- Heradi et al. [147] | 2018 | NeurIPS |
- Keams et al. [196] | 2018 | ICML |
- Zhang and Bareinboim [396] | 2018 | AAAI |
- Gupta et al. [140] | 2018 | arXiv |
- Olifat and Awan [274] | 2018 | AISTATS |
- Zhang and Bareinboim [395] | 2018 | NeurIPS |
- Komyaya et al. [210] | 2018 | ICML |
- Wu et al. [369] | 2018 | arXiv |
- Donati et al. [103] | 2018 | NeurIPS |
- Farnardi et al. [116] | 2018 | AIES |
- Nabi and Shipster [268] | 2018 | AAAI |
- Goel et al. [131] | 2018 | AAI |
- Wick et al. [363] | 2019 | NeurIPS |
- Celis et al. [53] | 2019 | FAccT |
- Cotter et al. [85] | 2019 | ICML |
- Balasankar et al. [29] | 2019 | arXiv |
- Agarwal et al. [12] | 2019 | ICML |
- Nabi et al. [267] | 2019 | ICML |
- Cotter et al. [87] | 2019 | ALT |
- Oneto et al. [276] | 2019 | AIES |
- Cotter et al. [86] | 2019 | JMLR |
- Jung et al. [178] | 2019 | arXiv |
- Lamy et al. [217] | 2019 | NeurIPS |
- Xu et al. [373] | 2019 | ThWebConf |
- Zafar et al. [385] | 2019 | JMLR |
- Wang et al. [359] | 2020 | NeurIPS |
- Chihen and Schruefer [81] | 2020 | arXiv |
- Lohaus et al. [235] | 2020 | ICML |
- Kilbertus et al. [201] | 2020 | AISTATS |
- Ding et al. [190] | 2020 | AAAI |
- Miatly et al. [248] | 2020 | arXiv |
- Cho et al. [74] | 2020 | NeurIPS |
- Padala and Gupta [278] | 2020 | ICAI |
- Oneto et al. [275] | 2020 | IJCNN |
- Chihen et al. [80] | 2020 | NeurIPS |
- Celis et al. [54] | 2021 | PMLR |
- Celis et al. [57] | 2021 | NeurIPS |
- Slowik and Bottou [333] | 2021 | arXiv |
- Li et al. [224] | 2021 | LAK |
- Scutari et al. [325] | 2021 | arXiv |
- Padul et al. [279] | 2021 | UAI |
- Zhang et al. [394] | 2021 | MOD |
- Zhao et al. [409] | 2021 | KDD |
- Petrovich et al. [290] | 2021 | Eng. Appl. Artif. Intell. |
- Perrone et al. [296] | 2021 | AIES |
- Cho et al. [75] | 2021 | AAAI |
- Du and Wu [165] | 2021 | CIKM |
- Lawless et al. [218] | 2021 | arXiv |
- Mishler and Kennedy [258] | 2021 | arXiv |
- Park et al. [280] | 2022 | WWW |
- Wang et al. [356] | 2022 | CAV |
- Zhao et al. [410] | 2022 | KDD |
- Boultatsakis-Logothetis [46] | 2022 | arXiv |
- Hu et al. [352] | 2022 | arXiv |
- Wu et al. [368] | 2022 | CleaR |
### Table 5. Publications on In-processing Bias Mitigation Methods - Part 2

| Type | Authors [Ref] | Year | Venue |
|------|---------------|------|-------|
| Adversarial | Beutel et al. [40] | 2017 | arXiv |
| | Agarwal et al. [11] | 2018 | ICML |
| | Gillen et al. [130] | 2018 | NeurIPS |
| | Raff and Sylvester [297] | 2018 | DSAA |
| | Wadsworth et al. [351] | 2018 | arXiv |
| | Kearsn et al. [196] | 2018 | ICML |
| | Zhang et al. [393] | 2018 | AIES |
| | Adel et al. [9] | 2019 | AAAI |
| | Beutel et al. [39] | 2019 | AIES |
| | Sadeghi et al. [316] | 2019 | ICCV |
| | Zhao and Gordon [412] | 2019 | NeurIPS |
| | Xu et al. [375] | 2019 | Big Data |
| | Grari et al. [138] | 2019 | ICDM |
| | Celis and Keswani [55] | 2019 | arXiv |
| | Garcia de Alford et al. [128] | 2020 | SMU DSR |
| | Yurochkin et al. [382] | 2020 | ICLR |
| | Roh et al. [307] | 2020 | ICML |
| | Deolbelte et al. [94] | 2020 | ASE |
| | Rezari et al. [304] | 2020 | AAAI |
| | Lahoti et al. [214] | 2020 | NeurIPS |
| | Grari et al. [137] | 2021 | arXiv |
| | Grari et al. [136] | 2021 | IJCAI |
| | Amend and Spurlock [21] | 2021 | JSCC |
| | Rezari et al. [305] | 2021 | AAAI |
| | Chen et al. [65] | 2022 | arXiv |
| | Liang et al. [230] | 2022 | arXiv |
| | Tao et al. [345] | 2022 | FSE |
| | Petrovic et al. [289] | 2022 | Neurocomputing |
| | Yang et al. [377] | 2022 | medRxiv |
| | Yazdani-Jahromi et al. [378] | 2022 | arXiv |

| Type | Authors [Ref] | Year | Venue |
|------|---------------|------|-------|
| Compositional | Calders and Verwer [19] | 2010 | EMKD |
| | Pleiss et al. [291] | 2017 | NeurIPS |
| | Dwork et al. [119] | 2018 | FAccT |
| | Ustun et al. [346] | 2019 | ICML |
| | Oneto et al. [276] | 2019 | AIES |
| | Iosifidis et al. [159] | 2019 | Big Data |
| | Monteiro and Reynoso-Meza [262] | 2021 | PLM |
| | Ranzato et al. [300] | 2021 | CIBM |
| | Mishler and Kennedy [258] | 2021 | arXiv |
| | Kobayashi and Nakao [208] | 2021 | DFTET |
| | Jin et al. [172] | 2022 | ICML |
| | Chen et al. [69] | 2022 | FSE |
| | Roy et al. [312] | 2022 | DS |
| | Liu and Vicente [233] | 2022 | CMS |
| | Blanzeisky and Cunningham [43] | 2022 | Knowl Eng Rev |
| | Boultsakis-Logothetis [46] | 2022 | arXiv |
| | Suretykumar et al. [340] | 2022 | arXiv |

| Type | Authors [Ref] | Year | Venue |
|------|---------------|------|-------|
| Adjusted | Luo et al. [241] | 2015 | DaWaK |
| | Joseph et al. [177] | 2016 | NeurIPS |
| | Johnson et al. [175] | 2016 | StatSci |
| | Kusner et al. [213] | 2017 | NeurIPS |
| | Joseph et al. [176] | 2018 | AIES |
| | Hashimoto et al. [145] | 2018 | ICML |
| | Madras et al. [246] | 2018 | NeurIPS |
| | Alabi et al. [18] | 2018 | COLT |
| | Hebert-Johnson et al. [146] | 2018 | ICML |
| | Chiappa and Isaac [73] | 2018 | IJIP |
| | Kilbertus et al. [200] | 2018 | ICML |
| | Kamishima et al. [191] | 2018 | DMKD |
| | Dimitrakakis et al. [98] | 2019 | AAAI |
| | Chiappa [72] | 2019 | AAAI |
| | Noriega-Campero et al. [271] | 2019 | AIES |
| | Chakraborty et al. [63] | 2019 | arXiv |
| | Madras et al. [245] | 2019 | FAccT |
| | Iosifidis and Ntoutsi [161] | 2019 | CIKM |
| | Mandel et al. [249] | 2020 | NeurIPS |
| | Kilbertus et al. [201] | 2020 | AISTATS |
| | Martinez et al. [252] | 2020 | ICML |
| | Iosifidis and Ntoutsi [162] | 2020 | DS |
| | Liu et al. [234] | 2020 | Preprint |
| | Hu et al. [153] | 2020 | DS |
| | da Cruz [90] | 2020 | Thesis |
| | Chakraborty et al. [62] | 2020 | FSE |
| | Kamani [181] | 2020 | Thesis |
| | Zhang and Ramesh [408] | 2020 | arXiv |
| | Ignatiev et al. [157] | 2021 | CP |
| | Sharma et al. [327] | 2021 | AIES |
| | Ezzeldin et al. [114] | 2021 | arXiv |
| | Wang et al. [357] | 2021 | FAccT |
| | Ozdayi et al. [277] | 2021 | arXiv |
| | Zhang et al. [401] | 2021 | PAKDD |
| | Perrone et al. [286] | 2021 | AIES |
| | Islam et al. [165] | 2021 | AIES |
| | Roh et al. [308] | 2021 | ICLR |
| | Horta and Sarro [150] | 2021 | ASE |
| | Valdivia et al. [347] | 2021 | Int. J. Intell. Syst. |
| | Lee et al. [222] | 2021 | ICML |
| | Ezzeldin et al. [114] | 2021 | arXiv |
| | Roy and Ntoutsi [313] | 2022 | ECML PKDD |
| | Wang et al. [353] | 2022 | arXiv |
| | Siddar et al. [331] | 2022 | FAccT |
| | Agarwal and Deshpande [13] | 2022 | FAccT |
| | Park et al. [286] | 2022 | WWW |
| | Dybouni [101] | 2022 | Eurosys |
| | Iosifidis et al. [163] | 2022 | KAIS |
| | Short and Mohler [329] | 2022 | Int. J. Forecast. |
| | Maheshwari and Perrot [247] | 2022 | arXiv |
| | Zhao et al. [410] | 2022 | KDD |
| | Tizpar-Niaei et al. [345] | 2022 | ICSE |
| | Roy et al. [312] | 2022 | DS |
| | Mohammadi et al. [260] | 2022 | arXiv |
| | Gao et al. [127] | 2022 | ICSE |
| | Huang et al. [155] | 2022 | Expert Syst. Appl. |
| | Candeliere et al. [51] | 2022 | arXiv |
| | Anahideh et al. [22] | 2022 | Expert Syst. Appl. |
| | Rateik et al. [301] | 2022 | FAccT |
| | Li et al. [228] | 2022 | arXiv |

To achieve fairness for multiple sensitive attributes and fairness definitions [195, 195, 196, 210, 279, 344] or extend existing adjustments, such as adding fairness regularization in addition to the L2 norm, which is used to avoid overfitting [189, 192].

#### 4.2.2 Adversarial Learning

Adversarial learning simultaneously trains classification models and their adversaries [92]. While the classification model is trained to predict ground truth values,
the adversary is trained to exploit fairness issues. Both models then compete against each other to improve their performance. 

Zhang et al. [393] trained a Logistic Regression model to predict the label $Y$ while preventing an adversary from predicting the protected attribute under consideration of three fairness metrics: Demographic Parity, Equality of Odds, and Equality of Opportunity. Both, predictor and adversary, are implemented as Logistic regression models.

Similarly, Beutel et al. [40] trained a neural network to predict two outputs: labels and sensitive attributes. While a high overall accuracy is desired, the adversarial setting reduces the ability to predict sensitive information. The network is designed to share layers between the two output, such that only one model is trained [9, 39, 94, 297, 316].

Lahoti et al. [214] proposed **Adversarially Reweighted Learning (ARL)** in which a learner is trained to optimize performance on a classification task while the adversary adjusts the weights of computationally identifiable regions in the input space with high training loss. By so doing, the learner can then improve performance in these regions.

Other than using adversaries to prevent the ability to predict sensitive attributes (e.g., for reducing bias according to population groups), it has also been used to improve robustness to data poisoning [307], to improve individual fairness [382], and to reweigh training data [289]. In particular, Petrović et al. [289] used adversarial training to learn a reweighing function for training data instances as an in-processing procedure (contrary to applying reweighing as pre-processing; see Section 4.1.2).

### 4.2.3 Compositional

Compositional approaches combat bias by training multiple classification models. Predictions can then be made by a specific classification model for each population group (e.g., privileged and unprivileged) [46, 49, 172, 276, 291, 340, 346] or in an ensemble fashion (i.e., a voting of multiple classification models at the same time) [69, 159, 208, 233, 258, 261, 300, 312].

While decoupled classification models for privileged and unprivileged groups can achieve improved accuracy for each group, the amount training data for each classifier is reduced. To reduce the impact of small training data sizes, Dwork et al. [110] utilized transfer training. With their transfer learning approach, they trained classifiers on data for the respective group and data from the other groups with reduced weight. Ustun et al. [346] built upon the work of Dwork et al. [110] and incorporated “preference guarantees,” which states that each group prefers their decoupled classifier over a classifier trained on all training data and any classifier of the other groups. Similarly, Suriyakumar et al. [340] followed the concept of “fair use,” which states that if a classification uses sensitive group information, then it should improve performance for every group.

Training multiple classification models with different fairness goals allows for the creation of a Pareto-front of solutions [43, 233, 258, 312, 347]. Practitioners can then choose which fairness-accuracy tradeoff best suits their need. For example, Liu and Vicente [233] treated bias mitigation as multi-objective optimization problem that explores fairness-accuracy tradeoffs under consideration of multiple fairness metrics. Mishler and Kennedy [258] proposed an ensemble method that builds classification models based on a weighted combination of metrics chosen by users.

### 4.2.4 Adjusted Learning

Adjusted learning methods mitigate bias via changing the learning procedure of algorithms or the creation of novel algorithms [108]. Changes have been suggested for a variety of classification models, including Bayesian models [98, 190], Markov Random Fields [408], Neural Networks [153, 252, 297], Decision Trees, bandits [26, 176, 177], boosting [146, 161, 162, 312], Logistic Regression [308]. We outline a selection of publications in the following to provide insight on techniques applied to different classification models.

Noriega-Campero et al. [271] proposed an active learning framework for training Decision Trees. During training, a decision maker is able to collect more information about individuals to achieve
fairness in predictions. In this context, not all information about individuals is available. There is an information budget that determines how many enquiries can be performed. Similarly, Anahideh et al. [22] used an active learning framework to balance accuracy and fairness by selecting instances to be labeled.

Madras et al. [246] proposed a rejection learning approach for joint decision-making with classification models and external decision makers. In particular, the classification model learns when to defer from making a prediction (i.e., when it is more useful to have predictions from external decision makers). If the coverage of classification can be reduced (i.e., the classification model abstains from making some of the predictions), then selective classification approaches can be used [222].

Martinez et al. [252] proposed the algorithm \textbf{Approximate Projection onto Star Sets (AP-Star)} to train Deep Neural Networks to minimize the maximum risk among all population groups. This procedure ensures that the final classifier is part of the Pareto Front [112]. Hu et al. [153] incorporated representation learning into the training procedure of Neural Networks to learn them jointly with the classifier.

Hébert-Johnson et al. [146] proposed \textit{Multicalibration}, a learning procedure similar to boosting. A classifier is trained iteratively. At each iteration, the predictions of the most biased subgroup are corrected until the classifier is adequately calibrated.

Hashimoto et al. [145] found fairness issues with the use of empirical risk minimization and proposed the use of \textit{distributionally robust optimization (DRO)} when training classifiers such as Logistic Regression. During training, DRO optimizes the worst-case risk over all groups present.

Kilbertus et al. [200] adjusted the training procedure for Logistic Regression to take privacy into account. Sensitive user information is encrypted such that it cannot be used for classification tasks while retaining the ability to verify fairness issues. By doing so, users can provide sensitive information without the fear that someone can read them.

The learning procedure of existing classification models has also been adjusted by tuning their hyper-parameters [62, 63, 89, 90, 150, 165, 286, 345, 347].

4.3 Post-processing Bias Mitigation Methods

Post-processing bias mitigation methods are applied once a classification model has been successfully trained. With 56 publications that apply post-processing methods (Table 6), post-processing methods are the least frequently applied of those covered in this survey.

4.3.1 \textbf{Input Correction}. Input correction approaches apply a modification step to the testing data. This is comparable to pre-processing approaches (Section 4.1) [108], which conduct modifications to training data (e.g., relabeling, perturbation, and representation learning).

We found only two publications that applied input corrections to testing data, both of which used perturbations. While Adler et al. [10] used perturbation in a post-processing stage, Li et al. [229] first performed perturbation in a pre-processing stage and then applied an identical procedure for post-processing.

4.3.2 \textbf{Classifier Correction}. Post-processing approaches can also directly be applied to classification models, which Savani et al. [323] called intra-processing. A successfully trained classification model is adapted to obtain a fairer one. Such modifications have been applied to Naive Bayes [49], Logistic Regression [170], Decision Trees [186, 194, 397], Neural Networks [104, 250, 255, 323], and Regression Models [80].

Hardt et al. [144] proposed the modification of classifiers to achieve fairness with respect to Equalized Odds and Equality of Opportunity. Given an unfair classifier \( \hat{Y} \), the classifier \( \hat{Y} \) is derived by solving an optimization problem under consideration of fairness loss terms. This approach has been adapted and extended by further publications [27, 140, 259, 264].
Woodworth et al. [366] showed that this kind of modification can lead to a poor accuracy, for example when the loss function is not strictly convex. In addition to constraints during training, they proposed an adaptation of the approach by Hardt et al. [144].

Pleiss et al. [291] split a classifier in two \((h_0, h_1)\), for the privileged and unprivileged group. To balance the false positive and false negative rate of the two classifiers, \(h_1\) is adjusted such that with a probability of \(\alpha\) the class mean is returned rather than the actual prediction. Noriega-Campero et al. [271] followed the calibration approach of Pleiss et al. [291].

Kamiran et al. [186] modified Decision Tree classifiers by relabeling leaf nodes. The goal of relabeling was to reduce bias while sacrificing as little accuracy as possible. A greedy procedure was followed that iteratively selects the best leaf to relabel (i.e., highest ratio of fairness improvement per accuracy loss). Kamanori and Arimura [193] formulated the modification of branching thresholds for Decision Trees as a mixed integer program.

Kim et al. [207] proposed Multiaccuracy Boost, a post-processing approach similar to boosting for training classifiers. Given a black-box classifier and a learning algorithm, Multiaccuracy Boost iteratively adapts the current classifier based on its predictive performance.

### 4.3.3 Output Correction

The latest stage of applying bias mitigation methods is the correction of the output. In particular, the predicted labels are modified.

Pedreschi et al. [282] considered the correction of rule-based classifiers, such as CPAR [380]. For each individual, the \(k\) rules with highest confidence are selected to determine the probability for each output label. Given that some of the rules can be discriminatory, their confidence level is adjusted to reduce biased labels.

Menon and Williamson [257] proposed a plugin approach for thresholding predictions. To determine the thresholds to use, the class probabilities are estimated using logistic regression.
Kamiran et al. [187, 188] introduced the notion of reject option, which modifies the prediction of individuals close to the decision boundary. In particular, individuals belonging to the unprivileged group receive a positive outcome and privileged individuals an unfavorable outcome. Similarly, Lohia et al. [237] relabeled individuals that are likely to receive biased outcomes, but rather than considering the decision boundary, they used an “individual bias detector” to find predictions that are likely suffer from individual discrimination. This work was extended in 2021, where individuals were ranked based on their “Unfairness Quotient” (i.e., the difference between regular prediction and with perturbed protected attribute). Fish et al. [121] proposed a confidence-based approach that returns a positive label for each prediction above a given threshold. This has also been applied to AdaBoost [120]. Other than using a general threshold for all instances, group-dependent thresholds can be used [15, 78, 159, 167, 208, 284, 391, 392].

Chiappa [72] addressed the fairness of causal models under consideration of a counterfactual world in which individuals belong to a different population group. The impact of the protected attribute on the prediction outcome is corrected to ensure that it coincides with counterfactual predictions. This way, sensitive information is removed while other information remains unchanged.

4.4 Combined Approaches

While most publications proposed the use of a single type of bias mitigation method, we found 70 that applied multiple techniques at the same time (e.g., two pre-processing methods, one in-processing and one post-processing). Table 7 summarizes these approaches.

Among these 70 publications, 86% (60 out of 70) applied in-processing, 54% (38 out of 70) applied pre-processing, and 31% (22 out of 70) applied post-processing methods.

Additionally, 26 out of 70 publications applied multiple types of bias mitigation methods at the same stage of the development process (e.g., two pre-processing approaches). In particular, there are 7 publications that applied multiple pre-processing methods. Among these 7 publications, 5 applied sampling and relabeling [47, 164, 185, 337, 418]. The remaining 19 out of 26 publications applied multiple in-processing methods, 17 of which include regularization or constraints.

Forty-seven publications applied at least two methods at different stages of the development process for ML models (e.g., one pre-processing and one in-processing method). This illustrates that bias mitigation methods can be used in conjunction [129]. Moreover, there are three publications that addressed bias mitigation at each stage: pre-processing, in-processing, and post-processing [49, 140, 159].

Calders and Verwer [49] proposed three approaches for achieving discrimination-free classification of naive Bayes models. At first, a latent variable is added to represent unbiased labels. The data is then used to train a model for each possible sensitive attribute value. Last, the probabilities output by the model are modified to account for unfavorable treatment (i.e., increasing the probability of positive outcomes for the unprivileged group and reducing it for the privileged group).

Gupta et al. [140] tackled the problem of bias mitigation for situations where group labels are missing in the datasets. To combat this issue, they created a latent “proxy” variable for the group membership and incorporated constraints for achieving fairness for such proxy groups in the training procedure. Last, they followed the approach of Hardt et al. [144] to debias and existing classifier by adding an additional variable to the prediction problem (see Section 4.3.2).

Iosifidis et al. [159] followed an ensemble approach of multiple AdaBoost classifiers. In particular, each classifier is trained on an equal amount of instances from each population group and label by sampling. Predictions are then modified by applying group-dependent thresholds.
Table 7. Publications with Multiple Bias Mitigation Methods @

| Authors                        | Pre | In | Post |
|--------------------------------|-----|----|------|
| Sun et al. [337]               | ☒   | ☒  | ☒    |
| Calders et al. [47]            | ☒   |    |      |
| Zliobaite et al. [418]         | ☒   |    |      |
| Hajian and Domingo-Ferrer [143]| ☒   |    |      |
| Kamiran and Calders [185]      | ☒   |    |      |
| Iosifidis et al. [164]         | ☒   |    |      |
| Chakraborty et al. [61]        | ☒   |    |      |
| Oneto et al. [276]             | ☒   | ☒  |      |
| Calders and Verwer [49]        | ☒   | ☒  | ☒    |
| Gupta et al. [140]             | ☒   | ☒  | ☒    |
| Iosifidis et al. [159]         | ☒   | ☒  |      |
| Pérez-Suay et al. [285]        | ☒   |    |      |
| Komiyama and Shimao [209]      | ☒   |    |      |
| Kilbertus et al. [202]         | ☒   |    |      |
| Grgić-Hlača et al. [139]      | ☒   |    |      |
| Madras et al. [245]            | ☒   |    |      |
| Xu et al. [375]                | ☒   |    |      |
| Abay et al. [7]                | ☒   |    |      |
| Hu et al. [153]                | ☒   |    |      |
| Chakraborty et al. [62]        | ☒   |    |      |
| Chuang and Mroueh [77]         | ☒   |    |      |
| Zhang et al. [401]             | ☒   |    |      |
| Grari et al. [137]             | ☒   |    |      |
| Du and Wu [105]                | ☒   |    |      |
| Amend and Spurlock [21]        | ☒   |    |      |
| Cruz et al. [89]               | ☒   |    |      |
| Chen et al. [65]               | ☒   |    |      |
| Liang et al. [230]             | ☒   |    |      |
| Agarwal and Deshpande [13]     | ☒   |    |      |
| Chen et al. [69]               | ☒   |    |      |
| Wu et al. [368]                | ☒   |    |      |
| Rateike et al. [301]           | ☒   |    |      |
| Kim and Cho [205]              | ☒   |    |      |
| Suriyakumar et al. [340]       | ☒   |    |      |
| Zhang et al. [400]             | ☒   |    |      |
| Wei et al. [362]               | ☒   |    |      |
| Penyala et al. [284]           | ☒   |    |      |
| Li et al. [229]                | ☒   |    |      |

"X" indicates that the publication applies a bias mitigation approach of the corresponding category.

4.5 Classification Models

Here, we outline the classification models on which the three types of bias mitigation methods (pre-, in-, post-processing) have been applied on. Table 8 shows the frequency with which each type of classification model has been applied.

Currently, the most frequently used classification model is Logistic Regression, for each method type (pre-, in-, post-processing), with a total of 140 unique publications using it for their experiments. The second most frequently used classification models are Neural Networks (NNs). A total of 102 publication used NNs for their experiments, with the majority being in-processing methods. Linear Regression models have been used in 22 publications.

Decision Trees (36 publications) and Random Forests (45 publications) are also frequently used. Moreover, different Decision Tree variants have been used, such as Hoeffding trees, C4.5, J48, and Bayesian random forests.

While the range of classification models is diverse, some of them are similar to one another:
Table 8. Frequency of Classification Model Usage for Evaluating Bias Mitigation Methods

| Model            | Unique | Pre | In  | Post |
|------------------|--------|-----|-----|------|
| Logistic Regression | 140    | 58  | 80  | 19   |
| Neural Network   | 102    | 34  | 65  | 17   |
| Random Forest    | 45     | 20  | 22  | 14   |
| SVM              | 37     | 15  | 18  | 9    |
| Decision Tree    | 36     | 14  | 16  | 9    |
| Naive Bayes      | 24     | 12  | 11  | 5    |
| Linear Regression| 22     | 4   | 20  | 3    |
| Nearest Neighbor | 13     | 7   | 2   | 5    |
| AdaBoost         | 8      | 1   | 5   | 4    |
| XGBoost          | 8      | 1   | 6   | 1    |
| Causal           | 7      | 2   | 6   | 1    |
| LightGBM         | 4      | 2   | 3   | 0    |
| Bandit           | 3      | 0   | 2   | 2    |
| Boosting         | 3      | 0   | 2   | 2    |
| J48              | 2      | 1   | 1   | 0    |
| Bayesian         | 2      | 0   | 1   | 1    |
| Hoeffding Tree   | 2      | 1   | 1   | 0    |
| Gaussian Process | 2      | 2   | 0   | 0    |
| CPAR             | 1      | 0   | 0   | 1    |
| RIPPER           | 1      | 1   | 0   | 0    |
| PART             | 1      | 1   | 0   | 0    |
| C4.5             | 1      | 1   | 0   | 0    |
| CBA              | 1      | 0   | 1   | 0    |
| Lattice          | 1      | 1   | 1   | 1    |
| SMOTEBoost       | 1      | 0   | 1   | 0    |
| Gradient boosted trees | 1  | 1 | 0 | 1 |
| Cox model        | 1      | 0   | 1   | 0    |
| Decision Rules   | 1      | 0   | 1   | 0    |
| Gradient Tree Boosting | 1  | 0 | 1 | 0 |
| Kmeans           | 1      | 0   | 1   | 0    |
| OSBoost          | 1      | 0   | 1   | 0    |
| POEM             | 1      | 0   | 1   | 0    |
| Markov random filed | 1    | 0 | 1 | 0 |
| MSGDGA           | 1      | 0   | 1   | 0    |
| Probabilistic circuits | 1 | 0 | 1 | 0 |
| Rule Sets        | 1      | 0   | 1   | 0    |
| Ridge Regression | 1      | 0   | 1   | 1    |
| Extreme Random Forest | 1 | 0 | 1 | 0 |
| Factorization Machine | 1 | 1 | 0 | 0 |
| Discriminant analysis | 1 | 0 | 1 | 0 |
| Generalized Linear Model | 1 | 0 | 1 | 0 |

Amounts are provided for each category and as a unique measure to avoid counting publications with multiple approaches double.

Fig. 4. Number of classification models (clf) used for evaluation.

— Boosting: AdaBoost, XGBoost, SMOTEBoost, Boosting, LightGBM, OSBoost, Gradient Tree Boosting, CatBoost;
— Rule-based: RIPPER, PART, CBA, Decision Set, Rule Sets, Decision Rules.

Figure 4 illustrates the number of different classification models considered during experiments. It is clear to see that the majority of publications (70%) applied their bias mitigation method to only one classification model. While in-processing methods are model-specific and directly modify the training procedure, pre-processing and most post-processing bias mitigation methods can be developed independently from the classification models they are used for. Therefore, they can be devised once and applied to multiple classification models for evaluating their performance. Our
observations confirm this intuition: Only 24% of publications with in-processing methods consider more than one classification model, while 35% and 43% of pre- and post-processing methods consider more than one, respectively.

5 DATASETS

In this section, we investigate the use of datasets for evaluating bias mitigation methods. Among these datasets, some have been divided into multiple subsets (e.g., risk of recidivism or violent recidivism, medical data for different time periods). For clarity, we treat data from the same source as a single dataset.

Following this procedure, we gathered a total of 83 unique datasets. We discuss these datasets in Section 5.1 (e.g., what is the most frequently used dataset?) and Section 5.2 (e.g., how many datasets do experiments consider?). Additionally, 56 publications created synthetic or semi-synthetic datasets for their experiments. Section 5.3 provides information on the creation of such synthetic data.

For further details on datasets, we refer to Le Quy et al. [219], who surveyed 15 datasets and provided detailed information on the features and dataset characteristics. Additionally, Kuhlman et al. [212] gathered 22 datasets from publications published in the ACM Fairness, Accountability, and Transparency (FAT) Conference and 2019 AAAI/ACM Conference on Artificial Intelligence, Ethics, and Society (AIES). Fairness datasets for a variety of domains (e.g., health, linguistics, social sciences, computer vision) can be found in the web app by Fabris et al. [115].

5.1 Dataset Usage

In this section, we investigate the frequency with which each dataset set has been used. The purpose of this analysis is to highlight the importance of each dataset and recommend the most important datasets to use for evaluating bias mitigation methods. For this purpose, we consider 324 of the 341 publications, as only these 324 publications perform empirical experiments. The remaining publications do not present any empirical experiment and thus do not consider any dataset.

Among the 83 datasets, 2 are concerned with synthetic data (i.e., “synthetic” and “semi-synthetic”), which we address in Section 5.3. Therefore, we are left with 81 datasets; 59% of the datasets (48 out of 81) are used only once during experiments. Another 14% of the datasets (11 out of 81) are used twice. Thereby, 73% of the datasets (59 out of 81) are used rarely (by one or two publications).

Table 9 lists the frequency of the remaining 22 datasets (used in three or more publications). A list of all datasets can be found in our online repository [25]. In addition to the frequency, a percentage is provided (i.e., how many of the 324 publications use this dataset). Among all datasets, the Adult dataset is used most frequently (by 77% of the publications). While the Adult dataset contains information from the 1994 US census, Ding et al. [99] derived new datasets from the US census from 2014 to 2018.

Five other datasets are used by 10% or more of the publications (COMPAS, German Communities and Crime, Bank, Law School). This shows that to enable a simple comparison with existing work, one should consider at least the Adult and COMPAS dataset. However, these two datasets have recently received some criticism for their use as benchmark datasets and suitability as real-world datasets. For instance, the Adult dataset applies a binary label to determine whether an individual has an income above 50,000 USD. Ding et al. [99] showed that the fairness of ML models and bias mitigation methods is depending on the income threshold, thereby potentially limiting the external validity of the Adult dataset for benchmarking. Bao et al. [32] addressed the use of the Risk

4http://fairnessdata.dei.unipd.it/
Table 9. Frequency of Widely Used Datasets

| Dataset Name                                   | Frequency | Percentage |
|------------------------------------------------|-----------|------------|
| Adult [107]                                    | 249       | 77%        |
| COMPAS [24]                                    | 166       | 51%        |
| German [107]                                   | 97        | 30%        |
| Communities and Crime [303]                    | 42        | 13%        |
| Bank [265]                                     | 38        | 12%        |
| Law School [364]                               | 33        | 10%        |
| Default [379]                                  | 24        | 7%         |
| Dutch Census [1]                               | 16        | 5%         |
| Health [3]                                     | 14        | 4%         |
| MEPS [2]                                       | 14        | 4%         |
| Drug [117]                                     | 9         | 3%         |
| Student [84]                                   | 8         | 2%         |
| Heart disease [107]                            | 7         | 2%         |
| National Longitudinal Survey of Youth [6]      | 6         | 2%         |
| SQF [4]                                        | 5         | 2%         |
| Arrhythmia [107]                               | 5         | 2%         |
| Wine [83]                                      | 4         | 1%         |
| Ricci [339]                                    | 4         | 1%         |
| University Anonymous (UNIV)                    | 3         | 1%         |
| Home credit [5]                                | 3         | 1%         |
| ACS [99]                                       | 3         | 1%         |
| MIMICIII [174]                                 | 3         | 1%         |

(i.e., used in at least three publications).

Assessment Instrument (RAI) datasets, in particular the COMPAS dataset, for benchmarking ML fairness. They outlined that the use of such datasets should consider domain context, rather than using them as a generic example to show the real-world performance of bias mitigation methods.

5.2 Dataset Frequency

In addition to detecting the most popular datasets for evaluating bias mitigation methods, we investigate the number of different datasets used, as this impacts the diversity of the performance evaluation [212]. Figure 5 visualizes the number of datasets used for each of the 324 publications.
The most commonly used number of datasets considered for experiments is 2, which has been observed in 104 out of 324 of the publications. Overall, it can be seen that the number of considered datasets is relatively small (90% of the publications use 4 or fewer datasets), with an average of 2.7 datasets per publication. Two publications stand out in particular, with 9 datasets (Chakraborty et al. [60]), and 11 datasets (Do et al. [102]), respectively. In accordance with existing work, new publications should evaluate their bias mitigation methods on 3 datasets and, if possible, more. Hereby, it can be of interest to consider a diverse range of datasets based on application domains, dimensionality, or protected attributes [219].

5.3 Synthetic Data

In addition to the 81 existing datasets for experiments, 54 publications created synthetic datasets to evaluate their bias mitigation method. Moreover, we found three publications that use semi-synthetic data (i.e., modify existing datasets to be applicable for evaluating bias mitigation methods) in their experiments [110, 201, 245].

The created datasets range from hundreds of data points [98, 145, 216, 274] to 100,000 and above [96, 148, 164, 388]. While the sampling procedures are well described, some publications do not state the dataset size used for experiments [29, 75, 134, 136, 203, 248, 255, 393].

As exemplary data creation procedure, we briefly outline the data generation approach applied by Zafar et al. [387], as it is the most frequently adapted approach by other publications [200, 203, 233, 280, 307–309, 386]. In particular, Zafar et al. [387] generated 4,000 binary class labels. These are augmented with 2-dimensional user features that are drawn from different Gaussian distributions. Last, the sensitive attribute is drawn from a Bernoulli distribution.

5.4 Data-split

In this section, we analyze whether existing publications provided information on the data-splits, in particular what sizing has been chosen. Moreover, we investigate how often experiments have been repeated with such data splits to account for training instability [123], therefore improving the conclusion validity of a study [293]. Our focus lies on the data-splits used when evaluating the bias mitigation methods (e.g., we are not interested in data-splits that are applied prior for hyperparameter tuning of classification models [51, 87, 155, 197, 216, 225, 275, 331, 376]).

Among the 324 publications that carry out experiments, 232 provide information on the data-split used and 143 provide information on the number of runs (different splits) performed. The high amount of publications that do not provide information on the data-split sizes could be explained by the fact that some of the 81 datasets provided default splits. For example, the Adult dataset has a pre-defined train-test split of 70%–30%, and Cotter et al. [85] used designated data splits for 4 datasets.

A widely adopted approach for addressing data-splits for applying bias mitigation methods is k-fold cross-validation. Such methods divide the data in k partitions and use each part once for testing and the remaining k – 1 partitions for training. Overall, 47 publications applied cross-validation: 10-fold (23 times), 5-fold (21 times), 3-fold (twice), 20-fold (once), and once without specification of k [131].

If the data-splits are not derived from k-folds, then the most popular sizes (i.e., train split size–test split size) are 80%–20% (39 times) and 70%–30% (35 times) followed by 67%–33% (16 times), 50%–50% (11 times), 60%–40% (5 times), and 75%–25% (5 times). In addition to these regular-sized data-splits, there are 23 publications that divide the data into very “specific” splits. For example, Quadrianto et al. [295] divided the Adult dataset into 28,222 training, 15,000 and 2,000 validation instance. Another example is the work by Liu and Vicente [233], who chose 5,000 training instances at random, using the remaining 40,222 instances for testing.
Once the data is split in training and testing data, experiments are repeated 10 times in 54 out of 143 and 5 times in 42 out of 143 cases. The most repetitions are performed in the work by da Cruz [90], who trained 48,000 models per dataset to evaluate different hyperparameter settings.

We have found 16 publications that use different training and test splits for experiments on multiple datasets. Reasons for that can be found in the stability of bias mitigation methods when dealing with a large amount of training data [35].

While most publications split the data in two parts (i.e., training and test split), there are 36 publications that use validation splits as well. The sizes for validation splits range from 5% to 30%, whereas the most common split uses 60% training data, 20% testing data, and 20% validation data. Furthermore, Mishler and Kennedy [258] allow for a division of the data in up to five different splits for evaluating their ensemble learning procedure.

Bias mitigation methods that process data in a streaming [162, 164, 329, 401, 402], federated learning [7, 114, 152, 284, 292], multi-source [158], sequential [20, 301, 409, 410] fashion need to be addressed differently, as they use small subsets of the training data instead of using all at once.

### 6 FAIRNESS METRICS

Fairness metrics play an integral part in the bias mitigation process. First they are used to determine the degree of bias a classification model exhibits before applying bias mitigation methods. Afterwards, the effectiveness of bias mitigation methods can be determined by measuring the same metrics after the mitigation procedure. In particular, this section focuses on metrics used for measuring bias, rather than general notions of fairness such as Fairness through Unawareness (i.e., not using the protected attribute).

Recent fairness literature has introduced a variety of different fairness metrics that each emphasize different aspects of classification performance.

To provide a structured overview of such a large amount of metrics, we devise metric categories and take into account the classifications by Caton and Haas [52] and Verma and Rubin [350]. Overall, we categorize the metrics used in the 341 publications in six categories, which are defined based on labels in dataset, predicted outcome, predicted and actual outcomes, predicted probabilities and actual outcome, similarity, causal reasoning.

In the following, we provide information on how these metric types have been used. In total, we found 109 unique metrics that have been used by the 324 publications that performed experiments. Most publications consider a binary setting (i.e., two populations groups and two class labels for prediction), whereas fairness has also been measured for non-binary sensitive attributes [16, 54, 57, 327, 392] and multi-class predictions [16, 19].

While some of the categories only contain a few different metrics (definitions based on labels in dataset, on predicted probabilities and actual outcome, and on similarity all have 13 or fewer different metrics); definitions based on predicted outcome have 22, definitions based on predicted and actual outcomes have 31, and definitions based on Causal Reasoning 27 different metrics. Therefore, we outline the most frequently used metrics for definitions based on predicted and actual outcomes and definitions based on causal reasoning.

On average, publications consider two fairness metrics when evaluating bias mitigation methods, with 45% of the publications only using one fairness metric. The most frequently used metrics are outlined in Table 10, while listing at least one metric per category. For detailed explanations of fairness metrics, we refer to Verma and Rubin [350].

In addition to quantifying the bias according to prediction tasks, we found metrics that determined fairness in accordance with feature usage (e.g., do users think this feature is fair [139]) and quality of representations [254, 320, 335] (see Section 4.1.4).
### Table 10. Popular Fairness Metrics

| Name                              | Section | # | Description                                                                 |
|-----------------------------------|---------|---|-----------------------------------------------------------------------------|
| Statistical Parity Difference     | 6.2     | 136 | Difference of positive predictions per group                                |
| Equality of Opportunity           | 6.3     | 91  | Equal TPR per population groups                                             |
| Disparate Impact, P-rule          | 6.2     | 60  | Ratio of positive predictions per group                                     |
| Equalized Odds                    | 6.3     | 51  | Equal TPR and FPR per population groups                                     |
| False Positive Rate               | 6.3     | 38  | False positive rate difference per group                                    |
| Accuracy Rate Difference          | 6.3     | 29  | Difference of prediction accuracy per group                                 |
| Causal Discrimination             | 6.5     | 7   | Different predictions for identical individuals except for protected attribute |
| Mean Difference                   | 6.1     | 6   | Difference of positive labels per group in the datasets                     |
| Mutual information                | 6.6     | 4   | Mutual information between protected attributes and predictions             |
| Strong Demographic Disparity      | 6.4     | 1   | Demographic parity difference over various decision thresholds              |

At least one metric for each category is provided.

**Notations.** To provide equations of fairness metrics, we use the following notation:
- $S$: sensitive attribute to divide populations in two groups ($s_1$, $s_2$).
- $y$: Ground truth label.
- $\hat{y}$: Predicted label (or probability, Section 6.4).
- $Pr$: Probability.
- $D$: Dataset, with $N$ instances.

#### 6.1 Definitions Based on Labels in Dataset

Fairness definition based on the dataset labels, also known as “dataset metrics,” are used to determine the degree of bias in an underlying dataset [36]. One purpose of datasets metrics is to determine whether there is a balanced representation of privileged and unprivileged groups in the dataset. This is particularly useful for pre-processing bias mitigation methods, as they are able to impact the data distribution of the training dataset.

Most frequently, datasets metrics are used to measure the disparity in positive labels for population groups, such as **Mean Difference (MD)**, elift and slift [264], defined as follows:

$$MD = Pr(y = 1|S = s_1) - Pr(y = 1|S = s_2)$$

$$elift = e^{-\epsilon} \leq \frac{Pr(y = 1|S = s)}{Pr(y = 1)} \leq e^\epsilon, \forall s \in S$$

$$slift = e^{-\epsilon} \leq \frac{Pr(y = 1|S = s)}{Pr(y = 1|S = s')} \leq e^\epsilon, \forall s, s' \in S.$$

elift and slift are parameterized by $\epsilon$, which allows for an easy comparison of bias between different classification models by contrasting the magnitude of their $\epsilon$ values. Perfect fairness is achieved by $\epsilon = 0$. Among these, MD is the most popular metric, used in six publications.

#### 6.2 Definitions Based on Predicted Outcome

Definitions based on predicted outcome, or “Parity-based” metrics, are used to determine whether different population groups receive the same degree of favor. For this purpose, only the predicted outcome of the classification needs to be known.

The most popular approach for measuring fairness according to predicted outcome is the concept of **Demographic Parity**, which states that privileged and unprivileged groups should receive an equal proportion of positive labels. This can be done as by computing their difference (Statistical Parity Difference) or their ratio (Disparate Impact). Similar to Disparate Impact, the
p-rule compares two ratios of positive labels ($group_1 / group_2$, $group_2 / group_1$) and among those two ratios, the minimum value is chosen. The mathematical definition of these metrics is given below:

Statistical Parity Difference (SPD) = $Pr(\hat{y} = 1 | S = s_1) - Pr(\hat{y} = 1 | S = s_2)$

Disparate Impact (DI) = $\frac{Pr(\hat{y} = 1 | S = s_1)}{Pr(\hat{y} = 1 | S = s_2)}$

P-rule = $\min \left( \frac{Pr(\hat{y} = 1 | S = s_1)}{Pr(\hat{y} = 1 | S = s_2)}, \frac{Pr(\hat{y} = 1 | S = s_2)}{Pr(\hat{y} = 1 | S = s_1)} \right)$.

If the direction of bias is of no interest (i.e., it is not important which group receives a favorable treatment), then the absolute bias values can be considered [94, 289, 290, 297]. While it is possible to compute fairness metrics based on differences as well as ratios between two groups, both of which have been applied in the past, Žliobaite [417] advised against ratios, as they are more challenging to interpret.

### 6.3 Definitions Based on Predicted and Actual Outcomes

Definitions based on predicted and actual outcomes are used to evaluate the prediction performance of privileged and unprivileged groups (e.g., is the classification model more likely to make errors when dealing with unprivileged groups?). Similar to definitions based on predicted outcomes, the rates for privileged and unprivileged groups are compared.

Frequently, metrics based on predicted and actual outcomes are computed from combinations of confusion matrix measures (i.e., True Positives (TP), False Positives (FP), False Negatives (FN), True Negatives (TN)), as follows:

True Positive Rate (TPR) = $\frac{TP}{TP + FN}$,

False Positive Rate (FPR) = $\frac{FP}{FP + TN}$,

False Negative Rate (FNR) = $\frac{FN}{FN + TP}$,

True Negative Rate (TNR) = $\frac{TN}{TN + FP}$,

Positive Predictive Rate (PPR) = $\frac{TP}{TP + FP}$,

Negative Predictive Rate (NPR) = $\frac{TN}{TN + FN}$,

False Discovery Rate (FDR) = $\frac{FP}{TP + FP}$.

The most popular metric of this type is Equality of Opportunity (used 90 times), followed by Equalized odds (used 52 times). While Equality of Opportunity is satisfied when population groups have equal TPR, Equalized odds is satisfied if population groups have equal TPR and FPR. An average score of TPR and FPR is provided by the Average Odds Difference. The formal definition of these metrics is shown below:

Equality of Opportunity = $TPR_{S=s_1} - TPR_{S=s_2}$,

Equalized Odds = $\left( FPR_{S=s_1} - FPR_{S=s_2} \right) + (TPR_{S=s_1} - TPR_{S=s_2})$,

Average Odds = $\frac{1}{2} \left( FPR_{S=s_1} - FPR_{S=s_2} \right) + (TPR_{S=s_1} - TPR_{S=s_2})$.
In addition to evaluating fairness in according to the confusion matrix (FPR - 38 times, TNR - 8 times), the accuracy rate (i.e., difference in accuracy for both groups) has been used 29 times. Moreover, conditional TNR and TPR have been evaluated [317, 319] and one can compare populations groups with regards to performance metrics, such as precision, recall, F1, and Area Under Curve.

### 6.4 Definitions Based on Predicted Probabilities and Actual Outcome

While Section 6.3 detailed metrics based on actual outcomes and predicted labels, this Section outlines metrics that consider predicted probabilities instead.

Jiang et al. [170] proposed **Strong Demographic Disparity (SDD)** and **Strong Pairwise Demographic Parity (SPDD)**, which are parity metrics computed over a variety of thresholds (i.e., prediction tasks apply a threshold of 0.5 by default):

$$\text{Strong Pairwise Demographic Parity (SPDD)} = \mathbb{E}_{\tau \sim U(\Omega)} |\Pr(\hat{y} > \tau | S = s_1) - \Pr(\hat{y} > \tau | S = s_2)|,$$

where $\mathbb{E}_{\tau \sim U(\Omega)}$ denotes the expectation over all possible thresholds $\tau$, uniformly sampled from all possible prediction outcomes $U(\Omega)$.

Chzhen et al. [80] also varied thresholds to compute the Kolmogorov-Smirnov distance. Heidari et al. [147] measured fairness based on positive and negative residual differences. Agarwal et al. [12] computed a **Bounded Group Loss (BGL)** to minimize the worst loss of any group, according to least squares.

Another notion of fairness based on predicted probabilities and actual outcomes is calibration [291]. Calibration describes a scenario where predicted probabilities have a semantic meaning; for example, if 100 individuals receive a prediction of 0.75, then 75 of them should have a positive label (i.e., a label of 1). Zhang and Weiss [404, 405] proposed the use of a related metric with **fair calibration (FC)**. FC first sorts predicted probabilities for each subgroup and divides them in 10 equally sized bins (e.g., 100 instances would result in 10 bins of 10 individuals). It is then evaluated whether the 10 bins of each population group are calibrated and in a second stage whether differences between predictions and actual outcomes are consistent across population groups. FC then generates a binary result, whether the model is fairly calibrated or not.

### 6.5 Definitions Based on Similarity

Definitions based on similarity are concerned with the fair treatment individuals. In particular, it is desired that individuals that exhibit a certain degree of similarity receive the same prediction outcome. For this purpose, different similarity measures have been applied. The most popular similarity metric used is **consistency** or **inconsistency** (used in four and one publications, respectively) [390]. **Consistency** compares the prediction of an individual with the k-nearest-neighbors according to the input space [390]:

$$\text{Consistency} = 1 - \frac{1}{Nk} \sum_n |\hat{y}_n - \sum_{j \in kNN(x_n)} \hat{y}_j|.$$

Luong et al. [242] also utilized k-nearest-neighbors to investigate the difference in predictions for different values of $k$.

Similarities between individuals have been computed according to $\ell_\infty$-distance [314] and Euclidean distance with weights for features [390]. Individuals have also been treated as similar if they have equal labels [37], are equal except for sensitive features, or based on predicted labels [349].
If similarity of individuals is determined solely by differences in sensitive features, then one is speaking of "causal discrimination" [237, 416].⁵

In contrast to determining similarity computationally, Jung et al. [178] allowed stakeholders to judge whether two individuals should receive the same treatment.

Moreover, Ranzato et al. [300] considered four types of similarity relations (Noise, CAT, Noise-CAT, conditional-attribute) when dealing with numerical and categorical features. Verma et al. [349] considered two types of similarities: input space (identical on non-sensitive features), output space (identical prediction). Lahoti et al. [216] built a similarity graph to detect similar individuals. This graph is built based on pairwise information on individuals that should be treated equally with respect to a given task.

### 6.6 Causal Reasoning

Fairness definitions based on causal reasoning take causal graphs in account to evaluate relationships between sensitive attributes and outcomes [350].

For example, Counterfactual fairness states that a causal graph is fair if the prediction does not depend on descendants of the protected attribute [213]. This definition has been adopted by four publications. Moreover, the impact of protected attributes on the decision has been observed in two ways: direct and indirect prejudice [399]. Direct discrimination occurs when the treatment is based on sensitive attributes. Indirect discrimination results in biased decision for population groups based on non-sensitive attributes, which might appear to be neutrals. This could occur due to statistical dependencies between protected and non-protected attributes.

Direct and indirect discrimination can be modeled based on the causal effect along paths taken in causal graphs [399]. To measure indirect discrimination, Prejudice Index (PI) or Normalized Prejudice Index (NPI) have been applied four times [189]. NPI quantifies the mutual information between protected attributes and predictions. The mathematical definition of these measures follow:

$$PI = \sum_{y,s \in D} Pr(y,s) \ln \frac{Pr(y,s)}{Pr(s)Pr(y)}$$

$$NPI = \frac{PI}{(\sqrt{H(Y)H(S)})}.$$

Here, \(H(X)\) is defined as the entropy function \(-\sum_{x \in D} Pr(x)\ln Pr(x)\).

Mutual information has also been used to determine the fairness of representations [266, 335]. Similar to determining the degree of mutual information between sensitive attributes and labels, the ability to predict sensitive information based on representations has been used in nine publications.

### 7 BENCHMARKING

After establishing on which datasets bias mitigation methods are applied, and which metrics are used to measure their performance (Section 6), we investigate how they have been benchmarked.

Benchmarking is important for ensuring the performance of bias mitigation methods. Nonetheless, we found 15 out of 324 publications that perform experiments but do not compare results with any type of benchmarking (i.e., out of the 341 publications, 324 perform experiments, among which 308 perform benchmarking). Therefore, the remaining section addresses 308 publications that: (1) perform experiments; (2) apply benchmarking.

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⁵Some publications refer to this as "Counterfactual fairness" [261, 382, 383], but we follow the guidelines of Verma and Rubin [350] and treat counterfactual fairness as a Causal metric.
For each bias mitigation category (i.e., pre-, in-, or post-processing), we count the type of benchmarking methods.

### 7.1 Baseline

To determine whether bias mitigation methods are able to reduce effectively, different types of baselines have been used. We use the term “baseline” to describe simple methods for benchmarking, which can be applied as a basic yet necessary check to determine whether a bias mitigation method is effective. Unlike methods presented in Section 7.2 and Section 7.3, these are not based on existing methods from the 341 publications.

The most general baseline is to compare the fairness achieved by classification models after applying a bias mitigation method with the fairness of a fairness-agnostic *Original Model*. If a method is not able to exhibit an improved fairness over a fairness-agnostic classification model, then it is not applicable for bias mitigation. Given that this is the minimum requirement for bias mitigation methods, it is the most frequently used baseline (used in 254 out of 308 experiments).

Another baseline method is *suppressing*, which performs a naive attempt of mitigating bias by removing the protected attribute from the training data. However, it has been found that solely removing protected attributes does not remove unfairness [47, 283], as the remaining features are often correlated with the protected attribute. To combat this risk, Kamiran et al. [186] suppressed not only the sensitive feature but also the k-most correlated ones. Suppressing has been used in 30 out of 308 experiments.

Random baselines constitute more competitive baselines than solely suppressing the protected attribute. Bias mitigation methods that outperform random baselines show that they are not only able to improve fairness but also able to perform better than naive methods. Random baselines have been used in 13 out of 308 experiments.

Moreover, we found four publications that considered a constant classifier for benchmarking (i.e., a classifier that returns the same label for every instance) [203, 260, 266, 359]. This serves as a fairness-aware baseline, as every individual and population group receives the same treatment [151].

### 7.2 Benchmarking against Bias Mitigation Methods

In addition to baselines, we investigate how methods are benchmarked against other, existing bias mitigation methods. In particular, we are interested in which methods are popular, how many bias mitigation methods are used for benchmarking, and to what category these methods belong.

At first, we investigate what type of bias mitigation methods are considered for benchmarking (e.g., are pre-processing methods more likely to benchmark against other pre-processing methods or in-/post-processing methods). Table 11 illustrates the results. In particular, # shows how many unique publications propose a given type of bias mitigation method (i.e., there are 114 publications with pre-processing methods). For each of these methods, we determine whether they benchmark against pre-, in- or post-processing methods. If no benchmarking against other bias mitigation methods is performed, then we count this as “None.”
We find that pre-processing methods are the most likely to not benchmark against other bias mitigation methods at 44% (50 out of 114); 36% (66 out of 184) of in-processing methods and 31% (16 out of 52) of post-processing methods do not benchmark against other bias mitigation methods. Furthermore, we can see that each bias mitigation type is more likely to benchmark against methods of the same type.

In addition to detecting the type of bias mitigation methods for benchmarking, we are interested in what approaches in particular are used for benchmarking. Therefore, we count how often each of the 341 bias mitigation methods we gathered have been used for benchmarking.

Overall, 137 bias mitigation methods have been used as a benchmark by at least one other publication. Figure 6 illustrates the most frequently used bias mitigation methods for benchmarking.

Among the 18 listed methods, all of which are used for benchmarking by at least eight other publications, eight are pre-processing, nine in-processing, and four post-processing. Notably, the five most-frequently used methods include each of the three types: sampling and relabeling for pre-processing [185], constraints [384, 387], and adversarial learning [393] for in-processing, and classifier modification for post-processing [144].

### 7.3 Benchmarking against Fairness-unaware Methods

In addition to benchmarking against existing bias mitigation methods, practitioners can use other methods for benchmarking, which are not designed for taking fairness into consideration. Overall, we found 51 publications that use fairness-unaware methods for benchmarking (i.e., using a general data augmentation method to benchmark fairness-aware resampling).

Table 12 shows the publications that benchmark their proposed method against at least one fairness-unaware method, according to the type of approach applied. Among the 13 types of approaches, as shown in Sections 4.1–4.3, 7 can be found to benchmark against fairness-unaware methods. This occurs rarely for post-processing methods, six publications in total, with at least
Table 12. Publications that Benchmark against at Least One Fairness-unaware Method

| Type     | Category | Section | References |
|----------|----------|---------|------------|
| Pre      | Sampling | 4.1.2   | Abusitta et al. [8], Celis et al. [36], Cruz et al. [89], Xu et al. [375] |
|          |          |         | Du and Wu [105], Roh et al. [309], Xu et al. [372], Yan et al. [376] |
|          |          |         | Dablain et al. [91], Pentyala et al. [284], Zhang et al. [401] |
|          |          |         | Balunović et al. [30], Galhotra et al. [126], Oh et al. [273], Qi et al. [292] |
|          |          |         | Jaiswal et al. [166], Lahoti et al. [215], Sarhan et al. [321], Shui et al. [330] |
|          |          |         | Representation 4.1.4 Creager et al. [88], Gupta et al. [141], Louizos et al. [238], Salazar et al. [317] |
|          |          |         | Dablain et al. [91], Pentyala et al. [284], Zhang et al. [401] |
|          |          |         | Balunović et al. [30], Galhotra et al. [126], Oh et al. [273], Qi et al. [292] |
|          |          |         | Jaiswal et al. [166], Lahoti et al. [215], Sarhan et al. [321], Shui et al. [330] |
|          |          |         | In Regularization 4.2.1 Jiang et al. [171], Liu et al. [234], Wang et al. [356], Zhang and Weiss [404, 405] |
|          |          |         | Constraints 4.2.1 Ding et al. [100], Du and Wu [105], Zhang et al. [394], Zhao et al. [409] |
|          |          |         | Adversarial 4.2.2 Lahoti et al. [214], Roh et al. [307], Sadeghi et al. [316], Xu et al. [375] |
|          |          |         | Rezaei et al. [305], Yazdani-Jahromi et al. [378] |
|          |          |         | Candelieri et al. [51], Sharma et al. [327], Wang et al. [353], Zhang et al. [401] |
|          |          |         | Lee et al. [222], Maheshwari and Perrot [247], Zhao et al. [410] |
|          |          |         | Adjusted 4.2.4 Cruz et al. [89], Iosifidis and Ntoutsi [162], Liu et al. [234], Luo et al. [241] |
|          |          |         | Post Input 4.3.1 Adler et al. [10] |
|          |          |         | Classifier 4.3.2 Mehrabi et al. [255], Wu and He [370] |
|          |          |         | Output 4.3.3 Alabdulmohsin and Lucic [17], Kamiran et al. [188], Pentyala et al. [284] |

one per approach type. A total of 23 and 27 publications for pre-processing and in-processing methods, respectively, benchmark against fairness-unaware methods.

7.4 Source Code Availability

To investigate whether existing work allows for reproducibility of the results and ease of use for benchmarking, we reviewed whether the 341 surveyed publications shared source code. Specifically, we have collected links to implementations from the publications directly. If no link was available, then we performed a Google search to check for resources we might have missed. With this additional search, we were able to find 64 implementations. Overall, we found 192 publications with available source code (56% of the 341 publications).  

For each publication, we searched for "paper title" and "paper title github" and checked the first page of search results for links to external resources.
Figure 7 illustrates the proportion of publications that publicly shared the source code used in their study, per year. Early years (2009–2016) show a high variation in the proportion of publications with source code available, ranging from 17% to 67%. Such a variation is caused by the small number of publications. In 2018 and 2019, the proportion of publications with shared source code is below 50%, 46%, and 49%, respectively. The most recent years showed an increase in shared implementations, with the maximum achieved in 2020 with 71% of the publications to share source code.

Moreover, we examined existing surveys for frameworks providing implementations of bias mitigation methods [52, 68, 108, 223, 256, 288, 336] and found three frameworks that do so: Themis-ML [31], AIF 360 [36], FairLearn [42]. In total, Themis-ML [31] implements bias mitigation from 3 publications, FairLearn [42] implements 4 methods, and AIF 360 [36] implements 13 methods.7

While our focus lies on the sharing and reuse of bias mitigation methods, datasets are also an important resource to share to allow for reproducibility. Many datasets are already publicly available, however, some datasets are proprietary and cannot be shared publicly. Where available, we provide links to datasets and source code implementations in our online repository [25].

8 CHALLENGES AND OPPORTUNITIES

This section provides further discussion and insights on the surveyed publications. We outline several challenges, based on the current literature, as well as discuss research opportunities for the creation and evaluation of new bias mitigation methods.

8.1 Challenges

Research on bias mitigation is fairly young and does therefore enable challenges and opportunities for future research. Here, we highlight five challenges that we extracted from the collected publications, which call for future action or extension of current work.

8.1.1 Fairness Definitions. A variety of different metrics has been proposed and used in practice (see Section 6), which can be applied to different use cases. However, with such a variety of metrics, it is difficult to evaluate bias mitigation on all and ensure their applicability. Consolidating a common set of metrics to use is still an open challenge [91, 128, 256], as can be seen by the use of 109 different fairness metrics in the literature, as discussed in Section 6. While consolidating existing fairness notions is one problem, it is also relevant to ensure that the used metrics are representative for the problem at hand [33, 322]. Often, this means evaluating fairness in a binary classification problem for two population groups. While this can be the correct way to model fairness scenarios,

7 1st of March 2023.
it is not sufficient to handle all cases, such that future work should focus on multi-class problems [55, 155, 185, 261, 264], and non-binary sensitive attributes, which was mentioned by only 15 publications [16, 28, 49, 55, 118, 119, 137, 183, 185, 189, 195, 257, 289, 302, 347].

Other challenges regarding metrics include the tradeoffs when dealing with accuracy and/or multiple fairness metrics [11, 52, 272, 287], as well as the allowance of some degree of discrimination as long it as explainable (e.g., enforcing a fairness criteria completely could lead to unfairness in another) [49, 184, 185, 390].

8.1.2 Fairness Guarantees. Guarantees are of particular importance when dealing with domains that fall under legislation and regulatory controls [118, 189]. Thereby, it is not always sufficient to establish the effectiveness of a bias mitigation method based on the performance on the test set without any guarantees. Fairness guarantees can help in this situation by providing performance guarantees with regards to a specific fairness metric and bound the degree of bias [53, 177]. In particular, Dunkelau and Leuschel [108] pointed out that most bias mitigation methods are evaluated on test sets, and their applicability to real-world tasks depends on whether the test set reliably represents reality. If that is not the case, then fairness guarantees could ensure that bias mitigation methods are able to perform well with respect to a given fairness metric and unknown data distributions. Therefore, eight publications considered fairness guarantees as a relevant avenue of future work. Similarly, allowing for interpretable and explainable methods can aid in this regard [173, 189, 295, 366].

8.1.3 Datasets. Another challenge that arises when applying bias mitigation methods is the availability and use of datasets. The most pressing concern is the reliability and access to protected attributes, which was mentioned in nine publications, as this information is often not available in practice [149].

Moreover, it is not guaranteed that the annotation process of the training data is bias-free [144]. If possible, then an unbiased data collection should be enforced [294]. Other options are the debiasing of ground truth labels [381, 416] or use of expert opinions to annotate data [104]. If feasible, then more data can be collected [66, 173], which is difficult from a research perspective, as commonly, existing and public datasets are used without the chance to manually collect new samples.

Besides, the variety of protected attributes addressed in previous experiments, as found by Kuhlman et al. [212], is lacking diversity, with the majority of cases considering race and gender only. In practice, “collecting more training data” is the most common approach for debiasing, according to interviews conducted by Holstein et al. [149]. However, an interviewee questioned whether such a fairness intervention is fair, as the targeting of subgroups for additional data collection may be a biased procedure.

8.1.4 Real-world Applications. While the experiments are conducted on existing, public datasets, it is not clear whether they can be transferred to real-world applications without any adjustments. For example, Hacker and Wiedemann [142] see the challenge of data distributions changing over time, which would require continuous implementations of bias mitigation methods.

Moreover, developers might struggle to detect the relevant population groups to consider when measuring and mitigating bias [149], whereas the datasets investigated in Section 5 often simplify the problem and already provide binarized protected attributes (e.g., in the COMPAS, six “demographic” categories are transformed to “Caucasian” and “not Caucasian” [36]). Therefore, Martinez et al. [252] stated that automatically identifying sub-populations with high-risk during the learning procedure as a field of future work.

Given the multitude of fairness metrics (as seen in Section 6), real-world applications could even suffer further unfairness after applying bias mitigation methods due to choosing incorrect
criteria [221]. Similarly, showing low bias scores does not necessarily lead to a fair application, as the choice of metrics could be used for “Fairwashing” (i.e., using fake explanations to justify unfair decisions) [23, 255]. Nonetheless, Sylvester and Raff [341] argue that considering fairness criteria while developing ML models is better than considering none, even if the metric is not optimal.

Sharma et al. [328] show the potential of user studies to not only provide bias mitigation methods that work well in a theoretical setting, but to make sure practitioners are willing to use them. In particular, they are interested in finding how comfortable developers and policy-makers are with regards to training data augmentation.

To facilitate the use and implementation of existing bias mitigation methods, metrics, and datasets, popular toolkits such as AIF360 [36] and FairLearn [42] can be used.

8.1.5 Extension of Experiments. Last, a challenge and field of future research is the extension of conducted experiments to allow for more meaningful results.

The most frequently discussed aspect of extending experiments is the consideration of further metrics (in 40 publications). Moreover, the usefulness of bias mitigation methods can be investigated when applied to additional classification models. This was pointed out by 12 publications. Given the 81 datasets that were used at least once, and on average 2.7 datasets used per publication, only eight publications see the consideration of further datasets as a useful consideration for extending their experiments [51, 62, 63, 90, 150, 211, 357, 376].

While the consideration of additional metrics, classification models, and datasets does not lead to changes in the training procedure and experimental design, there are also intentions to apply bias mitigation methods to other tasks and contexts, such as recommendations [195, 387], ranking [154, 189, 387], and clustering [189].

8.2 Research Opportunities

In the course of this survey, we have collected 341 publications with regards to various approaches for bias mitigation methods. This collection helps us understand which approaches have already been applied and allows us to outline some aspects that appear underexplored and provide opportunities for future research.

First, from the 341 publications we collected, it can be seen that in-processing methods are the most widely explored methods. There are almost twice as many publications with in-processing methods than pre-processing, and nearly four times as many in-processing methods than post-processing methods. Therefore, addressing post-processing bias mitigation method seems unexplored in contrast to the other two method types. In particular the modification of inputs in a post-processing stage has only been considered by two publications (Section 4.3.1) [10, 229]. However, this type of bias mitigation method could be further investigated without considerable effort by developing new methods, simply by applying existing pre-processing methods (Section 4.1) to the testing data.

Generally speaking, pre- and post-processing methods are classifier-agnostic and can be evaluated on a variety of classification models without modification to the underlying algorithm. Nonetheless, Bandits have been investigated with neither of these two method types, only by in-processing methods [130, 176, 177].

Moreover, the combination of pre- and post-processing methods has only been addressed four times [229, 284, 362, 400]. The number of classification models considered by these four publications range from 1 to 3. This is a promising combination of approaches, as one can perform experiments with bias mitigation methods at two different stages (i.e., before and after training) on various classification models and thereby collect extensive empirical evidence for fairness improvements. Additionally, we found several publications that applied multiple bias mitigation methods.
of the same type (e.g., two pre-processing methods). Six of these applied multiple pre-processing methods and 19 applied multiple in-processing methods (Table 7). However, we found no publication that applied multiple post-processing methods.

Last, our data collection shows that there exist a multitude of datasets and metrics, which can enable a rigorous evaluation of novel bias mitigation methods.

For one, bias mitigation methods can be evaluated on up to 81 datasets, whereas bias mitigation methods evaluated on three datasets exceed the average of 2.7 datasets used for evaluation. When applying bias mitigation methods to a dataset, it is important to mention the protected attributes considered and potential criticisms that could impact the ability to make claims about applicability for real-world systems [32, 99].

The 109 metrics used in the literature, thus far, are classified in six categories. Thereby, bias mitigation method can be evaluated by multiple metrics of a same category or multiple metrics from different categories. In addition to using fairness metrics to evaluate the performance of bias mitigation methods, performance metrics, such as accuracy, should be used to determine the fairness-accuracy tradeoff achieved when applying bias mitigation methods [151]. To ensure the competitiveness of results, methods must always be benchmarked against baselines as well as previous existing relevant methods, especially when their implementation is made publicly available (our survey highlights that 192 studies provided source code implementations, and as such they could be used as a benchmark for future proposals).

9 CURRENT BEST PRACTICES/RECOMMENDATIONS

In this section, we would like to outline current practices for the empirical evaluation of bias mitigation methods that we have observed from the 341 publications. However, we note that increasing the comprehensiveness of the empirical evaluation is always positive to support the validity of results (e.g., applying bias mitigation methods to a higher number of datasets or using more metrics for evaluation). Our recommendations, which will allow new experiments to be in line with prior experiments conducted, are as follows:

1. Check existing approaches to confirm the novelty of the bias mitigation method under evaluation.
2. Apply your bias mitigation method to at least three datasets, taking diversity and criticism into account when making claims about real-world impact.
3. State the protected attributes for each dataset.
4. Evaluate your bias mitigation method on at least two fairness metrics, as well as a performance metric (e.g., accuracy). We suggest using different metric types to reduce the correlation of individual fairness metrics.
5. Benchmark at least against the original model and consider similar, existing bias mitigation methods as well.
6. Apply your bias mitigation method to multiple classification models, in particular when proposing pre- or post-processing methods. Logistic regression and neural networks are frequently used.
7. Try to repeat experiments at least 10 times for standard training splits (e.g., 70% or pre-defined data-splits).
8. Share code and numerical results, in particular when results are presented in bar charts.

10 CONCLUSION

In this literature survey, we focused on the adoption of bias mitigation methods to achieve fairness in classification problems and provided an overview of 341 publications. Our survey first
categorizes bias mitigation methods according to their type (i.e., pre-processing, in-processing, post-processing). We found 123 pre-processing, 212 in-processing, and 56 post-processing methods, showing that in-processing methods are the most commonly used. We devised 13 categories for the three method types, based on their approach (e.g., pre-processing methods can perform sampling). The most frequently applied approaches perform changes to the loss function in an in-processing stage (51 publications applying regularization and 74 applying constraints). Other approaches are less frequently used, with input correction in a post-processing stage only being used twice.

We further provided insights on the evaluation of bias mitigation methods according to three aspects: datasets, metrics, and benchmarking. We found a total of 81 datasets that have been used at least once by one of the 341 publications, among which the Adult dataset is the most popular (used by 77% of publications). Even though 81 datasets are available for evaluating bias mitigation methods, only 2.7 datasets are considered, on average.

Similarly, we found a large number of fairness metrics that have been used at least once (109 unique metrics), which we divide into six categories. The most frequently used metrics belong to two categories: (1) Definitions based on predicted outcome; (2) Definitions based on predicted and actual outcomes.

When it comes to benchmarking bias mitigation methods, they can be compared against baselines, other bias mitigation methods, or non-bias mitigation approaches. Among the three baselines we found (original model, suppressing, random), the 82% of bias mitigation methods consider the original model (i.e., the classification model without any bias mitigation applied) as a baseline. Commonly, methods are compared against other bias mitigation methods. 51 publications benchmark against fairness-unaware methods. Among the collected publications, we found 56% (192 out of 341) that make their source code available, thereby supporting replicability and benchmarking. Moreover, we found three frameworks implementing and making available existing bias mitigation methods [31, 36, 42].

Last, we list current opportunities and challenges that have been discerned from the collected publications. This includes the synthesizing of fairness metrics, as there is no consensus reached on what metrics to use. In addition to measuring improvements, future bias mitigation methods can take fairness guarantees in account. The application of bias mitigation methods in practice is challenging, as developers might not be able to detect relevant population groups for which to measure bias and reliability of datasets (i.e., are prior observations biased?). Therefore, we hope that this survey helps researchers and practitioners to gain an understanding of the current, existing bias mitigation approaches and support the development of new methods.

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