

Promoting Fairness through Hyperparameter Optimization

André F. Cruz
Feedzai
andre.cruz@feedzai.com

Pedro Saleiro
Feedzai
pedro.saleiro@feedzai.com

Catarina Belém
Feedzai
catarina.belem@feedzai.com

Carlos Soares
Fraunhofer AICOS
Universidade do Porto
csoares@fe.up.pt

Pedro Bizarro
Feedzai
pedro.bizarro@feedzai.com

ABSTRACT

Considerable research effort has been guided towards algorithmic fairness but real-world adoption of bias reduction techniques is still scarce. Existing methods are either metric- or model-specific, require access to sensitive attributes at inference time, or carry high development and deployment costs. This work explores, in the context of a real-world fraud detection application, the unfairness that emerges from traditional ML model development, and how to mitigate it with a simple and easily deployed intervention: fairness-aware hyperparameter optimization (HO). We propose and evaluate fairness-aware variants of three popular HO algorithms: Fair Random Search, Fair TPE, and Fairband¹. Our method enables practitioners to adapt pre-existing business operations to accommodate fairness objectives in a frictionless way and with controllable fairness-accuracy trade-offs. Additionally, it can be coupled with existing bias reduction techniques to tune their hyperparameters. We validate our approach on a real-world bank account opening fraud use case, as well as on three datasets from the fairness literature. Results show that, without extra training cost, it is feasible to find models with 111% average fairness increase and just 6% decrease in predictive accuracy, when compared to standard fairness-blind HO.

KEYWORDS

Algorithmic fairness, Hyperparameter optimization

1 INTRODUCTION

Algorithmic bias arises when a Machine Learning (ML) model displays disparate predictive and error rates across sub-groups of the population, hurting individuals based on ethnicity, age, gender, or any other sensitive attribute [2–4]. This has several causes, from historical biases encoded in the data, to misrepresented populations in data samples, noisy labels, development decisions (*e.g.*, missing values imputation), or simply the nature of learning under severe class-imbalance [5].

Despite recent awareness, as of today, most companies are unsure of the cost implications of tackling algorithmic bias, not only from model accuracy degradation but also from extra development costs (both human and computational). The current ML landscape lacks practical methodologies and tools to seamlessly integrate fairness objectives and bias reduction techniques in existing real-world ML pipelines [6, 7]. As a consequence, treating fairness as a primary objective when developing ML systems is not yet standard practice.

Existing bias reduction techniques only target specific stages of the ML pipeline (*e.g.*, data sampling, model training), and often only apply to a single fairness definition or family of ML models [8, 9], limiting their adoption in practice. Moreover, the absence of major breakthroughs in algorithmic fairness suggests that an exhaustive

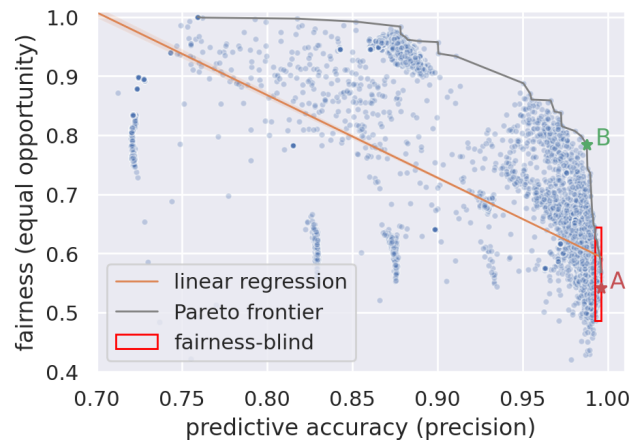


Figure 1: Fairness-accuracy trade-off of 10K models on the Adult dataset. Marked with an A, the model with highest accuracy; marked with a B, a model with 0.8% lower accuracy and 44.8% higher fairness than A, arguably a better trade-off.

¹This paper is an extension of Cruz *et al.* [1].

search over all possible ML models and bias reduction techniques may be necessary to find optimal trade-offs. Figure 1 illustrates this over thousands of models, each trained with a different hyperparameter configuration.

Currently, standard hyperparameter optimization (HO) and model selection processes are fairness-blind, solely optimizing for predictive accuracy. By doing so, these methods unknowingly target models with low fairness (region marked with a red rectangle). However, as shown by the plotted Pareto frontier [10], we can achieve significant fairness improvements at small accuracy costs. For instance, model B achieves 44.8% higher fairness than model A (the model with highest predictive accuracy), at a cost of 0.8% decrease in predictive accuracy, arguably a better trade-off. While current fairness-blind techniques target model A, we aim to target the region of optimal fairness-accuracy trade-offs to which model B belongs. Indeed, we observe a large spread over the fairness metric at any level of predictive accuracy, even within this fairness-blind region. Thus, it is absolutely possible to select fairer hyperparameter configurations without significant decrease in predictive accuracy.

This work explores, in the context of a large-scale real-world case-study of account opening fraud, the unfairness that emerges from traditional ML model development, and how to mitigate it with a simple and easily deployed intervention: fairness-aware hyperparameter optimization. By making the hyperparameter search fairness-aware while maintaining resource-efficiency, we are enabling ML practitioners to adapt pre-existing business operations to accommodate fairness with controllable extra cost, and without significant implementation friction.

We extend three popular hyperparameter tuners (Random Search, TPE [11] and Hyperband [12]) to optimize for both predictive accuracy and fairness through a weighted scalarization controlled by an α parameter. As budget (be it time or computational) is often limited in real-world scenarios, we give special focus to Fairband (our extension to Hyperband), and propose a heuristic to automatically find an adequate α value.

We applied our approach at Feedzai on a real-world bank account opening fraud detection problem. In account opening fraud, a malicious actor will attempt to open a new bank account using a stolen or synthetic identity (or both), in order to quickly max out its line of credit [13]. When developing ML models to detect fraud, banks optimize for a single metric of predictive accuracy (e.g., fraud recall). However, as shown in our experiments, the models with highest fraud recall have disparate false positive rates on specific groups of applicants. It is well known that the ability for a legitimate individual to open a bank account is essential to economic well being, and even declared a basic right by the European Parliament [14]. By applying our fairness-aware HO strategies we were able to find models with 111% improved fairness with just 6% drop in fraud recall when compared to the model with highest fraud recall obtained through standard HO methods.

The summary of our contributions are as follows:

- An approach for promoting model fairness that can be easily plugged into current ML pipelines with no extra development or computational cost.
- A set of competitive fairness-aware HO algorithms for multi-objective optimization of the fairness-accuracy trade-off that

are agnostic to both the explored hyperparameter space and the objective metrics.

- Strong empirical evidence that hyperparameter optimization is an effective way to navigate the fairness-accuracy trade-off.
- A heuristic to automatically set the fairness-accuracy trade-off parameter.
- Competitive results on a real-world fraud detection use case: fair HO achieves significantly improved fairness at a small predictive accuracy cost, and no extra budget when compared to literature HO baselines.

2 RELATED WORK

Algorithmic fairness research work can be broadly divided into three families: pre-processing, in-processing, and post-processing.

Pre-processing methods aim to improve fairness before the model is trained, by modifying the input data such that it no longer exhibits biases. The objective is often formulated as learning new representations that are invariant to changes in specified factors (e.g., membership in a protected group) [15–18]. However, by acting on the data itself, and in the beginning of the ML pipeline, fairness may not be guaranteed on the end model that will be used in the real-world.

In-processing methods alter the model’s learning process in order to penalize unfair decision-making. The objective is often formulated as optimizing predictive accuracy under fairness constraints (or optimizing fairness under predictive accuracy constraints) [8, 9, 19]. Another approach is optimizing for complex predictive accuracy metrics which include some fairness notion [20], akin to regularization. However, these approaches are highly model-dependent and metric-dependent, and even non-existent for numerous state-of-the-art ML algorithms.

Post-processing methods aim to adjust an already trained classifier such that fairness constraints are fulfilled. This is usually done by calibrating the decision threshold [21, 22]. However, one may argue that, by acting on the model *after* it was learned, this process is inherently sub-optimal [23]. It is akin to knowingly learning a biased model and then correcting these biases, instead of learning an unbiased model from the start. Moreover, these approaches require production-time access to sensitive features, forcing companies to ask all clients their ethnicity, religion, gender, or any other feature for fairness criteria.

Although a largely unexplored direction, algorithmic fairness can also be tackled from a Hyperparameter Optimization perspective.

Random Search (RS), one of the simplest and most flexible HO methods, iteratively selects combinations of random hyperparameter values and trains them on the full training set until the allocated budget is exhausted. Although simple in nature, RS has several advantages that keep it relevant nowadays, including having no assumptions on the hyperparameter space, on the objective function, or even on the allocated budget (e.g., it may run indefinitely). RS is known to generally perform better than grid search [24] and to converge to the optimum as budget increases.

Bayesian Optimization (BO) is a state-of-the-art HO approach that consists in placing a prior (usually a Gaussian process (GP)) over the objective function to capture beliefs about its behavior [25].

Previous work has extended BO to constrained optimization [26, 27], in which the goal is to optimize a given metric subject to any number of data-dependent constraints. Recently, Perrone et al. [28] applied this approach to the fairness setting by weighing the acquisition function by the likelihood of fulfilling the fairness constraints. However, constrained optimization approaches inherently target a single fairness-accuracy trade-off (which itself may not be feasible), leaving practitioners unaware of the possible fairness choices and their accuracy costs. Additionally, vanilla BO (based on GPs) cannot handle categorical hyperparameters, scales cubically in the number of data points, and performs poorly on high dimensional or conditional search spaces [29, 30].

The Tree-structured Parzen Estimator (TPE) [11] is a state-of-the-art BO algorithm that models the density of hyperparameter choices below and above some goal value, y^* , chosen to be some quantile of the observed goals. The densities are estimated using Parzen windows [31], and the ratio of densities, $\frac{p(\lambda|y>y^*)}{p(\lambda|y\leq y^*)}$, is used to suggest promising hyperparameter choices. As the Parzen estimators follow a tree-structure of conditional spaces, TPE shows good performance on high-dimensions and hierarchically-defined hyperparameters (e.g., the choice of model hyperparameters depends on the model choice). Nonetheless, BO has been shown to lack behind bandit-based methods when under tight budget constraints [12, 32].

Successive Halving (SH) [33, 34] casts the task of HO as identifying the best arm in a multi-armed bandit setting. Given a budget for each iteration, B_i , SH (1) uniformly allocates it to a set of arms (hyperparameter configurations), (2) evaluates their performance, (3) discards the worst half, and repeats from step 1 until a single arm remains. Thereby, the budget for each surviving configuration is effectively doubled at each iteration. SH’s key insight stems from extrapolating the rank of configurations’ performances from their rankings on diminished budgets (low-fidelity approximations). However, SH itself carries two parameters for which there is no clear choice of values: the total budget B and the number of sampled configurations n . We must consider the trade-off between evaluating a higher number of configurations (higher n) on an averaged lower budget per configuration (B/n), or evaluating a lower number of configurations (lower n) on an averaged higher budget. The higher the average budget, the more accurate the extrapolated rankings will be, but a lower number of configurations will be explored (and vice-versa). SH’s performance has been shown to compare favorably to several competing bandit strategies from the literature [35, 36].

Hyperband (HB) [12] addresses this “ n versus B/n ” trade-off by splitting the total budget into different instances of the trade-off, then calling SH as a subroutine for each one. This is essentially a grid search over feasible values of n . HB takes two parameters R , the maximum amount of resources allocated to any single configuration; and η , the ratio of budget increase in each SH round ($\eta = 2$ for the original SH). Each SH run, dubbed a bracket, is parameterized by the number of sampled configurations n , and the minimum resource units allocated to any configuration r . The algorithm features an outer loop that iterates over possible combinations of (n, r) , and an inner loop that executes SH with the aforementioned parameters fixed. The outer loop is executed $s_{max} + 1$ times, $s_{max} = \lfloor \log_\eta(R) \rfloor$, and the inner loop (SH) takes approximately B resources. Thus,

i	$s = 4$		$s = 3$		$s = 2$		$s = 1$		$s = 0$	
	n_i	r_i	n_i	r_i	n_i	r_i	n_i	r_i	n_i	r_i
0	81	1.2	34	3.7	15	11	8	33	5	100
1	27	3.7	11	11	5	33	2	100		
2	9	11	3	33	1	100				
3	3	33	1	100						
4	1	100								

Table 1: Number of sampled configurations, n_i , and budget per configuration, r_i , for each Hyperband bracket (when the ratio of budget increase $\eta = 3$, and the maximum budget per configuration $R = 100$).

the execution of Hyperband takes a budget of $(s_{max} + 1)B$. Table 1 displays the number of configurations and budget per configuration within each bracket when considering $\eta = 3$ and $R = 100$.

Hyperparameter optimization is simultaneously model independent, metric independent, and already an intrinsic component in existing real-world ML pipelines. On the other hand, current bias reduction methods either (1) act on the input data and cannot guarantee fairness on the end model, (2) act on the model’s training phase and can only be applied to specific model types and fairness metrics, or (3) act on a learned model’s predictions thus being limited to act on a sub-optimal space and requiring test-time access to sensitive attributes. Therefore, by introducing fairness objectives on the HO phase in an efficient way, we aim to help real-world practitioners to find optimal fairness-accuracy trade-offs in an easily pluggable manner, irrespective of the underlying model type or bias reduction method.

3 APPROACH

Persuading a large audience of ML practitioners and for-profit organizations to adopt fairness considerations into their ML pipeline requires minimizing implementation attrition. We address this issue through fairness-aware HO. By acting on the algorithms’ hyperparameter space, we promote fairness without changing the pipeline (i.e., the set of operators used to generate the model) and without changing the methods themselves (i.e., standard off-the-shelf learning algorithms and pre-processing methods are used), providing a flexible and off-the-shelf approach that can promptly be integrated into real-world ML standard practices.

As a case in point, Feedzai is a fintech company that leverages ML solutions to prevent financial fraud. The deployment of an ML model to a client is preceded by a heavy model selection stage where hundreds of models are trained and evaluated under some predetermined performance metric, defined according to business requirements (e.g. recall at 3% false positive rate). It is often the case that clients also demand for specific state-of-the-art models including deep learning or boosting-based models [37]. Accommodating fairer practices in such a complex setting poses many implementation challenges, including the integration of model-specific bias mitigation methods (which may not always comply with business demands) and guaranteeing low-latency requirements are met after model deployment (bias mitigation techniques often incur extra

train and evaluation time). Fairness-aware HO emerges as a seamless and flexible approach that allows decision-makers to have a finer control over which models fulfil the business requirements (both in terms of fairness, predictive accuracy, and latency requirements).

3.1 Optimizing for Fairness

The joint maximization of predictive accuracy and fairness is a multi-objective optimization (MOO) problem, defined as:

$$\arg \max_{\lambda \in \Lambda} G(\lambda) = (a(\lambda), f(\lambda)), \quad (1)$$

where λ is a hyperparameter configuration drawn from the hyperparameter space Λ , $a: \Lambda \mapsto [0, 1]$ is the predictive accuracy metric, and $f: \Lambda \mapsto [0, 1]$ is the fairness metric. In this context, there is no single optimal solution, but a set of Pareto optimal solutions. A solution λ^* is Pareto optimal if no other solution improves on an objective without sacrificing another objective. The set of all Pareto optimal solutions is dubbed the Pareto frontier [10].

MOO approaches generally rely on either Pareto-dominance methods or decomposition methods [38]. The former uses Pareto-dominance relations to impose a partial ordering in the population of solutions. However, the number of incomparable solutions can quickly dominate the size of the population (the number of sampled hyperparameter configurations). This is further exacerbated for high-dimensional problems [39, 40]. On the other hand, decomposition-based methods employ a *scalarizing* function to reduce all objectives to a single scalar output, inducing a total ordering over all possible solutions. A popular choice is the weighed l_p -norm:

$$\arg \max_{\lambda \in \Lambda} \|H(\lambda)\|_p = \left(\sum_{i=1}^k w_i h_i(\lambda)^p \right)^{\frac{1}{p}}, \quad (2)$$

where the weights vector w induces an *a priori* preference over the objectives.

MOO is notoriously arduous to apply at scale. However, we can draw key insights from observing that the Pareto frontier geometry in this context is most often *convex* (visible in Figures 1 and 2). This simplification of the original problem enables us to employ a decomposition-based method, known to converge faster, and to effectively target solutions on the Pareto frontier. All Pareto optimal solutions of a convex problem can be obtained by varying the weights vector w . Moreover, Giagkiozis and Fleming [39] demonstrate that the use of l_p -norms with a high p value leads to slower convergence, with a steep decrease in the likelihood of finding improved solutions as the search progresses. As such, we employ the l_1 -norm, carrying the same guarantees as using $p > 1$ for convex problems [38]. Our optimization metric g is defined as:

$$g(\lambda) = \|G(\lambda)\|_1. \quad (3)$$

As we optimize only two goals, we can further define, without loss of generality:

$$\alpha = w_1 = 1 - w_2, \quad (4)$$

$$g(\lambda) = \alpha \cdot a(\lambda) + (1 - \alpha) \cdot f(\lambda), \quad (5)$$

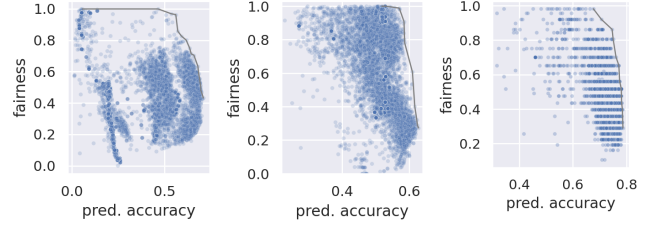


Figure 2: Fairness-accuracy Pareto frontier (grey line) on the in-house account opening fraud dataset (left), the Donors Choose dataset (middle), and the COMPAS dataset (right).

where $w_1 = \alpha$ is the relative importance of predictive accuracy, and $w_2 = 1 - \alpha$ is the relative importance of fairness. Our task is hence reduced to finding the hyperparameter configuration λ from a pre-defined hyperparameter search space Λ that maximizes the scalar objective function $g(\lambda)$:

$$\arg \max_{\lambda \in \Lambda} g(\lambda). \quad (6)$$

From an implementation standpoint, all models are evaluated in both fairness and predictive accuracy metrics on a holdout validation set. Computing fairness does not incur significant extra computational cost, as it is based on the same predictions used to estimate predictive accuracy. Additionally, fairness off-the-shelf assessment libraries are readily available [41].

In order to find all Pareto optimal solutions we must vary the weighting parameter $\alpha \in [0, 1]$. Nonetheless, α may indicate some predefined objective preference. For instance, in a punitive ML setting, an organization may decide it is willing to spend x \$ per each 1 less false positive in the underprivileged class², materializing an explicit fairness-accuracy trade-off. If no specific trade-off arises from domain knowledge beforehand, then the set of all Pareto optimal models should be displayed, and the decision on which trade-off to employ should be left to the model’s stakeholders.

3.2 Hyperparameter Tuners

As seen in Section 2, the best-suited choice of hyperparameter tuner depends on the task at hand. RS is the most flexible, carries the least assumptions on the optimization metric, and converges to the optimum as budget increases. TPE improves convergence speed by attempting to sample only useful regions of hyperparameter space. Bandit-based methods (*e.g.*, Successive Halving, Hyperband) are resource-aware, and thus have strong anytime performance, often being the most efficient when under budget constraints.

In this work, we propose to extend three popular hyperparameter tuners to optimize for fairness through a weighted scalarization controlled by an α parameter (default $\alpha = 0.5$). We propose fairness-aware variants for RS, TPE, and Hyperband, respectively dubbed *FairRS*, *FairTPE*, and *Fairband*. All of these variants can be easily incorporated in existing ML pipelines at a negligible cost. As budget

²In a punitive setting, the advised fairness metric is the ratio of group-wise false positive rates, also known as *predictive equality* [41, 42].

(be it time or computational) is seldom unrestricted in real-world projects, we give special focus to Fairband.

Fairband inherently benefits from resource-aware methods’ advantages: efficient resource usage, trivial parallelization, as well as being both model- and metric-agnostic. Furthermore, bandit-based methods are highly exploratory and therefore prone to inspect broader regions of the hyperparameter space. For instance, in our experiments, HB evaluates approximately six times more configurations than RS with the same budget³.

By employing a weighted scalarization technique in a bandit-based setting, we rely on the hypothesis that if model m_a represents a better fairness-accuracy trade-off than model m_b with a short training budget, then this distinction is likely to be maintained with a higher training budget. Thus, by selecting models based on both fairness and predictive accuracy, we are guiding the search towards fairer and better performing models. These low-fidelity estimates of future metrics on lower budget sizes is what drives HB’s and SH’s efficiency in hyperparameter search.

3.3 Fairband and Dynamic α

Aiming for a complete out-of-the-box experience without the need for specific domain knowledge, we further propose a heuristic for dynamically setting the value of α . With this heuristic our objectives are two-fold: first, we eliminate a hyperparameter that would need specific domain knowledge to be set; second, we promote a wider exploration of the Pareto frontier and a larger variability within the sampled hyperparameter configurations. We dub the variant of Fairband that employs this heuristic as *FB-auto*. We note this is not suited for model-based search methods (e.g., BO, TPE), as these rely on a stable optimization metric.

Assuming that α values can indeed guide the search towards different regions of the fairness-accuracy trade-off (which we will empirically see to be true), our aim is to efficiently explore the Pareto frontier in order to find a comprehensive selection of balanced trade-offs. As such, if our currently explored trade-offs correspond to high accuracy but low fairness, we want to guide the search towards regions of higher fairness (by choosing a lower α). Conversely, if our currently explored trade-offs correspond to high fairness but low accuracy, we want to guide the search towards regions of higher accuracy (by choosing a higher α).

To achieve the aforementioned balance we need a proxy-metric of our target direction of change. This direction is given by the difference, δ , between the expected model fairness, $\mathbb{E}_{\lambda \in D}[f(\lambda)] = \bar{f}$, and the expected model predictive accuracy, $\mathbb{E}_{\lambda \in D}[a(\lambda)] = \bar{a}$:

$$\delta = \bar{f} - \bar{a}, \delta \in [-1, 1]. \quad (7)$$

Expected values are measured as the mean of respective metric over the sample of hyperparameter configurations, $D \subseteq \Lambda$.

Hence, when this difference is negative ($\bar{f} < \bar{a}$), the models we sampled thus far tend towards better-performing but unfairer regions of the hyperparameter space. Consequently, we want to decrease α to direct our search towards fairer configurations. Conversely, when this difference is positive ($\bar{f} > \bar{a}$), we want to direct our search towards better-performing configurations, increasing α .

³With the parameters used on the HB seminal paper [12], it evaluates 128 configurations compared with 21 configurations evaluated by RS on an equal budget.

We want this change in α to be proportional to δ by some constant $k > 0$, such that

$$\frac{d\alpha}{d\delta} = k, k \in \mathbb{R}^+, \quad (8)$$

and by integrating this equation we get

$$\alpha = k \cdot \delta + c, c \in \mathbb{R}, \quad (9)$$

with c being the constant of integration. Given that $\delta \in [-1, 1]$, and together with the constraint that $\alpha \in [0, 1]$, the only feasible values for k and c are $k = 0.5$ and $c = 0.5$. Thus, the computation of dynamic- α is given by:

$$\alpha = 0.5 \cdot (\bar{f} - \bar{a}) + 0.5. \quad (10)$$

Earlier iterations of bandit-based methods are expected to have lower predictive accuracy (as these are trained on a lower budget), while later iterations are expected to have higher predictive accuracy. By computing new values of α at each Fairband iteration, we promote a dynamic balance between these metrics as the search progresses, predictably giving more importance to accuracy on earlier iterations but continuously moving importance to fairness as accuracy increases (a natural side-effect of increasing training budget). The pseudocode for FB-auto is given by Algorithm 1 in Appendix A.

The result of the MOO task is a collection of hyperparameter configurations that represent the fairness-accuracy trade-off. One could plot all available choices on the fairness-accuracy space and manually pick a trade-off, according to whichever business constraints or legislation are in place (see examples of Figure 4). For Fairband with static α , a target trade-off, α , has already been chosen for the method’s search phase, and we once again employ this trade-off for model selection (selection- α). For the FB-auto variant of Fairband, aiming for an automated balance between both metrics, we employ the same strategy for setting α as that used during search. By doing so, the weight of each metric is pondered by an approximation of their true range instead of blindly applying a pre-determined weight. For instance, if the distribution of fairness is in range $f \in [0, 0.9]$ but that of accuracy is in range $a \in [0, 0.3]$, then a balance would arguably be achieved by weighing accuracy higher, as each unit increase in accuracy represents a more significant relative change (this mechanism is achieved by Equation 10). However, at this stage we can use information from all brackets, as we no longer want to promote exploration of the search space but instead aim for a consistent and stable model selection. Thus, for FB-auto, the selection- α is chosen from the average fairness and predictive accuracy of all sampled configurations.

4 EXPERIMENTAL SETUP

In order to validate our proposal, we evaluate fairness-aware HO on a search space spanning multiple ML algorithms, model hyperparameters, and sampling hyperparameters, on a private large-scale case-study on bank account opening fraud dataset. For reproducibility, we further evaluate our method on three benchmark datasets from the fairness literature: COMPAS [2], Adult [43], and Donors Choose (DC) [44]. Details and results for literature datasets are in Appendix A⁴.

⁴Data, plots, and ML artifacts from all datasets at github.com/feedzai/fair-automl

In our evaluation suite, we include a selection of state-of-the-art HO algorithms (RS, TPE, and HB), together with our proposed fairness-aware versions (FairRS, FairTPE, and Fairband). For fairness-aware algorithms, we employ $\alpha = 0.5$ as the target trade-off. FB-auto will use our proposed dynamic- α heuristic.

4.1 Account Opening Fraud Dataset

The AOF dataset is a large-scale (500K instances) real-world dataset on online bank account opening fraud. In account opening fraud, a malicious actor will attempt to open a new bank account using a stolen or synthetic identity (or both), in order to quickly max out its line of credit [13]. Banks have to comply with anti-fraud regulations, and are liable for incurred losses when fraudsters gain illicit access to a credit line. At the same time, holding a bank account has been deemed a basic right by the European Union [14], region where our case-study takes place.

Our objective is to predict whether an individual’s request for opening a bank account is fraudulent. To do so, we have access to a wide range of behavioural and location data, as well as self-reported demographic features. Upon a positive prediction, the account opening application is denied. As a punitive ML setting, we select the ratio of false positive rates (FPR) across age groups as the fairness metric (predictive equality [42]):

$$\frac{\min_{a \in A} P[\hat{Y} = 1 | A = a, Y = 0]}{\max_{a \in A} P[\hat{Y} = 1 | A = a, Y = 0]}, \quad (11)$$

where A is the set of sensitive attributes (in our case, age groups). In this setting, a false positive is a genuine customer that sees her/his request unjustly denied, disturbing the customer’s life and costing the bank potential earnings. To maintain a low customer attrition, we target a global false positive rate of 5% (this target is a business requirement). Predictive accuracy is measured as the true positive rate (recall), as we want to promote models that correctly catch a high volume of fraud. All in all, our goal is to maximize recall at 5% FPR while preventing ageism.

4.2 Search Space

Firstly, we consider a broad hyperparameter space as a requirement for the effective execution of fairness-aware HO. We consider as hyperparameters any decision in the ML pipeline, as bias can be introduced at any stage of this pipeline [45]. Both accuracy and fairness metrics are seen as (possibly noisy) black-box functions of these hyperparameters. Thus, an effective search space includes which model type to use, the model hyperparameters which dictate how it is trained, and the sampling hyperparameters which dictate the distribution and prevalence rates of training data.

In order to validate our methods, we define a comprehensive hyperparameter search space, allowing us to effectively navigate the fairness-accuracy trade-off. We select five ML model types: LightGBM (LGBM) [37], Random Forest (RF) [46], Decision Tree (DT) [47], Logistic Regression (LR) [48], and feed-forward neural network (NN). Sampling a new hyperparameter configuration is seen as a hierarchical process, where we first select the model type, and afterwards we sample its model-specific hyperparameters. In

Algo.	Validation		Test	
	Pred. Acc.	Fairness	Pred. Acc.	Fairness
FB-auto	61.7 \blacklozenge	68.1 \blacklozenge	64.0 \blacklozenge	74.2 \blacklozenge
FB	50.7 \blacklozenge	76.0 \blacklozenge	52.6 \blacklozenge	81.3 \blacklozenge
FairRS	60.4 \blacklozenge	64.1 \blacklozenge	62.6	68.6 \blacklozenge
FairTPE	55.7 \blacklozenge	76.9 \blacklozenge	59.2 \blacklozenge	80.0 \blacklozenge
HB	68.4	32.3	68.4	35.2
RS	67.8	42.2	68.1	45.0
TPE	68.7	30.5	68.5	33.7

Table 2: Validation and test results on the AOF dataset. Statistical significance for fairness-aware methods is tested against their respective fairness-blind counterparts with a Kolmogorov-Smirnov test [49]. Results are marked with a \diamond when $p < 0.05$, and a \blacklozenge when $p < 0.01$.

order to tackle the severe class imbalance on the AOF dataset⁵, we further explore three undersampling strategies: targeting 20%, 10%, and 5% positive samples.

4.3 HO Parameters

For resource-aware HO algorithms, we define 1 budget unit as 1% of the training dataset. The maximum budget is defined as $R = 100$ (100% of the training dataset), and HB’s budget increase ratio is defined as $\eta = 3$. With these parameters, HB will run $s_{max} + 1 = \left\lfloor \log_{\eta}(R) \right\rfloor + 1 = 5$ iterations of SH. Each bracket will use at most $s_{max} + 1 = 5$ training slices of increasing size, corresponding to the following dataset percentages: 1.23%, 3.70%, 11.1%, 33.3%, 100%.

The training slices are sampled such that smaller slices are contained in larger slices, and such that the class-ratio is maintained (by stratified sampling). The number of configurations and budget per configuration within each bracket are displayed in Table 1.

5 RESULTS & DISCUSSION

In this section, we present and analyze the results from our fairness-aware HO experiments on the AOF case-study. Results for literature datasets are in Appendix A. To validate the methodology, we guide hyperparameter search by evaluating all sampled configurations on the same validation dataset, while evaluating the best-performing configuration (that maximizes Equation 5) on a held-out test dataset in the end. Likewise, the model thresholds are set on the validation dataset and then used on both the validation and test datasets, mimicking a production environment. All studied HO methods are given the same training budget: 2400 budget units.

Table 2 shows the validation and test results of running traditional HO methods on the AOF dataset, together with our proposed fairness-aware variants. Results are averaged over 15 runs, and statistical significant differences against the baseline methods are shown with \blacklozenge . This table comprises the training and evaluation of over 10K unique models. Together with the results on literature

⁵The AOF dataset features approximately 99 negatively-labeled samples per each positively-labeled sample, as most bank account applicants are genuine.

datasets we total over 40K models, one of the largest studies of the fairness-accuracy trade-off to date.

The differences in predictive accuracy and fairness between the proposed fairness-aware methods and their fairness-blind counterparts have strong statistical significance for all proposed HO algorithms on validation data. This is visible on test data as well, except for FairRS, which achieves significant fairness improvements with statistically insignificant accuracy decreases. This clear overall trend is also visible on the literature datasets. Additionally, FB-auto shows higher predictive accuracy than both FB and FairTPE ($p < 0.05$), while differences in fairness are not statistically significant for these pairs. In fact, the average fairness-accuracy trade-offs are Pareto optimal for all tuners except FairRS when measured among themselves, each representing a distinct trade-off.

Overall, FB-auto and FairTPE arguably achieve the best fairness-accuracy trade-offs to be put in a production environment. FB-auto achieves an averaged 111% improvement on the fairness metric, accompanied by a comparatively small 6% decrease on the accuracy metric, when compared with HB. FairTPE achieves a 137% fairness improvement, accompanied by a 14% decrease in accuracy, when compared with TPE. With these results we emphasize that, due to the practical Pareto frontier geometry, fairness increases are not proportional to accuracy decreases. From the fairness-blind baselines, steep fairness increases can be achieved with small accuracy decreases. From a practical standpoint, models selected by FB-auto on average approve 411 more bank accounts per month from legitimate older-aged individuals that would have been rejected by the HB-selected model.

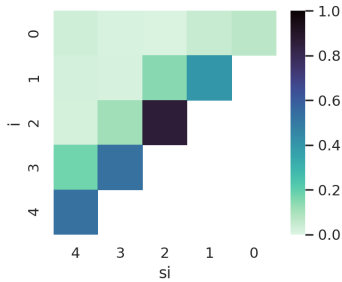


Figure 3: Average density of Pareto optimal models per FB-auto iteration on the AOF dataset. Refer to Table 1 for information on the configurations at each iteration.

5.1 Search Strategy

We evaluate the Fairband search strategy by analyzing the evolution of fairness and performance simultaneously, and whether we can effectively extend the practical Pareto Frontier as the search progresses. That is, whether optimal trade-offs are more likely to be found as we discard the worst performing models and further increase the allocated budget for top-performing models within each bracket (see Table 1). We focus on FB-auto, the fairness-aware variant of HB that automatically tunes the fairness-accuracy trade-off. Figure 3 shows a heat map of the average density of Pareto optimal

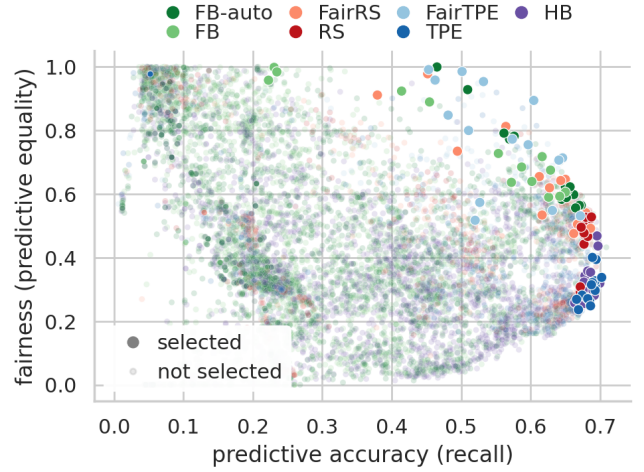


Figure 4: Fairness and predictive accuracy of models sampled (transparent smaller circles) and selected (larger circles) by evaluated hyperparameter tuners, on the AOF dataset (validation data).

models⁶ in each model-discard iteration, for 15 runs of the FB-auto algorithm, on the AOF dataset. As the iterations progress, under-performing configurations are pruned, and the density of Pareto optimal models steadily increases, confirming the effectiveness of the search strategy.

5.2 Model Selection

Figure 4 shows the final selected models for 15 runs of each method on the AOF dataset. The remaining models considered during the search are also shown, with lower opacity and smaller size, and with equal coloring pattern as selected models. As can be seen by the plots, Fairband (greens) consistently identifies good fairness-accuracy trade-offs from the universe of available configurations. Indeed, the models selected by Fairband are consistently close to or form the Pareto frontier. On the other hand, FairTPE seems to be able to find the best fairness-accuracy trade-offs, but with less reliable results. Most importantly, as evident by the spread of selected models, we can successfully navigate the fairness-accuracy Pareto frontier solely by means of HO. It is important to consider that the studied fairness-blind methods are the current standard in HO. By unfolding the fairness dimension, we show that strong predictive accuracy carries an equally strong real-world cost in unfairness, and this is hidden by traditional HO methods.

5.3 Optimizing Bias Reduction Hyperparameters

As an HO method, one fruitful approach to bias-mitigation is including traditional bias reduction methods into our hyperparameter search space. We introduce the Exponentiated Gradient (EG) reduction for fair classification algorithm [9] into our search space on the AOF dataset. EG is a state-of-the-art bias reduction algorithm

⁶Fraction of Pareto optimal models within each bracket, averaged over 15 runs.

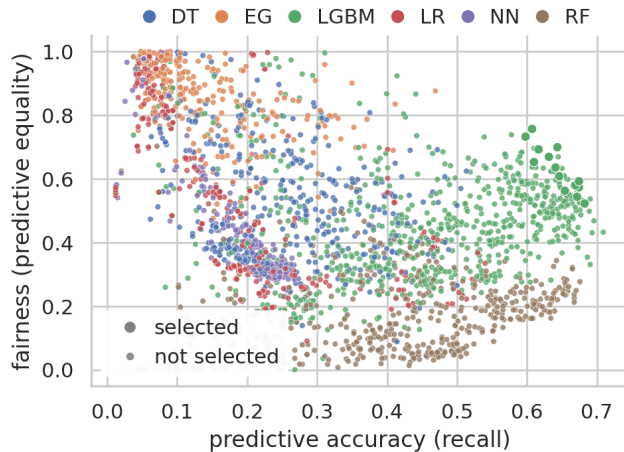


Figure 5: Fairness and predictive accuracy of selected models for FB-auto, discriminated by model type, on the AOF dataset. Search space includes the in-processing bias reduction method *Exponentiated Gradient* (EG) reduction [9], used together with Decision Tree classifiers.

that optimizes predictive accuracy subject to fairness constraints, and is compatible with any cost-sensitive binary classifier. In our setting, we target predictive equality (the fairness metric on AOF), and apply EG over a Decision Tree classifier.

Figure 5 shows a plot of the models selected by FB-auto over 15 runs on the AOF dataset, discriminated by model type. As can be seen, LGBM models on this particular task generally dominate all others. Only a single model on the Pareto frontier is not LGBM, and is indeed EG (orange circle on the 0.4 to 0.5 accuracy region and 0.8 to 1.0 fairness region). However, all models selected by FB-auto are LGBMs, and these clearly represent the better fairness-accuracy trade-offs. We note that different model types occupy distinct regions of the fairness-accuracy space (visible in both Figure 5 and appendix Figure 9), hinting that fairness may not be independent of model type. While including bias reduction methods in the HO search space may be useful for extending the Pareto frontier on some tasks, using *only* bias reduction methods may lead to severely worse fairness-accuracy trade-offs. Overall, these results support the fact that fairness-aware HO should be employed in all ML pipelines that aim for fair decision-making, together with a wide selection of ML algorithms to properly explore the fairness-accuracy search-space.

6 CONCLUSION

There have been widespread reports of real-world ML systems shown to be biased, causing serious disparate impact across different sub-groups, unfairly affecting people based on race, gender or age. Although the ML research community has embraced this issue, the current landscape of algorithmic fairness still lacks (1) practical methodologies and (2) tools for real-world practitioners.

This work aims to bridge that gap by providing a simple and flexible intervention to foster the incorporation of fairness objectives in real-world ML pipelines: fairness-aware hyperparameter

optimization. We propose and evaluate fairness-aware variants of state-of-the-art HO algorithms: Fair Random Search, Fair TPE, and Fairband. These fairness-aware methods jointly optimize predictive accuracy and fairness metrics by guiding the hyperparameter search towards fairer configurations⁷. We further propose a heuristic for setting the relative fairness-accuracy weight on a bandit-based context (FB-auto).

By introducing fairness notions into hyperparameter optimization, our method can be seamlessly integrated into real-world ML pipelines, at no extra training cost. Moreover, our method is easy to implement, resource-efficient, and both model- and metric-agnostic, providing no obstacles to its widespread adoption.

We evaluate our method on a large-scale online account opening fraud case-study as well as three benchmark datasets from the fairness literature. Fairness-aware HO is shown to provide significant fairness improvements at a small cost in predictive accuracy, when compared to traditional HO techniques. On the AOF dataset, FB-auto achieves 111% averaged improvement on the fairness metric, accompanied by a comparatively small 6% decrease on the accuracy metric, when compared with HB.

We show that it is both possible and effective to navigate the fairness-accuracy trade-off through hyperparameter optimization. At the same time, we observe that there is a wide spread of attainable fairness values at any level of predictive accuracy, and once again document the known inverse relation between fairness and predictive accuracy. Crucially, we empirically show that by only optimizing a single predictive accuracy metric (as is standard practice in real-world ML systems) we are inherently targeting unfairer regions of the hyperparameter space.

ACKNOWLEDGEMENTS

The project CAMELOT (reference POCI-01-0247-FEDER-045915) leading to this work is co-financed by the ERDF - European Regional Development Fund through the Operational Program for Competitiveness and Internationalisation - COMPETE 2020, the North Portugal Regional Operational Program - NORTE 2020 and by the Portuguese Foundation for Science and Technology - FCT under the CMU Portugal international partnership.

REFERENCES

- [1] André F. Cruz, Pedro Saleiro, Catarina Belém, Carlos Soares, and Pedro Bizarro. A bandit-based algorithm for fairness-aware hyperparameter optimization, 2020.
- [2] Julia Angwin, Jeff Larson, Lauren Kirchner, and Surya Mattu. Machine bias: There’s software used across the country to predict future criminals, and it’s biased against blacks. <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing>, May 2016. Accessed: 2020-01-09.
- [3] Robert Bartlett, Adair Morse, Richard Stanton, and Nancy Wallace. Consumer-Lending Discrimination in the FinTech Era. Technical report, National Bureau of Economic Research, 2019.
- [4] Joy Buolamwini and Timnit Gebru. Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification. In Sorelle A Friedler and Christo Wilson, editors, *Proc. of the 1st Conf. on Fairness, Accountability and Transparency*, volume 81 of *Proc. of Machine Learning Research*, pages 77–91, New York, NY, USA, 2018. PMLR.
- [5] Harini Suresh and John V. Gutttag. A framework for understanding unintended consequences of machine learning, 2019.
- [6] Kit T Rodolfa, Pedro Saleiro, and Rayid Ghani. Chapter 11: Bias and Fairness. In Ian Foster, Rayid Ghani, Ron S Jarmin, Frauke Kreuter, and Julia Lane, editors, *Big data and social science: A practical guide to methods and tools*. crc Press, 2020.

⁷Fair HO is subject to the fairness-accuracy trade-offs the input hyperparameter search space is able to attain.

- [7] Pedro Saleiro, Kit T Rodolfa, and Rayid Ghani. Dealing with bias and fairness in data science systems: A practical hands-on tutorial. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 3513–3514, 2020.
- [8] Muhammad Bilal Zafar, Isabel Valera, Manuel Gomez Rogriguez, and Krishna P. Gummadi. Fairness Constraints: Mechanisms for Fair Classification. In Aarti Singh and Jerry Zhu, editors, *Proc. of the 20th Int. Conf. on Artificial Intelligence and Statistics*, volume 54 of *Proc. of Machine Learning Research*, pages 962–970, Fort Lauderdale, FL, USA, 20–22 Apr 2017. PMLR.
- [9] Alekh Agarwal, Alina Beygelzimer, Miroslav Dudík, John Langford, and Hanna Wallach. A Reductions Approach to Fair Classification. In Jennifer Dy and Andreas Krause, editors, *Proc. of the 35th Int. Conf. on Machine Learning*, volume 80 of *Proc. of Machine Learning Research*, pages 60–69, Stockholmssmässan, Stockholm Sweden, 2018. PMLR.
- [10] Vilfredo Pareto. *Manuale di economia politica, societa editrice libraria. Manual of political economy*, 1971, 1906.
- [11] James Bergstra, Rémi Bardenet, Yoshua Bengio, and Balázs Kégl. Algorithms for hyper-parameter optimization. *Advances in Neural Information Processing Systems 24: 25th Annual Conf. on Neural Information Processing Systems 2011, NIPS 2011*, pages 1–9, 2011.
- [12] Lisha Li, Kevin Jamieson, Giulia DeSalvo, Afshin Rostamizadeh, and Ameet Talwalkar. Hyperband: A Novel Bandit-Based Approach to Hyperparameter Optimization. *Journal of Machine Learning Research*, 18:1–52, mar 2016.
- [13] Aisha Abdallah, Mohd Aizaini Maarof, and Anazida Zainal. Fraud detection system: A survey. *Journal of Network and Computer Applications*, 68:90 – 113, 2016.
- [14] European Parliament and Council. Directive 2014/92/EU of the European Parliament and of the Council of 23 July 2014 on the comparability of fees related to payment accounts, payment account switching and access to payment accounts with basic features. *Official Journal of the European Union (OJ)*, 57:214, 2014.
- [15] Flavio Calmon, Dennis Wei, Bhanukiran Vinzamuri, Karthikeyan Natesan Ramamurthy, and Kush R Varshney. Optimized pre-processing for discrimination prevention. In *Advances in Neural Information Processing Systems*, pages 3992–4001, 2017.
- [16] Elliot Creager, David Madras, Jörn-Henrik Henrik Jacobsen, Marissa A. Weis, Kevin Swersky, Toniann Pitassi, and Richard Zemel. Flexibly Fair Representation Learning by Disentanglement. In Kamalika Chaudhuri and Ruslan Salakhutdinov, editors, *Proc. of the 36th Int. Conf. on Machine Learning*, volume 2019-June, pages 2600–2612. PMLR, jun 2019.
- [17] Harrison Edwards and Amos Storkey. Censoring Representations with an Adversary. In *4th Int. Conf. on Learning Representations, ICLR 2016 - Conf. Track Proceedings*, pages 1–14, 2016.
- [18] Richard S Zemel, Yu Wu, Kevin Swersky, Toniann Pitassi, and Cynthia Dwork. Learning fair representations. *30th Int. Conf. on Machine Learning, ICML 2013*, 28(PART 2):325–333, 2013.
- [19] Andrew Cotter, Heinrich Jiang, and Karthik Sridharan. Two-Player Games for Efficient Non-Convex Constrained Optimization. *Proc. of the 30th Int. Conf. on Algorithmic Learning Theory*, 98:300–332, apr 2018.
- [20] Yahav Bechavod and Katrina Ligett. Penalizing unfairness in binary classification, 2017.
- [21] Benjamin Fish, Jeremy Kun, and Ádám D. Lelkes. A confidence-based approach for balancing fairness and accuracy. *Proc. of the 2016 SIAM Int. Conf. on Data Mining*, pages 144–152, 2016.
- [22] Moritz Hardt, Eric Price, Eric Price, and Nati Srebro. Equality of opportunity in supervised learning. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems 29*, pages 3315–3323. Curran Associates, Inc., 2016.
- [23] Blake Woodworth, Suriya Gunasekar, Mesrob I. Ohanessian, and Nathan Srebro. Learning Non-Discriminatory Predictors. *Proc. of the 2017 Conf. on Learning Theory*, 65(1):1920–1953, feb 2017.
- [24] James Bergstra and Yoshua Bengio. Random search for hyper-parameter optimization. *Journal of Machine Learning Research*, 13:281–305, 2012.
- [25] Bobak Shahriari, Kevin Swersky, Ziyu Wang, Ryan P. Adams, and Nando De Freitas. Taking the human out of the loop: A review of Bayesian optimization. *Proc. of the IEEE*, 104(1):148–175, 2016.
- [26] Jacob Gardner, Matt Kusner, Zhixiang, Kilian Weinberger, and John Cunningham. Bayesian optimization with inequality constraints. In Eric P. Xing and Tony Jebara, editors, *Proceedings of the 31st International Conference on Machine Learning*, volume 32 of *Proceedings of Machine Learning Research*, pages 937–945, Beijing, China, 22–24 Jun 2014. PMLR.
- [27] Michael A. Gelbart, Jasper Snoek, and Ryan P. Adams. Bayesian optimization with unknown constraints. In *Proc. of the Thirtieth Conf. on Uncertainty in Artificial Intelligence, UAI’14*, page 250–259, Arlington, Virginia, USA, 2014. AUAI Press.
- [28] Valerio Perrone, Michele Donini, Muhammad Bilal Zafar, Robin Schmucker, Krishnamurthy Kethapadi, and Cédric Archambeau. Fair bayesian optimization, 2021.
- [29] Katharina Eggenberger, Matthias Feurer, Frank Hutter, James Bergstra, Jasper Snoek, Holger Hoos, and Kevin Leyton-Brown. Towards an Empirical Foundation for Assessing Bayesian Optimization of Hyperparameters. In *NIPS workshop on Bayesian Optimization in Theory and Practice*, volume 10, page 3, 2013.
- [30] Frank Hutter, Lars Kotthoff, and Joaquin Vanschoren. *Automated Machine Learning: Methods, Systems, Challenges*. Springer Publishing Company, Incorporated, 1st edition, 2019.
- [31] Emanuel Parzen. On estimation of a probability density function and mode. *Ann. Math. Statist.*, 33(3):1065–1076, 09 1962.
- [32] Frank Hutter, Holger H. Hoos, and Kevin Leyton-Brown. Sequential model-based optimization for general algorithm configuration. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 6683 LNCS:507–523, 2011.
- [33] Zohar Karnin, Tomer Koren, and Oren Somekh. Almost optimal exploration in multi-armed bandits. *30th Int. Conf. on Machine Learning, ICML 2013*, 28(PART 3):2275–2283, 2013.
- [34] Kevin Jamieson and Ameet Talwalkar. Non-stochastic best arm identification and hyperparameter optimization. *Proc. of the 19th Int. Conf. on Artificial Intelligence and Statistics, AISTATS 2016*, pages 240–248, 2016.
- [35] Jean-Yves Audibert and Sébastien Bubeck. Best Arm Identification in Multi-Armed Bandits. In *COLT - 23th Conf. on Learning Theory - 2010*, page 13 p., Haifa, Israel, jun 2010.
- [36] Eyal Even-Bar, Shie Mannor, and Yishay Mansour. Action elimination and stopping conditions for the multi-armed bandit and reinforcement learning problems. *Journal of Machine Learning Research*, 7:1079–1105, 2006.
- [37] Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, and Tie-Yan Liu. Lightgbm: A highly efficient gradient boosting decision tree. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems 30*, pages 3146–3154. Curran Associates, Inc., 2017.
- [38] Kaisa Miettinen. *Nonlinear multiobjective optimization*, volume 12. Springer Science & Business Media, 2012.
- [39] Ioannis Giagkiozis and Peter J Fleming. Methods for multi-objective optimization: An analysis. *Information Sciences*, 293:338–350, 2015.
- [40] O. Schutze, A. Lara, and C. A. C. Coello. On the influence of the number of objectives on the hardness of a multiobjective optimization problem. *IEEE Transactions on Evolutionary Computation*, 15(4):444–455, 2011.
- [41] Pedro Saleiro, Benedict Kuester, Abby Stevens, Ari Anisfeld, Loren Hinkson, Jesse London, and Rayid Ghani. Aequitas: A bias and fairness audit toolkit. *arXiv preprint arXiv:1811.05577*, 2018.
- [42] Sam Corbett-Davies, Emma Pierson, Avi Feller, Sharad Goel, and Aziz Huq. Algorithmic Decision Making and the Cost of Fairness. In *Proc. of the 23rd ACM SIGKDD Int. Conf. on Knowledge Discovery and Data Mining - KDD ’17*, pages 797–806, New York, New York, USA, jan 2017. ACM Press.
- [43] Dheeru Dua and Casey Graff. UCI Machine Learning Repository, 2017.
- [44] Diunuge Buddhika Wijesinghe, Saravanaperumal Paraneetharan, Thamayanthy Gogulan, and Burusothman Ahiladas. Predicting excitement at donorschoose.org - kdd cup 2014. 08 2014.
- [45] Solon Barocas and Andrew D Selbst. Big data’s disparate impact. *Calif. L. Rev.*, 104:671, 2016.
- [46] Leo Breiman. Random Forests. *Machine Learning*, 45(1):1–33, 2001.
- [47] Leo Breiman, Jerome Friedman, Charles J Stone, and Richard A Olshen. *Classification and regression trees*. CRC press, 1984.
- [48] Strother H. Walker and David B. Duncan. Estimation of the Probability of an Event as a Function of Several Independent Variables. *Biometrika*, 54(1/2):167, jun 1967.
- [49] Hubert W Lilliefors. On the Kolmogorov-Smirnov Test for Normality with Mean and Variance Unknown. *Journal of the American Statistical Association*, 62(318):399–402, jun 1967.

A SUPPLEMENTARY MATERIALS

Algorithm 1 Pseudocode for FB-auto

Input: maximum budget per configuration R ,
ratio of budget increase η (default $\eta = 3$),
fairness-accuracy trade-off α (default $\alpha = \text{auto}$)

```

1:  $s_{\max} \leftarrow \lfloor \log_{\eta}(R) \rfloor$  ▷ number of SH brackets
2: for  $s \in \{s_{\max}, s_{\max} - 1, \dots, 0\}$  do ▷ HB loop
3:    $n \leftarrow \lfloor \frac{s_{\max}+1}{s+1} \cdot \eta^s \rfloor$ ,  $r \leftarrow R \cdot \eta^{-s}$  ▷ SH bracket parameters
4:    $T \leftarrow$  sample  $n$  hyperparameter configs.
5:   for  $i \in \{0, \dots, s\}$  do ▷ run SH
6:      $M \leftarrow$  train configs.  $T$  with budget  $r_i = \lfloor r\eta^i \rfloor$ 
7:      $A, F \leftarrow$  evaluate accuracy and fairness metrics for all  $M$ 
8:     if  $\alpha = \text{auto}$  then ▷ compute dynamic  $\alpha$  if applicable
9:        $\alpha_i \leftarrow 0.5 \cdot (\sum_j F_j / |F| - \sum_j A_j / |A|) + 0.5$ 
10:    else ▷ using static  $\alpha$ 
11:       $\alpha_i \leftarrow \alpha$ 
12:     $G \leftarrow \{\alpha_i \cdot A[m_{\lambda}] + (1 - \alpha_i) \cdot F[m_{\lambda}] : m_{\lambda} \in M\}$ 
13:     $T \leftarrow$  keep top  $k = \lfloor \lfloor n \cdot \eta^{-i} \rfloor / \eta \rfloor$  from  $T$  ordered by  $G$ 
14: return  $\lambda^*$ , configuration with maximal intermediate goal

```

A.1 Experiments on Public Datasets

We further validate our methodology on three benchmark datasets from the fairness literature. The choice of accuracy and fairness metrics is highly dependent on the task for which a given model is trained, and the real-world setting in which it will be deployed [6]. Thus, we detail a task for each of the datasets we employ, subsequently deriving the metrics we use for each. Additionally, we set target prediction thresholds aiming to cover a wide range of realistic scenarios. When exact threshold targets aren't attainable due to score ties, predictions are untied randomly.

The **Donors Choose** dataset [44] consists in data pertaining to thousands of projects proposed for/by K-12 schools. The objective is to identify projects at risk of getting underfunded to provide tailored interventions. As an assistive funding setting, we select balanced true positive rates across schools from different poverty levels as the fairness metric, also known as equal opportunity [22]. We set a limit of 1000 positive predictions (PP) as a realistic budget for this task. We use precision as a metric of predictive accuracy.

The **Adult** dataset [43] consists on data from the 1994 US census, including age, gender, race, occupation, and income, among others. In order to properly employ this dataset, we devise a scenario of a social security program targeting low-income individuals. In this setting, a positive prediction indicates an income of less than \$50K per year, thus making that person eligible for the assistive program. As an assistive setting, we select balanced true positive rates across genders as the fairness metric (equal opportunity). We target a global true positive rate (recall) of 50%, catching half of the total universe of individuals at need of assistance. Regarding predictive accuracy, we use the precision metric.

The **COMPAS** dataset [2] is a real-world criminal justice dataset. The objective is predicting whether someone will re-offend based on the person's criminal history, demographics, and prior jail time. In this setting, a false positive is an individual that will not re-offend

Algo.	Validation		Test	
	Pred. Acc.	Fairness	Pred. Acc.	Fairness
Donors Choose				
FB-auto	54.2 \blacklozenge	98.2 \blacklozenge	50.7 \blacklozenge	86.5 \blacklozenge
FB	54.2 \blacklozenge	97.7 \blacklozenge	50.4 \blacklozenge	85.5 \blacklozenge
FairRS	51.7 \blacklozenge	97.0 \blacklozenge	50.4 \blacklozenge	79.5 \blacklozenge
FairTPE	52.3 \blacklozenge	96.3 \blacklozenge	50.6 \blacklozenge	79.1 \blacklozenge
HB	60.9	28.7	53.6	35.0
RS	59.9	24.9	53.4	32.4
TPE	61.0	27.1	53.3	33.4
Adult				
FB-auto	92.0 \blacklozenge	94.7 \blacklozenge	91.6 \blacklozenge	90.9 \blacklozenge
FB	92.7 \blacklozenge	94.0 \blacklozenge	92.3 \blacklozenge	89.5 \blacklozenge
FairRS	93.6 \blacklozenge	79.4 \blacklozenge	93.8 \blacklozenge	78.6 \blacklozenge
FairTPE	93.3 \blacklozenge	82.2 \blacklozenge	93.5 \blacklozenge	80.7 \blacklozenge
HB	99.4	53.5	99.0	54.1
RS	99.4	55.7	99.1	56.6
TPE	99.4	54.9	99.1	55.6
COMPAS				
FB-auto	74.0 \blacklozenge	95.8 \blacklozenge	70.1 \blacklozenge	90.0 \blacklozenge
FB	71.2 \blacklozenge	95.5 \blacklozenge	67.6 \blacklozenge	80.7 \blacklozenge
FairRS	67.4 \blacklozenge	77.4 \blacklozenge	64.2 \blacklozenge	67.8 \blacklozenge
FairTPE	67.1 \blacklozenge	81.8 \blacklozenge	63.9 \blacklozenge	69.5 \blacklozenge
HB	78.1	45.4	73.6	51.2
RS	77.7	43.8	73.2	43.4
TPE	78.0	42.8	73.5	46.6

Table 3: Validation and test results on Adult, Donors Choose, and COMPAS datasets. Statistical significance for fairness-aware methods is tested against their respective fairness-blind counterparts with a Kolmogorov-Smirnov test [49]. Results are marked with a \diamond when $p < 0.05$, and a \blacklozenge when $p < 0.01$.

and thus could be re-introduced early into society (e.g., released on bail), but will be wrongfully kept in jail. As a punitive setting, we select balanced false positive rates for individuals of different races as the fairness metric, also known as predictive equality [42]. At the same time, we target a global false positive rate of 10%, in order to maintain a low number of individuals unjustly deemed at “high risk” of re-offending. Regarding predictive accuracy, we use the precision metric.

A.2 Results

Table 3 displays results from all evaluated methods on benchmark datasets from the literature. Figures 6, 7, and 8 show selected models for Adult, COMPAS, and Donors Choose datasets, respectively. We note that the Adult and Donors Choose datasets are approximately one order of magnitude smaller AOF, while COMPAS is two orders of magnitude smaller. Overall results are in accordance with those of the AOF case-study.

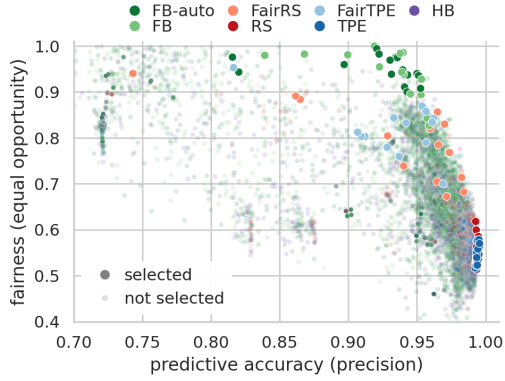


Figure 6: Fairness and predictive accuracy of models sampled and selected by evaluated hyperparameter tuners, on the Adult dataset (validation data).

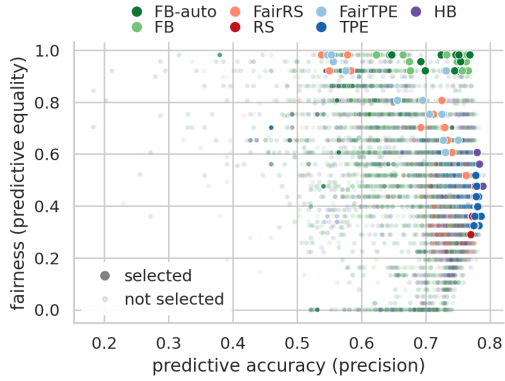


Figure 7: Fairness and predictive accuracy of models sampled and selected by evaluated hyperparameter tuners, on the COMPAS dataset (validation data).

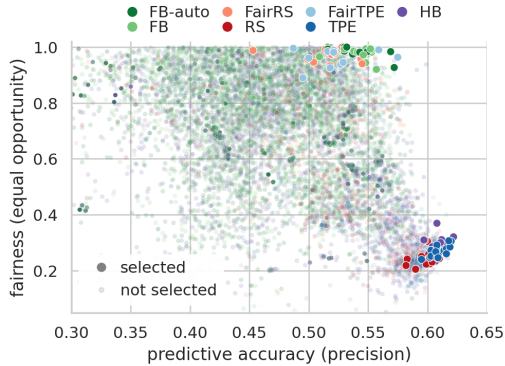


Figure 8: Fairness and predictive accuracy of models sampled and selected by evaluated hyperparameter tuners, on the Donors Choose dataset (validation data).

A.3 Optimizing Bias Reduction Hyperparameters on Adult Dataset

Figure 9 shows a plot of the models selected by FB-auto over 15 runs on the Adult dataset. The introduction of EG creates a new cluster of models in our search space (shown in orange), consisting of possible fairness-accuracy trade-offs in a previously unoccupied region (compare with Figure 6). However, even though these models were trained specifically targeting our fairness metric (equality of opportunity) while the remaining models were trained in a fairness-blind manner, Fairband chooses other model types more often than not. Indeed, the selected NNs and DTs arguably represent the best fairness-accuracy trade-offs. Interestingly, the types of ML models on the Pareto frontier is distinctly different from those observed on the AOF dataset (Figure 5). However, once again, RF consistently displays worse fairness-accuracy trade-offs than LGBM, and these relations between specific hyperparameters and better/worse fairness will be studied in future work. Similarly to the results on the AOF dataset, it is shown that blindly applying bias reduction techniques may lead to sub-optimal fairness-accuracy trade-offs.

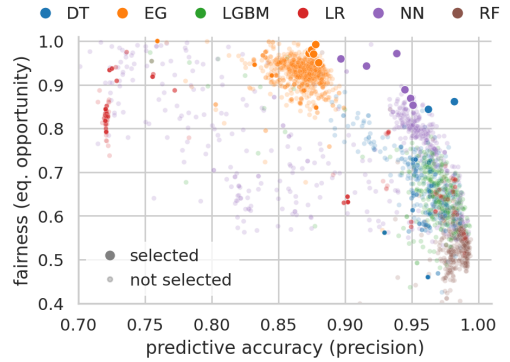


Figure 9: Fairness and predictive accuracy of selected models for FB-auto, discriminated by model type, on the Adult dataset. Search space includes the in-processing bias reduction method *Exponentiated Gradient* (EG) reduction [9], used together with Decision Tree classifiers.