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There are several bias mitigators that can reduce algorithmic bias in machine learning models but, unfortunately, the effect of mitigators on fairness is often not stable when measured across different data splits. A popular approach to train more stable models is ensemble learning. Ensembles, such as bagging, boosting, voting, or stacking, have been successful at making predictive performance more stable. One might therefore ask whether we can combine the advantages of bias mitigators and ensembles? To explore this question, we first need bias mitigators and ensembles to work together. We built an open-source library enabling the modular composition of 10 mitigators, 4 ensembles, and their corresponding hyperparameters. Based on this library, we empirically explored the space of combinations on 13 datasets, including datasets commonly used in fairness literature plus datasets newly curated by our library. Furthermore, we distilled the results into a guidance diagram for practitioners. We hope this paper will contribute towards improving stability in bias mitigation.

# **1 INTRODUCTION**

Algorithmic bias and discrimination in machine learning are a huge problem. If learned estimators make biased predictions, they might discriminate against underprivileged groups in various domains including job hiring, healthcare, loan approvals, criminal justice, higher education, and even child care. These biased predictions can reduce diversity, for instance, in the workforce of a company or in the student population of an educational institution. Such lack of diversity can cause adverse business or educational outcomes. In addition, several of the above-mentioned domains are governed by laws and regulations that prohibit biased decisions. And finally, biased decisions can severely damage the reputation of the organization that makes them. Of course, bias in machine learning is a sociotechnical problem that cannot be solved with technical solutions alone. That said, to make tangible progress, this paper focuses on *bias mitigators* that can reduce bias in machine learning models. We acknowledge that bias mitigators can, at most, be a part of a larger solution.

A bias mitigator either improves or replaces an existing machine learning estimator (e.g., a classifier) so it makes less biased predictions (e.g., class labels) as measured by a fairness metric (e.g., disparate impact). Unfortunately, bias mitigation often suffers from high volatility. There is usually less training data available for underrepresented groups. Less data means the learned estimator has fewer examples to generalize from for these groups. That in turn means the

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estimator is less stable with respect to group fairness metrics, which are computed based on predictive performance for different groups. For instance, empirical studies (e.g. [4]) have shown that volatility in fairness metrics tends to exceed volatility in accuracy metrics. With an unlucky train-test split, in the worst case, this volatility can even cause a model to appear fair when measured on training data while being unfair on production data.

Given that ensembles (e.g., bagging or boosting) can improve stability for accuracy metrics, intuitively, we would expect that they can also improve stability for group fairness metrics. For instance, bagging ensembles work best when the base model is unstable [30]: they turn instability from a drawback into an advantage. Prior work either explores bias mitigation without any consideration of ensembles, or entangles the two [5, 14, 19, 22, 25]. In contrast, our paper hypothesizes that bias mitigators and ensembles can be modular building blocks: instead of being entangled with each other, they can be combined as needed. The advantage of keeping ensembles and bias mitigators modular is a larger space of possible combinations to explore. Furthermore, when there are future advances in either ensembling or bias mitigation, modularity helps extend these advances to their combination.

This paper explores the question, "*Can modular ensembles help with fairness, and if yes, how?*" We conducted a comprehensive empirical study with 10 bias mitigators from AIF360 [4]; bagging, boosting, voting, and stacking ensembles from the popular scikit-learn library [7]; and 13 datasets of varying baseline fairness with sizes ranging from 118 to 48,842 rows. Our findings confirm the intuition that ensembles often improve stability of not just accuracy but also the group fairness metrics we explored. Occasionally, ensembles even lead to better places in the combined fairness/accuracy space. However, the best configuration of mitigator and ensemble depends on dataset characteristics, learning objectives, and even worldviews [12]. Therefore, this paper includes a guidance diagram that we systematically distilled out of our extensive experimental results.

To support these experiments, we assembled a library of pluggable ensembles, bias mitigators, and fairness datasets. For the original components, we reused popular and well-established open-source technologies including scikit-learn [7], pandas [24], AIF360 [4], and OpenML [29]. However, we found that out-of-the-box, these components were often not able to plug-and-play with each other. Hence, our library makes several new adaptations to get components to work well together by exposing the right interfaces. Since we wanted our library to be useful not just for research but also for real-world adoption, we added thorough tests and documentation and made everything available as open-source code (https://github.com/IBM/lale). Modular ensembles can have additional advantages related to fairness. For instance, it has been shown that there is a fundamental trade-off between fairness and accuracy [18]. Modular ensembles let data scientists navigate the fairness/accuracy space by varying the mitigation of base estimators in the ensemble or by mixing different kinds of mitigators [22].

To summarize, this paper makes the following contributions:

- (1) An open-source library of modular ensembles and bias mitigators, c.f. Section 3.
- (2) An empirical study of ensembles and bias mitigators, c.f. Section 4.
- (3) A guidance diagram to help practitioners combine ensembles with bias mitigators, c.f. Section 5.

Overall, this paper answers the question "*Can modular ensembles help with fairness*?" with "*yes*. The follow-up question "*If yes, how*?" is more important but harder to address. This paper answers it by showing that ensembles improve fairness stability, i.e., they yield estimators whose fairness generalizes better to new data. This is a step towards a future where we can better trust machine learning to be fair.

### 2 RELATED WORK

A few pieces of prior work have used ensembles for fairness, but they use specialized ensembles and bias mitigators, in contrast to our work, which uses off-the-shelf modular components. The discrimination-aware ensemble uses a heterogeneous collection of base estimators [19]. When all base estimators agree, the ensemble returns the consensus prediction, otherwise, it classifies instances as positive if and only if they belong to the unprivileged group. This can be viewed as a form of stacking ensemble with a simple policy-based final estimator. The random ensemble also uses a heterogeneous collection of base estimators, and picks one of them at random to make a prediction [14]. This can be viewed as a form of stacking ensemble with a random final estimator. The paper offers a synthetic case where the resulting ensemble is both more fair and more accurate than all base estimators, but lacks experiments with real datasets. The exponentiated gradient reduction trains a sequence of base estimators using a game, where one player seeks to maximize fairness violations by the estimators so far and the other player seeks to build a fairer next estimator [1]. In the end, for predictions, it uses weights to pick a random base estimator. Even though the authors do not frame their algorithm in ensemble terminology, it has aspects reminiscent of boosting ensembles. The fair AdaBoost algorithm modifies boosting ensembles to boost not for accuracy but for fairness [5]. It trains a sequence of base estimators, where the training data for the next estimator puts more weight on instances that the previous estimator predicted unfairly, based on an individual fairness measure. In the end, for predictions, it gives a base estimator higher weight if it was fair on more instances from the training set. The fair voting ensemble uses a heterogeneous collection of base estimators [22]. For each prediction, it votes among the base estimators  $\phi_t$ ,  $t \in 0..n - 1$ , with weights  $W_t = \alpha \cdot A_t / (\sum_{t=0}^{n-1} A_j) + (1 - \alpha) \cdot F_t / (\sum_{t=0}^{n-1} F_j)$ , where  $A_t$  is an accuracy metric and  $F_t$  is a fairness metric. The fair double ensemble algorithm uses stacked predictors, where the final estimator is linear, with a novel approach to train the weights of the final estimator to satisfy a system of accuracy and fairness constraints [25].

Each of the above-listed approaches uses an ensemble-specific bias mitigator, whereas we experiment with ten different off-the-shelf modular mitigators. Similarly, each of these approaches uses one specific kind of ensemble, whereas we experiment with off-the-shelf modular implementations of bagging, boosting, voting, and stacking. Using off-the-shelf mitigators and ensembles facilitates plug-and-play between the best available independently-developed implementations. Given that fair learning is a rapidly evolving field, specialized mitigator-ensemble combinations may be appropriate. However, we believe that it is still useful to study off-the-shelf tools given that these have established open-source implementations and are more readily available, as opposed to specialized tools that are still in the process of being hardened. Out of the work on fairness with ensembles discussed above, one paper has an experimental evaluation with five datasets [1] and the other papers use at most three datasets. In contrast, we use 13 datasets. Finally, unlike these earlier papers, our paper specifically explores fairness stability, extracting that as one of the goals for our auto-generated guidance diagram.

Our work takes inspiration from earlier empirical studies and comparisons of fairness techniques [6, 13, 17, 23, 27, 28, 31], which help practitioners and researchers better understand the state of the art. But unlike these works, we experiment with ensembles and with fairness stability.

Our work offers a new library of bias mitigators. While there have been excellent prior fairness toolkits such as ThemisML [2], AIF360 [4], and FairLearn [1], none of them support ensembles. Ours is the first that is modular enough to investigate a large space of unexplored mitigator-ensemble combinations. We previously published some aspects of our library in a non-archival workshop with no official proceedings, but that paper did not yet discuss ensembles [16].

## **3 LIBRARY AND DATASETS**

Our experiments were made possible by multiple Python libraries and 13 different datasets. The subsections that follow provide more information about these libraries and datasets and describe how they interact with each other.

#### 3.1 Lale and fairness metrics

Lale is an open-source library for semi-automated data science [3]. It automates parts of the iterative model-building process and serves as an intuitive frontend for scikit-learn [7] and several other machine learning libraries. Aside from our experiments, one contribution of our work is implementing Lale compatibility with another library: the AI Fairness 360 (AIF360) Toolkit [4], especially with regard to interoperability between scikit-learn's ensemble learning algorithms and AIF360's bias mitigation algorithms through Lale's operator framework. Building this functionality and handling quirks in AIF360 and scikit-learn as necessary was a key part of this research.

As Lale is compatible with scikit-learn, its models take X and y arguments corresponding to features and labels, respectively. To provide a unified API to fairness metrics and mitigators, we added a format to Lale for specifying information about favorable and unfavorable labels as well as privileged and unprivileged groups that reflect bias in a dataset. This is done via a fairness\_info dictionary with fields for favorable\_labels and protected\_attributes that represent favorable outcomes and privileged groups. We then wrote wrappers for bias mitigators (e.g., DisparateImpactRemover) and metrics (e.g., disparate\_impact) in AIF360 that understand this fairness\_info format in addition to the usual scikit-learn style X and y arguments, given as pandas dataframes. Fig. 1 shows an example.

```
i fairness_info = {
    "favorable_labels": [1], # values of `y` that indicate a favorable outcome
    "protected_attributes": [ # columns of `X` and values that indicate a privileged group
        {"feature": "race", "reference_group": ["White"]},
        {"feature": "sex", "reference_group": ["male div/sep", "male mar/wid", "male single"]},
        ],
        ],
        j,
        intigator = DisparateImpactRemover(**fairness_info)
        pipeline = make_pipeline(mitigator, DecisionTreeClassifier())
        trained = pipeline.fit(X, y)
        predictions = trained.predict(test_X)
```

Fig. 1. Sample code showing bias mitigation workflow with Lale and AIF360 through fairness\_info.

While the example in Fig. 1 configures operators with their default hyperparameters, the programming model also supports more general configuration. For instance, DisparateImpactRemover(\*\*fairness\_info, repair\_level=0.8) tunes the mitigator, and DecisionTreeClassifier(max\_depth=10, criterion="entropy") tunes the estimator. Once models are trained, Lale assists in auditing their performance from both accuracy and fairness standpoints. Metrics used here include, but are not limited to:

- Accuracy: ratio of number of examples correctly predicted to total number of examples predicted
- *F*<sup>1</sup> score: harmonic mean of precision and recall
- Disparate Impact: ratio of positive outcomes for unprivileged group to positive outcomes for privileged group (as described in [11])

For convenience, just as scikit-learn provides scorer objects for accuracy metrics, we added Lale scorer objects for fairness metrics. Fig. 2 shows an example demonstrating how to use scorers from both packages. Manuscript submitted to ACM

```
12 accuracy_scorer = sklearn.metrics.make_scorer(sklearn.metrics.accuracy_score)
```

```
13 accuracy_measured = accuracy_scorer(trained, test_X, test_y)
```

```
14 di_scorer = lale.lib.aif360.disparate_impact(**fairness_info) # uses fairness_info defined in Line 1
```

15 di\_measured = di\_scorer(trained, test\_X, test\_y)

Ensemble	Algorithm	Composition
Bagging	Train $n$ base estimators in parallel on random subsets of training data.	Homogeneous
Boosting	Train $n$ base estimators in series where each subsequent base estimator is fit on data incorrectly classified by a previous base estimator.	Homogeneous
Voting	Train <i>n</i> base estimators in parallel and determine overall predictions by choosing the most frequently occurring output from base estimators.	Heterogeneous
Stacking	Train <i>n</i> base estimators in parallel as well as a <i>final estimator</i> that makes overall predictions given outputs of the other <i>n</i> base estimators as input. In addition, the final estimator can optionally also use the original input data (passthrough=True).	Heterogeneous

Fig. 2. Sample code showing scorer objects.

Table 1. Overview of ensemble types used in our experiments.

Two types of the most commonly used fairness metrics are group fairness metrics (like disparate impact) and individual fairness metrics (like those described in [10] that "treat similar individuals similarly"). Since the mitigators in our experiments focus on group fairness, our experiments focus on group fairness.

### 3.2 Ensembles

The main idea behind ensemble learning is to use multiple weak models to form one strong model. This can be done by training more models on data that is difficult to fit, combining predictions of models trained on various subsets of the input data, or combining predictions of different types of models to improve robustness through model diversity [30]. Scikit-learn supports several types of ensembles [7]. We use four in our experiments, specifically classifier implementations from scikit-learn that are supported by Lale. These are summarized in Table 1.

Following scikit-learn, we use the following terminology to characterize ensembles: A *base estimator* is an estimator that serves as a building block for the ensemble. An ensemble supports one of two *composition* types: whether the ensemble consists of identical base estimators (*homogeneous*) or can consist of different ones (*heterogeneous*). Similarly, each ensemble supports one of two *training styles*: whether the ensemble trains base estimators one at a time sequentially (*series*) or independently from each other (*parallel*).

Additionally, it is necessary to choose specific base estimators to use in the ensembles. For the experiments in this paper, this choice was constrained by the fact that both boosting ensembles and post-estimator bias mitigators require base estimators that can return not just target labels but class probabilities (i.e., predict\_proba in scikit-learn). While other ensembles do not impose that restriction, they can still benefit from predict\_proba if it is present, such as stacking. Furthermore, using the same base estimators across all experiments helps in making apples-to-apples comparisons between configurations. Specifically, for the homogeneous ensembles (bagging and boosting), we used their most common base estimator in practice: the decision-tree classifier. For the heterogeneous ensembles (voting and stacking), Manuscript submitted to ACM

Kind	Mitigator	Hyperparameters				
		Name	Description			
r	DisparateImpactRemover [11]	repair_level	repair amount			
nato	LFR [32]	k	number of prototypes			
stin		$A_{x}$	input reconstruction quality term weight			
re-e		$A_y$ $A_z$	fairness constraint term weight			
ц	Reweighing [18]	N/A				
	AdversarialDebiasing [33]	adversary_loss_weight	strength of adversarial loss			
		num_epochs	number of training epochs			
		batch_size	batch size			
•.		classifier_num_niaaen_units debias	learn classifier with or without debiasing			
ator	GerryFairClassifier [21]	C	maximum L1 Norm for the dual variables			
stim		max_iters	time horizon for fictitious play dynamic			
n-e		γ	fairness approximation parameter			
-1		fairness_def	fairness notion			
		predictor	hypothesis class for the Learner			
	MetaFairClassifier [8]	τ	fairness penalty parameter			
	Projudice Pomover [20]	iype	fairness populty parameter			
		η				
tim	CalibratedEqOddsPostprocessin	g [26] cost_constraint	fpr, fnr, or weighted			
t-es	EqOddsPostprocessing [15]	(not used in experim	nents due to lack of predict_proba)			
sod	ଞ୍ଚି RejectOptionClassification [19] (not used in experiments due to lack of predict					

Table 2. Mitigators and their hyperparameters and originating papers. Hyperparameter descriptions from AIF360 documentation. Bolded hyperparameters control mitigation strength. All mitigators support *favorable\_labels* and *protected\_attributes* from Section 3.1.

we used a set of base estimators that are typical in common practice: XGBoost [9], random forest, k-nearest neighbors, and support vector machines. Finally, for stacking, we also used XGBoost as the final estimator.

#### 3.3 Mitigators

We added support in Lale for bias mitigation from AIF360 [4]. AIF360 distinguishes three kinds of mitigators for improving group fairness: *pre-estimator mitigators*, which are learned input manipulations that reduce bias in the data sent to downstream estimators; *in-estimator mitigators*, which are specialized estimators that directly incorporate debiasing into their training; and *post-estimator mitigators*, which attempt to reduce bias in predictions made by an upstream estimator. Table 2 lists the specific mitigators along with their hyperparameters and originating papers.

Fig. 3 visualizes the combinations of ensemble types and mitigator kinds we explored in our experiments. It also shows each combination as pseudo-code, using the following notation. PreMit(est) applies a pre-estimator mitigator before an estimator est; InMit denotes an in-estimator mitigator, which is itself an estimator; and PostMit(est) applies a post-estimator mitigator after an estimator est. Bag(est, n) is short for BaggingClassifier with n instances of base estimator est; Boost(est, n) is short for AdaBoostClassifier with n instances of base estimator est; Vote(est<sub>i</sub>) applies a VotingClassifier to a list of base estimators est<sub>i</sub>; and Stack(est<sub>i</sub>, est<sub>n</sub>) applies a StackingClassifier to a list of Manuscript submitted to ACM

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Fig. 3. Combinations of ensembles and mitigators. For stacking, the passthrough option is represented by a dashed horizontal arrow.

```
StackingClassifier(
stimators=[
XGBClassifier(use_label_encoder=False, verbosity=0),
RandomForestClassifier(),
KNeighborsClassifier(),
SVC(probability=True),
],
final_estimator=make_pipeline(
LFR(**fairness_info, k=5, Ax=0.01, Ay=10, Az=5),
XGBClassifier(use_label_encoder=False, verbosity=0)
),
passthrough=False
)
```

Fig. 4. Possible instantiation for the pseudo-code Stack(esti, PreMit(estn)) using actual Python code in our library.

base estimators  $est_i$  and a final estimator  $est_n$ . The pseudo-code notation is a short-hand for the actual code one can write with our library, shown in Fig. 4. Fig. 3 highlights the modularity of our approach. Mitigation strategies can be applied at the level of either the base estimator or the entire ensemble. However, it turns out that by the fundamental nature of some ensembles and mitigators, not all combinations are feasible. We had to limit ourselves to less than the full Cartesian product for the following reasons.

First, post-estimator mitigators typically do not implement a predict\_proba function as described in the previous subsection. This functionality is required for some ensemble methods and recommended for others. To that end, in the process of ensuring that AIF360 mitigators could work with scikit-learn ensembles, we ended up exposing predict\_proba functionality not exposed by AIF360 by default but produced by underlying in-estimator and post-estimator mitigators. While we were able to get predict\_proba working for all of the in-estimator mitigators we wanted to test, calibrating probabilities from post-estimator mitigators has been shown to be tricky [26]. Hence, we only exposed it for CalibratedEqOddsPostprocessing.

Additionally, it is impossible to apply an in-estimator mitigator at the ensemble level because in that case, both the ensemble and mitigator would be performing the same task — estimation — so there is no way to combine them. Results for that part of the product are undefined and excluded from our analysis. Finally, we decided to omit some combinations that are technically feasible but less interesting to explore. For example, it is possible to mitigate at multiple points, say, at both the ensemble and estimator level of bagging or both the base and final estimators of a stacking ensemble. While our library supports these configurations, we elided them from Fig. 3 and from our experiments.

#### 3.4 Datasets

We gathered the datasets for our experiments from OpenML [29]. Some of these datasets have been used extensively as benchmarks in other parts of the algorithmic fairness literature (including but not limited to COMPAS, Adult, and Credit-g). We pulled novel datasets from OpenML based on whether they had demographic data that could be considered protected attributes (such as race, age, or gender) and there were associated baseline levels of disparate impact found in the dataset. This dataset discovery process yielded additional datasets like TAE, Titanic, and SpeedDating.

In all, we used 13 datasets in our research, summarized in Table 3. When running experiments, we split the datasets using stratification by not just the target labels but also the protected attributes [16]. This stratification approach leads to moderately more homogeneous fairness results across different splits. We use pandas for data cleaning and preprocessing operations [24]. The exact details of the preprocessing operations we use can be found in the open-source code for our library for reproducibility, but at a high level, the preprocessing generally involves operations such as:

- Removing columns that are irrelevant to model fitting (e.g., in the case of Titanic, such columns include ones with names, ticket type, cabin, and final destination).
- Binarizing protected attribute and outcome values and condensing them to one column each.
- Producing fairness\_info based on these operations.
- Standardizing (subtracting the mean and dividing by the standard deviation) each numerical column. The same coefficients (mean and standard deviation) learned at training time are applied at test time.

### 4 EMPIRICAL STUDY

This section uses our library of bias mitigators, ensembles, and datasets to empirically explore their combinations.

### 4.1 Methods

To make sense of our experimental results, and to ask and answer research questions about fairness and ensembles, we first had to narrow our experiments to a reasonably-sized space. The entire space of all possible combinations is large due to the combinatorial effect of the sets of possible choices: collectively, the ten bias mitigators have many hyperparameters (see Table 2); the four ensembles also have hyperparameters of their own (e.g., *n* and *passthrough* in Fig. 3); and we are experimenting with thirteen datasets (see Table 3). On top of that, we are exploring five different Manuscript submitted to ACM

Dataset	Description	Privileged group(s)	Nrows	<b>N</b> <sub>cols</sub>	DI
COMPAS Violent	ProPublica data from audit of North- pointe's recidivism algorithm but only considering violent recidivism	White women	3,377	10	0.822
Credit-g	German Credit dataset quantifying credit risk	Men and older people	1,000	58	0.748
COMPAS	ProPublica data from audit of North- pointe's recidivism algorithm	White women	5,278	10	0.687
Ricci	Test scores from fire department promo- tion exam with demographic info and pro- motion result	White men	118	6	0.498
TAE	Teacher Assistant Evaluation results from U Wisconsin, Madison	Native English speakers	151	6	0.449
Titanic	Demographic info of Titanic passengers and whether they survived	Women and children	1,309	37	0.263
SpeedDating	Preferences of participants in experimen- tal speed dating events at Columbia Busi- ness School	Same race	8,378	70	0.853
Bank	Data from Portuguese bank marketing campaign predicting whether client will subscribe to a term deposit	Older people	45,211	51	0.840
MEPS 19	Utilization results from Panel 19 of Medi- cal Expenditure Panel Survey	White individuals	15,830	138	0.490
MEPS 20	Same as MEPS 19 except for Panel 20	White individuals	17,570	138	0.488
Nursery	Nursery school application results during a competitive time period in Ljubljana, Slovenia	"Pretentious parents"	12,960	25	0.461
MEPS 21	Same as MEPS 19 except for Panel 21	White individuals	15,675	138	0.451
Adult	1994 US Census data predicting salary over \$50K	White men	48,842	100	0.277

Table 3. Qualitative and quantitative summary information of the datasets. The datasets are ordered by first partitioning by whether they contain at least 8,000 rows (we picked 8,000 to get a roughly even split; the partition is represented by the horizontal line in the middle of the table) and then sorting by descending baseline disparate impact (DI). Values for the number of rows ( $N_{rows}$ ), number of columns ( $N_{cols}$ ), and baseline disparate impact displayed here are computed *after* preprocessing techniques are applied.

performance dimensions: we measure predictive performance as F1 score, precision, and recall; we measure fairness performance as disparate impact, equal opportunity difference, statistical parity difference, and average odds difference; we quantify fairness volatility based on the standard deviation of the aforementioned fairness metrics; we measure time efficiency in seconds; and we measure memory efficiency in megabytes.

Therefore, we organize our experiments into two steps. The first step is a preliminary search that finds "best" mitigators without ensembles. Since mitigators without ensembles have been studied elsewhere, this paper does not present detailed results for this step of the experiments. Instead, this paper focuses on the second step, which is the main set of experiments with ensembles, described in Section 4.2. The second step uses only the mitigator configurations Manuscript submitted to ACM

selected by the first step. By limiting the second step to fewer mitigator configurations, we can more easily attribute performance differences to changes in ensembling configurations.

In the first step, the main difficulty is how to decide what configured mitigators (see Table 2) are "best". Since we are doing an empirical study, we mean *best* in an empirical sense of best encountered and picked during the search, not in a theoretical sense of optimality. That said, we still need to define what to consider best given the different dimensions of performance, mitigators, datasets, etc. To this end, we first run separate grid searches for each dataset, exploring bias mitigators with their hyperparameters. We run each configuration with five trials of 3-fold cross validation, where splits are stratified not just by outcome labels but also by protected groups [16]. We group the grid search results by dataset and mitigator *kind*: for each dataset, we consider three sets of mitigator configurations, one each for pre-, in-, and post-estimator mitigation. More specifically, for pre-estimator mitigation, the group contains three mitigators and their hyperparameters; for in-estimator mitigation, the group contains four mitigators and their hyperparameters; for in-estimator mitigation, the group contains four mitigators and their hyperparameters; and for post-estimator mitigation, the group contains only one mitigator, CalibratedEq0ddsPostprocessing, and its hyperparameters, as it is the only mitigator with predict\_proba in that category.

Given the results for each of the 39 groups (3 mitigator kinds  $\times$  13 datasets), the first step then needs to pick a best configuration in each group. Picking a best configuration is complicated by the five often conflicting performance dimensions. The relative priorities between the performance dimensions depend on the usage scenario. After data exploration and discussion, we settled on the following filtering and selection approach:

- (1) Filter configurations to ones with acceptable fairness, defined as mean disparate impact between 0.8 and 1.25.
- (2) Further filter to ones with nontrivial precision on average, i.e., nonzero true positive rate.
- (3) Additionally filter configurations to ones with acceptable predictive performance, defined as mean F1 (across 5 trials) greater than the average of all mean F1 values (average of the means over each set of 5 trials) or the median of all mean F1 values (median of those means), whichever is greater.
- (4) Finally, select the mitigator and hyperparameters with maximum precision (in case of COMPAS, since true positives should be prioritized) or recall (all other datasets, since false negatives should be avoided).

Tables 9 and 10 in the appendix list the chosen pre-estimator and in-estimator configurations (the only post-estimator configuration is CalibratedEqOddsPostprocessing(cost\_constraint="weighted")).

After the first step is done, the second step comprises the main set of experiments over the Cartesian product of ensembles and mitigators of Fig. 3 plus ensemble hyperparameters. For bagging and boosting, the only ensemble-related hyperparameter varied between configurations was the number of base estimators used in the ensemble. Values used for bagging configurations included {1, 5, 10, 50, 100} and values used for boosting included {1, 10, 50, 100, 500}.

Voting and stacking utilize lists of heterogeneous base estimators as hyperparameters. In our experiments, these lists contained either 4 mitigated base estimators or 4 unmitigated base estimators (i.e. for a given configuration, either all base estimators were mitigated or none of them were). When testing in-estimator mitigation with heterogeneous estimators, all four base estimators are replaced with in-estimator mitigators, specifically hyperparameter-optimized versions of PrejudiceRemover, GerryFairClassifier, MetaFairClassifier, and AdversarialDebiasing.

Lastly, stacking configurations also controlled the value of *passthrough* (whether dataset features were fed directly to the final estimator) and the mitigation of the final estimator. Specifically, if *passthrough* was set to True, either the base estimators or final estimators could be mitigated, but not both. However, if *passthrough* was set to False, only the base estimators could be mitigated because the final estimator lacks parameters corresponding to the dataset features, which in turn are required by mitigation techniques.

Just like the first step, the second step also ran 5 trials of 3-fold cross validation for each experiment configuration, and we recorded the same raw and mean-aggregated metrics. We used a computing cluster to run these experiments where each compute node has an Intel Xeon E5-2667 processor @ 3.30GHz. Every experiment configuration run was allotted 4 cores and 12 GB memory.

#### 4.2 Results

To determine whether ensembles help with fairness (and if so, how?), we analyze the metrics from our Cartesian product evaluation through answering several research questions:

- (1) Do ensembles help with fairness?
- (2) Do ensembles help predictive performance when there is mitigation?
- (3) How does ensemble size affect resource consumption?
- (4) Can ensemble-level mitigation achieve the same fairness as estimator-level?

4.2.1 *Result preprocessing steps.* Recall that we use a variety of different datasets. Since these datasets can have vastly different numbers of examples, feature space sizes, and baseline disparate impact values, learning fair models is an easier task with some datasets than others. This in turn makes comparing performance across datasets difficult. We alleviate this problem by applying the following procedure on a per-dataset basis for each metric of interest: first, we compile all of the results for each combination of ensemble type and mitigator kind, then we filter out results with trivial values for those metrics (corresponding to problems with model fitting). Subsequently, we map all values to the same region of metric space around the point of optimal fairness (i.e. for ratio-based metrics where 1 is optimal, we use the reciprocal of a value for downstream calculations if the value is larger than 1, and for difference-based metrics where 0 is optimal, we use the absolute value). Finally, we perform min-max scaling on the mean and standard deviation of the metric of interest, separately. After doing this for all datasets, we can group the data by mitigation kind and ensemble type, and average the scaled values over all datasets for each group to draw meaningful conclusions.

Given a metric x, we refer to the metric resulting from scaling of the mean values of x as "standardized x outcome" and to the metric resulting from scaling of the values of x's standard deviation as "standardized x volatility". Thus, in the tables and figures that follow, note that the values represented are ones that have been normalized through this process.

4.2.2 Do ensembles help with fairness? Table 4 shows the results of the normalizing process described above with disparate impact as the metric of interest. This table shows that mitigation techniques almost always improved disparate impact outcomes to some degree, regardless of whether ensemble learning was used or not. In general, ensemble learning by itself incurs a slight penalty on disparate impact compared to the corresponding no-ensemble baseline. This is an important finding, as it rules out the possibility that solely by using an ensemble learning technique can one hope to achieve fairer results from an outcome perspective relative to a single estimator. On the other hand, ensemble learning does generally lower the volatility of disparate impact. This suggests that ensembles *do* help with fairness, in particular when mitigation is applied, mainly by improving stability at the cost of average performance.

4.2.3 Do ensembles help predictive performance when there is mitigation? Table 5 shows the results of the normalizing process applied to F1 score. It illustrates that even with ensemble learning, there is still a trade-off between predictive performance and fairness when bias is present in the input data. In other words, bias mitigation decreases predictive performance. Moreover, while the configurations with optimal F1 outcomes are generally ensembles as opposed to single estimators, Manuscript submitted to ACM

	Not Mit.		Pı	·e-	In-		Post-	
	SDO	SDV	SDO	SDV	SDO	SDV	SDO	SDV
No ensemble	0.441	0.163	0.741	0.350	0.865	0.379	0.529	0.213
Bagging	0.363	0.079	0.566	0.177	0.742	0.329	0.494	0.066
Boosting	0.407	0.065	0.723	0.394	0.803	0.296	0.507	0.076
Voting	0.322	0.063	0.553	0.315	0.408	0.353	0.200	0.114
Stacking	0.424	0.189	0.616	0.269	0.460	0.357	0.379	0.228

Table 4. Standardized Disparate impact Outcome (SDO) and Volatility (SDV). Highest SDO and lowest SDV are bolded for each mitigation type. Note that SDO and SDV utilize different scales.

these tend to have worse volatility. Conversely, the configurations that improve stability the most do not have a great effect on SFO. Therefore, ensembles *can* help with predictive performance on average *or* they can help with F1 volatility.

	No Mit.		Pı	·e-	In-		Post-	
	SFO	SFV	SFO	SFV	SFO	SFV	SFO	SFV
No ensemble	0.746	0.182	0.579	0.379	0.573	0.483	0.652	0.174
Bagging	0.859	0.114	0.522	0.146	0.567	0.167	0.687	0.108
Boosting	0.804	0.222	0.479	0.253	0.626	0.177	0.669	0.093
Voting	0.816	0.082	0.436	0.279	0.511	0.476	0.597	0.159
Stacking	0.821	0.237	0.579	0.497	0.675	0.583	0.768	0.285

Table 5. Standardized F1 outcome (SFO) and volatility (SFV). Highest SFO and lowest SFV are bolded for each mitigation type.

4.2.4 How does ensemble size affect resource consumption? Intuitively, we expect that there should be resource consumption differences between ensemble-level mitigation and estimator-level mitigation when many estimators are used. Fig. 5 aggregates and displays data in such a way to analyze this possibility. Specifically, the values plotted correspond to consumed time and memory resources (in seconds and MB respectively) for pre-estimator-mitigated bagging and different numbers of estimators mitigated at the ensemble-level versus the estimator-level in order to obtain the associated disparate impact and F1 results. As expected, ensemble-level mitigation generally consumes fewer resources in both time and space. Our final question asks if those savings represent a performance trade-off.

4.2.5 Can ensemble-level mitigation achieve the same fairness as estimator-level? Tables 6 and 7 show standardized disparate impact outcome and volatility values per ensemble learning method across all pre-estimator mitigation techniques and datasets. Table 6 additionally shows standardized statistical parity difference outcome and volatility for the homogeneous ensembles. Both tables demonstrate how group fairness changes as a function of different ensemble hyperparameters and configurations, especially where mitigation is performed (at the ensemble level versus at the estimator level).

Given that there are resource trade-offs associated with performing mitigation at different levels, knowing what levels of resulting mitigation to expect could be helpful in making a decision regarding how much mitigation to use. Overall, ensemble-level mitigation and estimator-level mitigation have roughly equivalent disparate impact outcomes, but estimator-level mitigation tends to have lower volatility. Moreover, note that the same results hold for statistical Manuscript submitted to ACM



Fig. 5. Standardized Time Outcome (STO) and Standardized Memory Outcome (SMO) along with previously defined outcome and volatility metrics versus number of bagging estimators for ensemble-level and estimator-level approaches.

parity difference in the homogeneous cases. Additional results with other group fairness metrics (equal opportunity difference and average odds difference) can be found in Table 8 located in our appendix.

When configuring stacking, it is best to either not pass the data to the final estimator or ensure that it is appropriately protected from bias in the data via a mitigation technique. This is reflected in the extremely poor disparate impact outcome associated with "Base estimator mitigation; Passthrough; No final mitigation" in Table 7. As stated previously, it is not enough to use an ensemble without proper configuration (via algorithmic bias mitigators, for instance) and expect less bias.

## 5 GUIDANCE FOR METHOD SELECTION

What we have summarized thus far are the results of many experiments with various data and model configurations. One might ask "given these results, what are the best configurations for future experiments?"

We attempt to answer this question with Fig. 6, which displays the best results from our experiments for particular metrics and data setups. Note that this approach is largely driven by the outcomes of our experiments with minimal hand-tuning and qualitative analysis to create the final tree. Specifically, we perform the following steps:

- (1) Organize all results by dataset and create Outcome and Volatility metrics per dataset (as described in the previous section).
- (2) Filter results for each dataset to ones that occur in the top 33% of results for both Standardized Disparate Impact Outcome and Standardized F1 Outcome.
- (3) Place each result into one of four groups, or quadrants, based on responses to binary questions related to the corresponding dataset.

Is the dataset "large"? (Yes or No)

Ensemble type	n		Estimat	or-level			Ensemble-level		
		SDO	SDV	SSO	SSV	SDO	SDV	SSO	SSV
Bagging	1	0.643	0.507	0.392	0.735	0.713	0.457	0.541	0.693
	5	0.414	0.259	0.632	0.287	0.499	0.453	0.532	0.617
	10	0.294	0.371	0.604	0.298	0.394	0.628	0.531	0.522
	50	0.363	0.336	0.489	0.120	0.351	0.423	0.601	0.558
	100	0.372	0.315	0.549	0.179	0.430	0.443	0.508	0.460
Boosting	1	0.473	0.329	0.514	0.526	0.730	0.430	0.298	0.551
	10	0.300	0.341	0.564	0.427	0.443	0.459	0.518	0.528
	50	0.475	0.491	0.524	0.476	0.446	0.490	0.534	0.548
	100	0.606	0.501	0.466	0.367	0.420	0.397	0.543	0.483
	500	0.672	0.212	0.414	0.214	0.393	0.387	0.480	0.569

Table 6. Standardized DI Outcome (SDO) and Volatility (SDV) in addition to Standardized Statistical parity difference Outcome (SSO) and Volatility (SSV) comparing homogeneous ensembles of various numbers of base estimators (n) with pre-estimator mitigation where mitigation was performed either at the estimator level or ensemble level. Highest SDO, lowest SDV, lowest SSO, and lowest SSV are bolded by ensemble type.

Ensemble type	Configuration	SDO	SDV
Voting	Ensemble-level	0.462	0.615
	Estimator-level	0.462	<b>0.308</b>
Stacking	Ensemble-level	0.803	0.642
	Base estimator mitigation; No passthrough	<b>0.832</b>	0.515
	Base estimator mitigation; Passthrough; No final mitigation	0.106	<b>0.229</b>
	No base estimator mitigation; Passthrough; Only final mitigation	0.670	0.506

Table 7. Standardized DI outcome (SDO) and volatility (SDV) comparing heterogeneous ensembles with pre-estimator mitigation. Highest SDO and lowest SDV are bolded by ensemble.

Is the dataset "very unfair"? (Yes or No)

Defining "large" as containing more than 8,000 rows and "very unfair" as having baseline disparate impact under 0.49 led to roughly even divisions of results. The Cartesian product of these responses defines the quadrants (i.e. large and unfair, small and fair, etc.).

- (4) Average each metric in each quadrant while grouping by model configuration.
- (5) Report the top 3 model configurations for each metric in each quadrant.

The notation used in Fig. 6 is similar to that of Fig. 3, which in turn resembles Lale syntax. One key difference is that there is no corresponding syntax in the previous figure to emphasize the absence of an ensemble; here we use NoEnsemble(...) to represent these cases.

We hope that such a quantitative analysis of our experimental data and representation of our results can help practitioners determine best configurations for future experiments. For instance, our figure suggests using boosting with a large number of in-estimator mitigators to optimize for fairness on a large and unfair dataset. Alternatively, it suggests post-estimator mitigation with stacking for a small unfair dataset, to optimize for a variety of different metrics. Manuscript submitted to ACM

As noted in other parts of this paper, "best configuration" and even "best results" are highly dependent on context. The branching and myriad of different settings displayed in this figure additionally highlight this fact. While this figure provides guidance for future model-building experiments and deployments related to algorithmic fairness, it is intended to merely augment but not replace sound human judgment.

### 6 CONCLUSION

In summary, we have detailed the results of our empirical study that utilizes the modularity provided by our open-source library to test various configurations of ensemble learning and mitigation techniques across thirteen datasets. We find that some configurations work better in certain situations and yield more stable fairness metrics than others, but regardless of context, fairness and ensemble hyperparameters must be set properly in order to obtain beneficial results.

We have distilled our findings in the form of a tree in Fig. 6 that suggests various promising models depending on dataset and metric characteristics. Going forward, we hope that future practitioners can reproduce our experimental results via our library and obtain beneficial results in new settings via our guidance diagram.

### REFERENCES

- Alekh Agarwal, Alina Beygelzimer, Miroslav Dudik, John Langford, and Hanna Wallach. 2018. A Reductions Approach to Fair Classification. In International Conference on Machine Learning (ICML). 60–69. http://proceedings.mlr.press/v80/agarwal18a.html
- [2] Niels Bantilan. 2017. Themis-ML: A fairness-aware machine learn-ing interface for end-to-end discrimination discovery and mitigation. https: //arxiv.org/abs/1710.06921
- [3] Guillaume Baudart, Martin Hirzel, Kiran Kate, Parikshit Ram, Avraham Shinnar, and Jason Tsay. 2021. Pipeline Combinators for Gradual AutoML. In Advances in Neural Information Processing Systems (NeurIPS).
- [4] Rachel K. E. Bellamy, Kuntal Dey, Michael Hind, Samuel C. Hoffman, Stephanie Houde, Kalapriya Kannan, Pranay Lohia, Jacquelyn Martino, Sameep Mehta, Aleksandra Mojsilovic, Seema Nagar, Karthikeyan Natesan Ramamurthy, John Richards, Diptikalyan Saha, Prasanna Sattigeri, Moninder Singh, Kush R. Varshney, and Yunfeng Zhang. 2018. AI Fairness 360: An Extensible Toolkit for Detecting, Understanding, and Mitigating Unwanted Algorithmic Bias. https://arxiv.org/abs/1810.01943
- [5] Dheeraj Bhaskaruni, Hui Hu, and Chao Lan. 2019. Improving Prediction Fairness via Model Ensemble. In International Conference on Tools with Artificial Intelligence (ICTAI). 1810–1814. https://doi.org/10.1109/ICTAI.2019.00273
- [6] Sumon Biswas and Hridesh Rajan. 2021. Fair Preprocessing: Towards Understanding Compositional Fairness of Data Transformers in Machine Learning Pipeline. In Symposium on the Foundations of Software Engineering (FSE). https://arxiv.org/abs/2106.06054
- [7] Lars Buitinck, Gilles Louppe, Mathieu Blondel, Fabian Pedregosa, Andreas Mueller, Olivier Grisel, Vlad Niculae, Peter Prettenhofer, Alexandre Gramfort, Jaques Grobler, Robert Layton, Jake VanderPlas, Arnaud Joly, Brian Holt, and Gaël Varoquaux. 2013. API Design for Machine Learning Software: Experiences from the scikit-learn Project. https://arxiv.org/abs/1309.0238
- [8] L. Elisa Celis, Lingxiao Huang, Vijay Keswani, and Nisheeth K. Vishnoi. 2019. Classification with Fairness Constraints: A Meta-Algorithm with Provable Guarantees. In Conference on Fairness, Accountability, and Transparency (FAT). 319–328. https://doi.org/10.1145/3287560.3287586
- [9] Tianqi Chen and Carlos Guestrin. 2016. XGBoost: A Scalable Tree Boosting System. In Conference on Knowledge Discovery and Data Mining (KDD). 785–794. http://doi.acm.org/10.1145/2939672.2939785
- [10] Cynthia Dwork, Moritz Hardt, Toniann Pitassi, Omer Reingold, and Richard Zemel. 2012. Fairness through awareness. In Proceedings of the 3rd innovations in theoretical computer science conference. 214–226.
- [11] Michael Feldman, Sorelle A. Friedler, John Moeller, Carlos Scheidegger, and Suresh Venkatasubramanian. 2015. Certifying and Removing Disparate Impact. In Conference on Knowledge Discovery and Data Mining (KDD). 259–268. https://doi.org/10.1145/2783258.2783311
- [12] Sorelle A. Friedler, Carlos Scheidegger, and Suresh Venkatasubramanian. 2021. The (Im)Possibility of Fairness: Different Value Systems Require Different Mechanisms for Fair Decision Making. Communications of the ACM (CACM) 64, 4 (March 2021), 136–143. https://doi.org/10.1145/3433949
- [13] Sorelle A. Friedler, Carlos Scheidegger, Suresh Venkatasubramanian, Sonam Choudhary, Evan P. Hamilton, and Derek Roth. 2019. A comparative study of fairness-enhancing interventions in machine learning. In *Conference on Fairness, Accountability, and Transparency (FAT\*)*. 329–338. https://dl.acm.org/doi/10.1145/3287560.3287589
- [14] Nina Grgic-Hlaca, Muhammad Bilal Zafar, Krishna P. Gummadi, and Adrian Weller. 2017. On fairness, diversity and randomness in algorithmic decision making. In Workshop on Fairness, Accountability, and Transparency in Machine Learning (FAT/ML). https://arxiv.org/abs/1706.10208
- [15] Moritz Hardt, Eric Price, Eric Price, and Nati Srebro. 2016. Equality of Opportunity in Supervised Learning. In Conference on Neural Information Processing Systems (NIPS). 3315–3323. https://papers.nips.cc/paper/2016/hash/9d2682367c3935defcb1f9e247a97c0d-Abstract.html
- [16] Martin Hirzel, Kiran Kate, and Parikshit Ram. 2021. Engineering Fair Machine Learning Pipelines. In Non-archival ICLR Workshop on Responsible AI (RAI@ICLR).



Fig. 6. Breakdown of optimal ensembles with respect to metric of choice and dataset configuration. Edges connecting leaf nodes correspond to Outcome and Volatility metrics described in the previous section. Each leaf node lists model configurations using the notation introduced in Fig. 3 and Fig. 4.

- [17] Kenneth Holstein, Jennifer Wortman Vaughan, Hal Daumé, Miro Dudik, and Hanna Wallach. 2019. Improving Fairness in Machine Learning Systems: What Do Industry Practitioners Need?. In Conference on Human Factors in Computing Systems (CHI). 1–16. https://doi.org/10.1145/3290605.3300830
- [18] Faisal Kamiran and Toon Calders. 2012. Data preprocessing techniques for classification without discrimination. *Knowledge and Information Systems* 33 (2012), 1–33. https://doi.org/10.1007/s10115-011-0463-8
- [19] Faisal Kamiran, Asim Karim, and Xiangliang Zhang. 2012. Decision Theory for Discrimination-Aware Classification. In International Conference on Data Mining (ICDM). 924–929. https://doi.org/10.1109/ICDM.2012.45
- [20] Toshihiro Kamishima, Shotaro Akaho, Hideki Asoh, and Jun Sakuma. 2012. Fairness-Aware Classifier with Prejudice Remover Regularizer. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases (ECML PKDD). 35–50. https://doi.org/10.1007/978-3-642-33486-3\_3
- [21] Michael Kearns, Seth Neel, Aaron Roth, and Zhiwei Steven Wu. 2018. Preventing Fairness Gerrymandering: Auditing and Learning for Subgroup Fairness. In International Conference on Machine Learning (ICML). 2564–2572. http://proceedings.mlr.press/v80/kearns18a.html
- [22] Patrik Joslin Kenfack, Adil Mehmood Khan, S.M. Ahsan Kazmi, Rasheed Hussain, Alma Oracevic, and Asad Masood Khattak. 2021. Impact of Model Ensemble On the Fairness of Classifiers in Machine Learning. In International Conference on Applied Artificial Intelligence (ICAPAI). 1–6. https://doi.org/10.1109/ICAPAI49758.2021.9462068
- [23] Michelle Seng Ah Lee and Jatinder Singh. 2021. The Landscape and Gaps in Open Source Fairness Toolkits. In Conference on Human Factors in Computing Systems (CHI). https://papers.srn.com/sol3/papers.cfm?abstract\_id=3695002
- [24] Wes McKinney. 2011. pandas: a Foundational Python Library for Data Analysis and Statistics. Workshop on Python for High Performance and Scientific Computing (PyHPC) (2011), 1-9. https://www.dlr.de/sc/Portaldata/15/Resources/dokumente/pyhpc2011/submissions/pyhpc2011 submission 9.pdf
- [25] Alan Mishler and Edward Kennedy. 2021. FADE: FAir Double Ensemble Learning for Observable and Counterfactual Outcomes. https://arxiv.org/ abs/2109.00173
- [26] Geoff Pleiss, Manish Raghavan, Felix Wu, Jon Kleinberg, and Kilian Q. Weinberger. 2017. On Fairness and Calibration. In Conference on Neural Information Processing Systems (NIPS). https://proceedings.neurips.cc/paper/2017/hash/b8b9c74ac526fffbeb2d39ab038d1cd7-Abstract.html
- [27] Moninder Singh, Gevorg Ghalachyan, Kush R. Varshney, and Reginald E. Bryant. 2021. An Empirical Study of Accuracy, Fairness, Explainability, Distributional Robustness, and Adversarial Robustness. In KDD Workshop on Measures and Best Practices for Responsible AI (Responsible AI@KDD). https://arxiv.org/abs/2109.14653
- [28] Inês Valentim, Nuno Lourenço, and Nuno Antunes. 2019. The Impact of Data Preparation on the Fairness of Software Systems. In International Symposium on Software Reliability Engineering (ISSRE). 391–401. https://doi.org/10.1109/ISSRE.2019.00046
- [29] Joaquin Vanschoren, Jan N. van Rijn, Bernd Bischl, and Luis Torgo. 2014. OpenML: Networked Science in Machine Learning. SIGKDD Explorations Newsletter 15, 2 (June 2014), 49–60. http://doi.acm.org/10.1145/2641190.2641198
- [30] Ian H. Witten, Eibe Frank, Mark A. Hall, and Christopher Pal. 2016. Data Mining: Practical Machine Learning Tools and Techniques (fourth ed.). Morgan Kaufmann.
- [31] Ke Yang, Biao Huang, Julia Stoyanovich, and Sebastian Schelter. 2020. Fairness-Aware Instrumentation of Preprocessing Pipelines for Machine Learning. In Workshop on Human-In-the-Loop Data Analytics (HILDA). https://hilda.io/2020/proceedings/HILDA2020\_paper9.pdf
- [32] Rich Zemel, Yu Wu, Kevin Swersky, Toni Pitassi, and Cynthia Dwork. 2013. Learning Fair Representations. In International Conference on Machine Learning (ICML). 325–333. http://proceedings.mlr.press/v28/zemel13.html
- [33] Brian Hu Zhang, Blake Lemoine, and Margaret Mitchell. 2018. Mitigating Unwanted Biases with Adversarial Learning. In Conference on AI, Ethics, and Society (AIES). 335–340. https://doi.org/10.1145/3278721.3278779

#### A SUPPLEMENTAL MATERIAL

Ensemble type	n		Estimat	or-level			Ensem	ole-level	
		SAO	SAV	SEO	SEV	SAO	SAV	SEO	SEV
Bagging	1	0.487	0.763	0.383	0.746	0.466	0.718	0.463	0.726
	5	0.614	0.454	0.513	0.336	0.408	0.683	0.384	0.595
	10	0.503	0.305	0.442	0.313	0.500	0.570	0.500	0.456
	50	0.555	0.122	0.458	0.142	0.482	0.538	0.388	0.448
	100	0.598	0.232	0.490	0.182	0.500	0.459	0.616	0.410
Boosting	1	0.284	0.555	0.395	0.459	0.346	0.605	0.457	0.708
	10	0.538	0.325	0.550	0.409	0.546	0.571	0.483	0.409
	50	0.726	0.378	0.554	0.465	0.418	0.505	0.416	0.577
	100	0.575	0.279	0.363	0.358	0.586	0.484	0.521	0.504
	500	0.669	0.237	0.536	0.388	0.505	0.489	0.489	0.613

Table 8. Standardized Average odds difference Outcome (SAO) and Volatility (SAV) in addition to Standardized Equal opportunity difference Outcome (SEO) and Volatility (SEV) comparing homogeneous ensembles of various numbers of base estimators (n) with pre-estimator mitigation where mitigation was performed either at the estimator level or ensemble level. Lowest SAO, lowest SAV, lowest SEO, and lowest SEV are bolded by ensemble type.

Dataset	Mitigator	Hyperparameters
COMPAS Violent	DisparateImpactRemover	1
Credit-g	LFR	k=5, Ax=0.01, Ay=10, Az=5
COMPAS	DisparateImpactRemover	0.4
Ricci	LFR	k=5, Ax=0.01, Ay=5, Az=10
TAE	LFR	k=5, Ax=0.01, Ay=50, Az=5
Titanic	DisparateImpactRemover	0.8
SpeedDating	DisparateImpactRemover	0.2
Bank	DisparateImpactRemover	0.2
MEPS 19	LFR	k=5, Ax0.01, Ay=1, Az=10
MEPS 20	LFR	k=5, Ax=0.01, Ay=1, Az=10
Nursery	LFR	k=20, Ax=0.01, Ay=1, Az=10
MEPS 21	LFR	k=5, Ax=0.01, Ay=1, Az=10
Adult	LFR	k=5, Ax=0.01, Ay=1, Az=10

Table 9. Optimal pre-estimator mitigator configurations (with corresponding hyperparameters) per dataset. Hyperparameter names are not provided if the mitigation technique only accepts one. If a hyperparameter is not listed in the rightmost column, the configuration utilizes the default value.

Dataset	Mitigator	Hyperparameters
COMPAS Violent	MetaFairClassifier	0.5
Credit-g	AdversarialDebiasing	classifier_num_hidden_units=10
COMPAS	MetaFairClassifier	0.5
Ricci	MetaFairClassifier	0.8
TAE	MetaFairClassifier	0.8
Titanic	MetaFairClassifier	1
SpeedDating	MetaFairClassifier	0.9
Bank	PrejudiceRemover	100
MEPS 19	PrejudiceRemover	1000
MEPS 20	AdversarialDebiasing	classifier_num_hidden_units=500
Nursery	MetaFairClassifier	0.5
MEPS 21	AdversarialDebiasing	classifier_num_hidden_units=500
Adult	PrejudiceRemover	1000

Table 10. Optimal in-estimator mitigator configurations (with corresponding hyperparameters) per dataset. Hyperparameter names are not provided if the mitigation technique only accepts one. If a hyperparameter is not listed in the rightmost column, the configuration utilizes the default value.